An adaptive multi-objective framework for the scheduling of environmental flow management alternatives using ant colony optimization

Joanna Margaret Szemis
BEng (Civil & Structural) Hons

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Contents

Abstract

Rivers and their adjacent wetlands and floodplains worldwide have been altered or have vanished as a result of river regulation and development (such as dams, locks and weirs), as well as water over-allocation. In recent years, environmental flow management has been suggested as a means to mitigate these negative impacts. One approach in order to do this is through the scheduling of environmental flow management alternatives (EFMAs), such as reservoir releases and the operation of wetland regulators. However, this is not an easy task for the following reasons: (i) there are generally many wetlands and floodplains in any particular river system, all containing a wide range of biota that have different flow requirements; (ii) there is generally limited water allocated for environmental purposes, since there are multiple users (e.g. irrigation, domestic), all competing for the same water source; (iii) the schedules are generally developed over multiple years; and (iv) there are multiple competing objectives and constraints that need to be considered. This problem therefore lends itself to be formulated as an optimization problem, where the aim is to maximise the ecological integrity of the system, while also considering humans needs and the constraints of the system.

In this thesis, a generic adaptive multi-objective optimization framework for determining the optimal schedule of EFMAs for rivers and their associated wetlands and floodplains is developed and tested. In order to achieve this, ant colony optimization algorithms are selected, since they can take into account the conditional dependencies and sequential nature of the scheduling problem explicitly. This is possible, as the solution space can be represented by a graph structure that can be adjusted dynamically based on the choices made at

previous points in the decision graph, thereby reducing the size of the decision space and increasing the proportion of feasible solutions. This is not possible when most other metaheuristics are used. In addition to this, the framework is adaptive and able to incorporate forecasts of environmental water allocation, such that the environmental water can be used most efficiently in order to maximize ecological response.

The major research contributions are presented in three journal publications. Firstly, the initial single-objective formulation of the optimisation framework, which incorporates the temporal dependencies associated with the scheduling of EFMAs is presented and validated using a hypothetical case study. The framework is then extended to incorporate multiple objectives and applied to a river section in the South Australian River Murray, so that the trade-off between the ecological response and environmental water allocation can be examined. Finally the framework is further extended to incorporate adaptive features by using forecasts of environmental water allocation in the development of EFMA schedules, as well as an additional objective which aims to minimise the number of differences of EFMA schedules developed at subsequent time steps. Thus the framework provides valuable insight to managers into the EFMA scheduling problem, as it can be applied to investigate a wide variety of problems, such as investigating the likely ecological benefit gained from an increase in environmental allocation, the impact of system constraints on ecological response and the potential advantages of investment in additional infrastructure.

Statement of Originality

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List of Figures

List of Tables

Chapter 1

1 Introduction

Freshwater ecosystems, including rivers, wetlands and floodplains are amongst the most endangered systems in the world (*Jenkins*, 2003). This is due to the increase of the global population intensifying the conflict over water resources, and the threat of climate change, which could possibly lead to further river development (e.g. dams) and, in turn, additional stress on rivers and their associated wetlands and floodplains (*Arthington et al.*, 2006). There is a growing consensus that rivers are "legitimate" water users and as such, environmental flow management, which involves releasing flows specifically for the environment, should be undertaken to protect, maintain and restore these systems (*Arthington et al.*, 2006). In the past, environmental flow management involved releasing a minimum flow, however, the concept of the "natural flow paradigm" introduced by Poff et al., (1997), where the flows that existed prior to river development are reintroduced, should form the basis of any environmental flow management plan. Poff et al., (1997) highlighted five key flow components, including duration, timing, magnitude, frequency and rate of change of flow that should be take into account, since these factors govern structure and function, and in turn, the ecological health of rivers, wetlands and floodplains (*Junk et al.*, 1989).

In order to achieve the required ecological response, there are a number of management alternatives, including reservoir releases and/or the operation of structures, such as wetland regulators, that can be employed. The decisions involved in scheduling management alternatives are made at discrete timesteps, with additional decisions relating to time, magnitude and duration of the management alternative also needing to be made. For instance, the operation of a wetland regulator would involve selection of the duration and the time at which a gate should be opened or closed. Because these decisions are generally made over long temporal scales (e.g. multiple years) and different spatial scales (e.g. numerous locations of regulators or reservoirs), the search space of possible management alternatives is extremely large.

The scheduling of environmental flow management alternatives (EFMAs) becomes even more complicated because: (i) not only does the river need to be considered, but also adjacent wetlands and floodplains; (ii) there are different ecological processes that must be taken into account, including the maintenance of adult species and the recruitment of juveniles (e.g. breeding of wildlife), which results in different flow requirements (*Rogers*, 2011b); (iii) there are many species that, at times, have competing flow requirements; (iv) the schedules generally need to be developed over multiple years, since there are species, such as the Black Box woodland (*Eucalyptus largiflorens*), that require a maintenance flood frequency of 1 in 2 to 5 years (*Rogers*, 2011b), thereby introducing temporal dependencies into the scheduling process (i.e. decisions made at each time step are not independent of each other); (v) generally there is limited water available for environmental purposes, given that there are number of users (e.g. irrigation, domestic), all competing for the same water source (*Wallace et al.*, 2003); and (vi) there might be flow restrictions as a consequence of system constraints within the area of interest. Given this complexity, there is potential benefit in employing optimization approaches to schedule EFMAs to maximise the chance that rivers, wetlands and floodplains are restored and preserved for future generations in locations where environmental water is limited.

There have been a number of optimization studies in environmental flow management, however many have considered ecological objectives in a simplistic manner, with some studies not considering the five key flow components, (*Chang et al.*, 2010; *Chaves et al.*, 2003), while in others, the importance of competing ecological objectives is neglected (*Cardwell et al.*, 1996; *Tilmant et al.*, 2010; *Yang*, 2011; *Yang and Cai*, 2011). In almost all of the studies, there was no consideration of both the river and downstream wetlands and floodplains, or the temporal dependencies between management options (*Homa et al.*, 2005; *Shiau and Wu*, 2004; 2007; 2013; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2011). *Higgins et al.* (2011) was the only study to take into account the river and adjacent wetlands and floodplains They employ optimization to obtain optimal operating regimes for wetland regulators and weirs by matching the flood timing, dry period and flood duration in natural conditions. However, there is no existing optimization framework that can be used to: (i) develop schedules that maximize the ecological response of rivers and their wetlands and floodplains for a given environmental water allocation; (ii) incorporate the five flow components as defined by Poff et al. (1997); (iii) develop schedules that favor certain ecological process or species; and (iv) assess the optimal trade-offs between water allocated to the environment and the corresponding optimal ecological responses of affected wetlands and floodplains or particular species, which is of interest to water and wetland managers who operate EFMAs.

In addition to this, previous optimization studies depend on the historical natural flow hydrology or a known volume of water being available for the environment in their assessment. This is a significant shortcoming, as environmental water is most likely to change annually as a result of the natural variability of hydrological regimes within rivers, wetlands and floodplains (*GSA*, 2013). Given that EFMA schedules are developed over extended time periods, as mentioned previously, the schedules developed based on assumed water availabilities are most likely not truly optimal and, as a result, for a specific environmental water allocation, the optimal ecological outcome may not be achieved. Thus, there is a need to also develop an adaptive optimization approach, where EFMA schedules are updated at regular intervals over the planning horizon, such that updated information on hydrological conditions can be considered (e.g incoporating environmental water allocation forecasts). Simultaneously, restrictions to any changes made to optimal schedules developed previously must be considered, such that the possible negative impacts on the EFMA schedules and related resource schedules (e.g. human resources, equipment) are kept to a minimum during the re-optimization process.

1.1 Research Objectives

This research aims to develop a generic adaptive multi-objective optimization framework for the scheduling of environmental flow management alternatives, which can take into account the river, wetlands and floodplains over large spatial and long temporal scales. The development of the framework will ultimately aid water and wetland managers in making informed decisions in relation to environmental flow management, such that the ecological response of rives, wetlands and floodplains is maximised when there is a limited volume of environmental water available and the operation of the system is subject to constraints. To achieve the overall aim of this research, two main research objectives have been identified, each of which has a number of sub-objectives, as given below. The linking of each of these objectives is shown in Figure 1.1.

Objective 1: To develop an adaptive multi-objective optimization framework for the scheduling of environmental flow management alternatives (EFMAs) (Journal Papers 1, 2 and 3)

Objective 1.1: To formulate a single-objective optimization framework, which incorporates temporal dependencies associated with the scheduling of EFMAs over long planning horizons (Journal Paper 1)

Objective 1.2: To extend the framework in Objective 1.1, such that multiple objectives can be considered in the scheduling of EFMAs (Journal Paper 2)

Objective 1.3: To develop an adaptive approach by extending the framework in Objective 1.2 (Journal Paper 3)

Objective 2: To demonstrate the utility of the framework (Journal Papers 1, 2 and 3)

Objective 2.1: To validate and apply the framework developed in Objective 1.1 to a hypothetical case study based on the South Australian River Murray (Journal Paper 1)

Objective 2.2: To apply the framework to a real case study of the South Australian River Murray (Journal Papers 2, 3)

Objective 2.3: To develop and assess the trade-offs between ecological response and environmental water allocation for a range of infrastructure options using the framework developed in Objective 1.2 (Journal Paper 2)

Objective 2.4: To assess the utility of the adaptive features incorporated in the approach developed in Objective 1.3, which include (i) the use of environmental water allocation forecasts and (ii) the assessment of the trade-off between limiting the number of differences of schedules at subsequent timesteps and the ecological response . (Journal Paper 3)

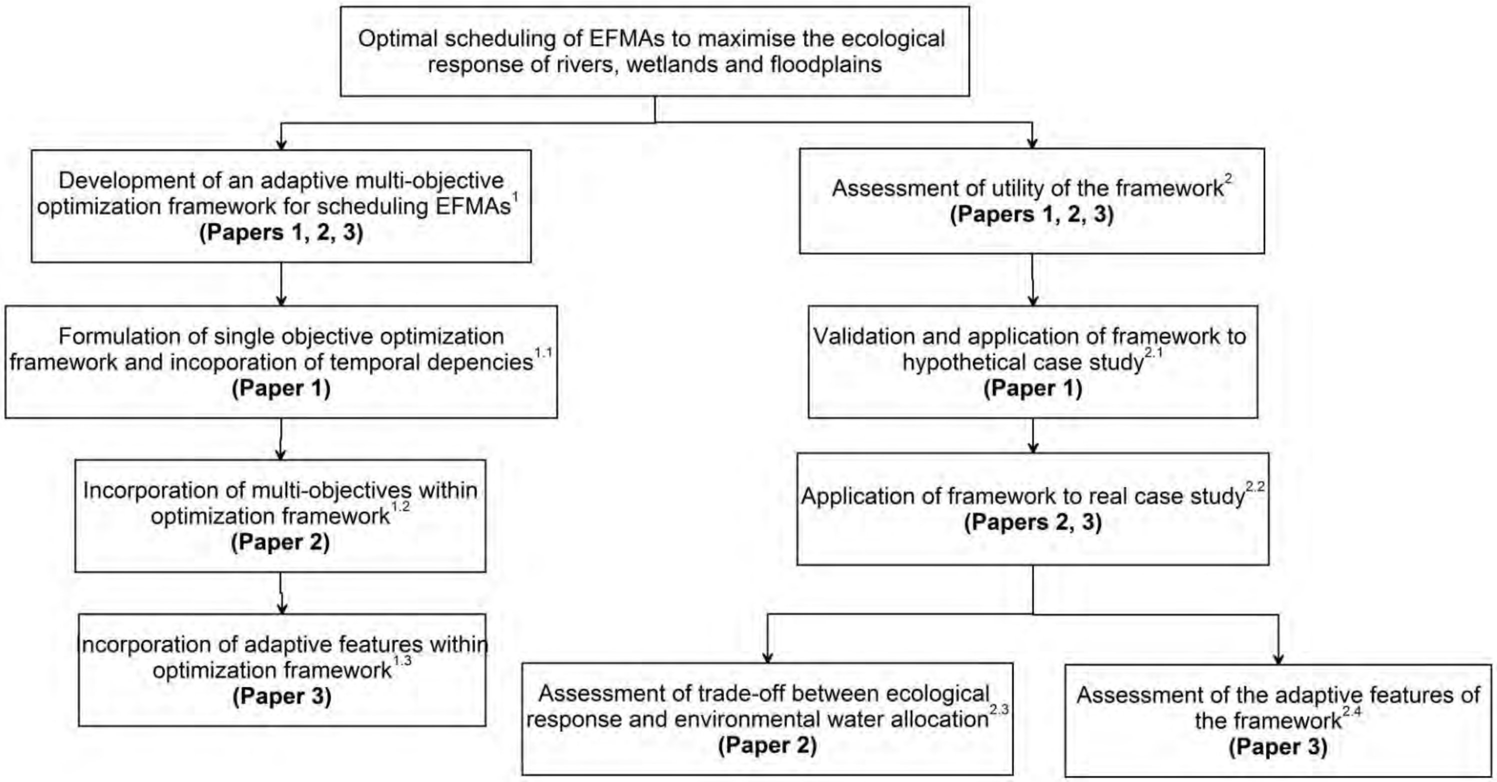

Figure 1.1: Research objectives and their hierarchy. Objectives are denoted by the superscript numbers in each of the flowchart boxes.

1.2 Thesis Overview

This thesis consist of five chapters, with the main body presented in **Chapters 2** to **4**, which correspond to three journal papers (*Szemis et al.*, 2012; *Szemis et al.*, 2013; *Szemis et al.*, 2014).

In **Chapter 2**, a new optimisation framework for the scheduling of EFMAs for rivers, wetlands and floodplains is presented (**Objective 1**), where the formulation and the incorporation of temporal dependencies associated with the problem are described (*Objective 1.1*). The utility of the framework is demonstrated (**Objective 2**) by validating and applying it using a hypothetical case study (*Objective 2.1*).

In **Chapter 3**, the framework in **Chapter 2** is extended to incorporate multiple objectives (*Objective 1.2*) and is then applied to real case study of a river section of the South Australian River Murray (*Objective 2.2*), where the trade-offs between ecological response and environmental water allocation are assessed (*Objective 2.3*).

In **Chapter 4**, the work in **Chapter 2** is further extended to incorporate adaptive features (*Objective 1.3*) and is again applied to the real case study in order to demonstrate the utility of the adaptive features, that is, the consideration of forecasts of future environmental water allocation, as well as an assessment of the trade-off between the limitation of disruptions to the EFMA schedules and ecological response (*Objective 2.4*).

The linking of each of the papers to the objectives is shown in Figure 1.1. Although the manuscripts have been reformatted in accordance with University guidelines, and sections renumbered for inclusion within this thesis, the material within these papers is otherwise presented herein as published. Copies of the first two papers "as published" are provided in Appendices A and B.

Conclusions of the research within this thesis are provided in **Chapter 5**, which summarises: 1) the research contributions, 2) limitations and 3) future directions for further research.

Chapter 2

2 A framework for using ant colony optimization to schedule environmental flow management alternatives for rivers, wetlands, and floodplains (Paper 1)

Statement of Authorship

Title of Paper	A framework for using ant colony optimization to schedule environmental flow management alternatives for rivers, wetlands, and floodplains
Publication Status	⦿ Published, O Accepted for Publication, O Submitted for Publication, O Publication style
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Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Joanna Szemis		
Contribution to the Paper	Conceptual and algorithm development, analysis of results, manuscript preparation and corresponding author.		
Signature		Date	11/06/2014

Name of Co-Author	Holger Maier		
Contribution to the Paper	Research supervision and review of manuscript		
Signature		Date	06/06/2014

Name of Co-Author	Graeme Dandy		
Contribution to the Paper	Research supervision and review of manuscript		
Signature		Date	11/06/2014

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Abstract

Rivers, wetlands, and floodplains are in need of management as they have been altered from natural conditions and are at risk of vanishing because of river development. One method to mitigate these impacts involves the scheduling of environmental flow management alternatives (EFMA); however, this is a complex task as there are generally a large number of ecological assets (e.g., wetlands) that need to be considered, each with species with competing flow requirements. Hence, this problem evolves into an optimization problem to maximize an ecological benefit within constraints imposed by human needs and the physical layout of the system. This paper presents a novel optimization framework which uses ant colony optimization to enable optimal scheduling of EFMAs, given constraints on the environmental water that is available. This optimization algorithm is selected because, unlike other currently popular algorithms, it is able to account for all aspects of the problem. The approach is validated by comparing it to a heuristic approach, and its utility is demonstrated using a case study based on the Murray River in South Australia to investigate (1) the trade-off between plant recruitment (i.e., promoting germination) and maintenance (i.e., maintaining habitat) flow requirements, (2) the trade-off between flora and fauna flow requirements, and (3) a hydrograph inversion case. The results demonstrate the usefulness and flexibility of the proposed framework as it is able to determine EFMA schedules that provide optimal or near-optimal trade-offs between the competing needs of species under a range of operating conditions and valuable insight for managers.

2.1 Introduction

Rivers and their associated wetlands and floodplains provide vital ecosystem services that people depend upon, such as water purification, habitat for wildlife and climate mitigation (*MEA*, 2005). Many of these systems have been severely altered, or have even vanished, due to the development of infrastructure, such as channelization and dams, land conversion, and the over allocation of water for human needs (*Brookes*, 1988; *Kingsford*, 2000; *MEA*, 2005; *Nel et al.*, 2008). This has altered the hydrological regime, reducing the level of connectivity and flooding between rivers and associated floodplains and wetlands, thereby changing their ecology and causing the death or poor health of their biota (*Kingsford*, 2000; *Kingsford and Auld*, 2005). According to National Research Council (1992), the rate at which freshwater ecosystems are being altered or destroyed is much greater now than at any other time in human history. To mitigate the impacts of these alterations, there is an urgent need to improve the connectivity between rivers and their adjacent wetlands and floodplains, so that they can be maintained and protected for future generations.

In order to address the problem outlined above, the provision of water for environmental flows has been suggested (*Arthington et al.*, 1998; *Kingsford*, 2000). In the past, this consisted of releasing a minimum flow, which has now been deemed to be inadequate (*Arthington et al.*, 2006). Instead, it has been suggested that managed flow regimes should follow the 'natural flow paradigm' developed by *Poff et al*. (1997) in order to reintroduce the flow variability that has been lost as a result of human induced flow alteration (*Poff*, 2009). Five flow components were presented by *Poff et al*. (1997) as the key to ensuring the ecological integrity of river systems, including the timing, duration, magnitude, frequency and rate of rise/fall of flow. These components are also important when flooding adjacent wetlands and floodplains, as it is these factors that govern the structure and function, and in turn, the health of wetlands and floodplains (*Junk et al.*, 1989). For example, the timing of inundation can affect the recruitment and regeneration of plants (e.g. (*Cordes et al.*, 1997)), flood duration can influence plant cover and diversity (e.g. (*Busch and Smith*, 1995)), while a combination of the timing, duration and rate of change of flooding can impact the life cycles of fish species (*Junk et al.*, 1989). River, wetland and floodplain biota are dependent on these flow components and a significant amount of research has been undertaken to quantify these ecological responses (*Poff and Zimmerman*, 2010).

The pursuit of environmental integrity criteria, such as those developed by *Poff et al*. (1997) constitute the primary objective of any management program. A number of management alternatives are available for achieving the corresponding environmental flow requirements for rivers, wetlands and floodplains, including environmental flow releases from upstream storages and the operation of flow control infrastructure, such as regulators and pumps. Decisions have to be made in relation to the timing, magnitude and duration of potential flow releases and infrastructure operation. In other words, at discrete points in time (e.g., day, week, month), decisions have to be made whether an environmental flow release should be made and/or whether a change should be made to the setting of flow control infrastructure. These decisions must be made in pursuit of an objective that seeks to maximize some measure of ecological health. If the decision is made to release environmental flows and/or make a change to the setting of flow control infrastructure, a choice has to be made in relation to what fraction of the available environmental flow allocation to release at this time and/or which of the available infrastructure change options should be implemented, and how long this management action should persist. Given that these decisions generally have to be made at discrete time steps over a given planning horizon (e.g., several years) and at numerous locations (e.g., locations of reservoirs, regulators and pumps), the search space of potential management alternatives in this scheduling problem is generally extremely large, particularly when dealing with extended spatial and temporal scales.

The scheduling of environmental flow management alternatives (EFMAs) is further complicated by the fact that (i) there are often different processes that must be accounted for in managing a single species, such as (a) promoting the maintenance of adult species and the recruitment of juveniles (e.g., germination of plant species and breeding of wildlife), resulting in varying flow requirements (*Rogers*, 2011b), or (b) ensuring the succession and retrogression of floodplain vegetation, which introduces an additional shear stress factor (*Benjankar et al.*, 2011), (ii) flow requirements are generally different for each species of flora and fauna, and may be in competition with each other, which is a problem that is often exacerbated when considering extended spatial scales, as the number of species that need to be considered is generally larger, and (iii) schedules generally need to be developed over multiple years, since there are species, such as the Black Box woodland (Eucalyptus largiflorens), that require a maintenance flood frequency of 1 in 2–5 years (*Rogers*, 2011b), thereby introducing temporal dependencies into the scheduling process (i.e., decisions made at each time step are not independent of each other).

Given the extremely large search space of management options, the large number of generally competing environmental flow requirements, and the temporal dependencies between management alternatives, the problem of scheduling EFMAs so as to maximize ecological outcomes is extremely difficult. However, such a goal is very important, particularly given that limited amounts of water are generally available for environmental purposes, as there is competition for water resources between various uses, such as irrigation, domestic and industrial water supply, power generation, recreation, and the restoration, rehabilitation and maintenance of ecological services. Given this complexity, there is potential benefit in using formal optimization approaches for addressing the environmental flow management problem. However, previous optimization studies in this field have primarily focused on the higher-level problem of the development of optimal reservoir/weir operating rule parameters or monthly reservoir releases, while trying to maintain an adequate balance between the needs of the environment and other water users (e.g., irrigation), rather than the specific problem of how to allocate a given environmental water allocation so as to maximize ecological outcomes. As a result, ecological objectives have been treated in a rather simplistic manner in past optimization studies. For example, in some studies, there was no consideration of the important flow components (*Chang et al.*, 2010; *Chaves et al.*, 2003), while in others, the importance of competing ecological objectives was neglected (*Cardwell et al.*, 1996; *Tilmant et al.*, 2010; *Yang*, 2011; *Yang and Cai*, 2011). In almost all of the studies, there was no consideration of both river and downstream wetlands and floodplains, or the temporal dependencies between management options (*Homa et al.*, 2005; *Shiau and Wu*, 2004; 2007; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2010). Only *Higgins et al.* (2011) considered the river, wetlands and floodplains on a landscape scale and used optimization to determine the best locations and operating regimes for wetland regulators and weirs by mimicking the natural flood timing, dry period and flood duration. However, there is no existing optimization framework that can be used to (i) develop schedules that maximize the ecological response of rivers and their wetlands and floodplains for a given environmental water allocation, (ii) incorporate not only flood timing, dry period, and duration but also depth (which affects seed germination (*Rogers*, 2011b)), and (iii) develop schedules that favor certain ecological process or species. Consequently, there is a need to develop and test a generic framework for determining the optimal schedule of EFMAs for rivers and their wetlands and floodplains for a given environmental water allocation that takes into account (i) rivers and adjacent wetlands and floodplains, (ii) a large number of potential management alternatives, (iii) multiple and potentially competing environmental objectives associated with important flow components, process and species, and (iv) temporal dependencies associated with the important flow components.

In order to meet this need, the specific objectives of this paper are (i) to develop an optimization framework for maximizing the ecological response of rivers and their wetlands and floodplains (e.g., by using the Murray Flow Assessment Tool (MFAT) developed by *Young et al.* (2003), as is done in the case study presented in this paper) for a given environmental flow allocation, by determining the optimal scheduling of predetermined EFMAs, such as flow releases and regulator settings, which is able to take account of (a) a large number of possible management alternatives, (b) a range of environmental objectives (e.g., ecological responses of flora and fauna species and associated processes), (c) constraints associated with environmental water allocations, and (d) the temporal dependencies associated with the management alternatives; (ii) to develop an approach that is capable of solving the optimization problem formulated in objective i, and (iii) to apply the optimization framework and solution methodology developed in objectives i and ii to a case study in order (a) to demonstrate how they are applied in practice, (b) to validate their performance, (c) to illustrate how they can be used to account for competing requirements of individual species, (d) to illustrate how they can be used to account for competing requirements of flora and fauna, and (e) to illustrate how they can be used to deal with environmental water allocations of different magnitude and timing (e.g., hydrograph inversion).

The remainder of this paper is organized as follows. The novel optimization framework is introduced in section 2.2, followed by the optimization approach for solving it in section 2.3. The case study used to illustrate the utility and validate the proposed formulation and solution approach is introduced in section 2.4, while details of the numerical experiments conducted are provided in section 2.5. Results and discussion are presented in section 2.6, followed by a summary and conclusions in section2 .7.

2.2 Framework for the Optimal Scheduling of Environmental Flow Management Alternatives

In this section, the framework for the optimal scheduling of EFMAs aimed at restoring, protecting and maintaining rivers and their wetlands and floodplains is introduced (objective i), which has been adapted from the systems approach proposed by *Biswas* (1976) and is shown in Figure 2.1.

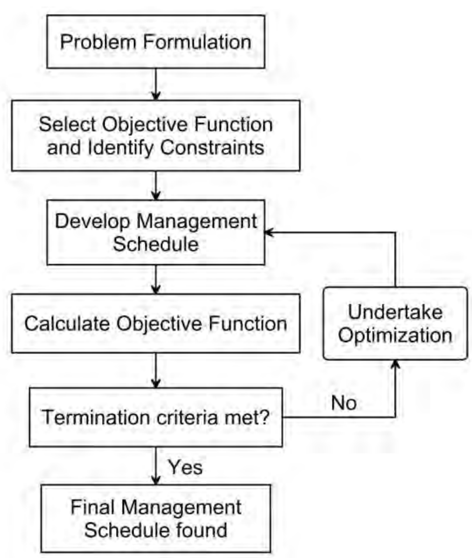

Figure 2.1: Representation of the optimal scheduling of environmental flow management alternative

The first step in the optimization framework is problem formulation, which includes identification of the wetlands, floodplains and river reaches to be managed, identification and selection of appropriate ecological indicators (e.g., flora/fauna species, flow components or shear stress), the planning horizon over which the schedule for the EFMAs is to be developed (e.g., number of years), the time interval (e.g., monthly or yearly time steps) at which alternatives are to be scheduled, and finally, specification of the EFMAs that are available for achieving the desired ecological response (e.g., flow release options, regulator settings, pumping schedule), as well as the suboptions associated with each of these alternatives (e.g., magnitude, duration). Next, the objective function (e.g., maximization of ecological response) and any constraints (e.g., maximum available environmental water allocation) need to be defined, after which a schedule for the EFMAs can be developed. The objective function (e.g., overall ecological response of the system under consideration) is then calculated to assess the utility of the selected schedule. The process of selecting different schedules and evaluating their utility is generally repeated many times and guided by the selected optimization method in order to find optimal or near-optimal solutions (e.g., schedules of EFMAs). Each of these steps is discussed in more detail in sections 2.2.1–2.2.4

2.2.1 Problem Formulation

The first step in formulating the optimal scheduling problem, shown in Figure 2.2, involves the identification of the q wetlands, floodplains and river reaches that require protection, restoration or maintenance, where the wetlands, floodplains and river reaches are defined as H_i, and i ranges from 1 to q.

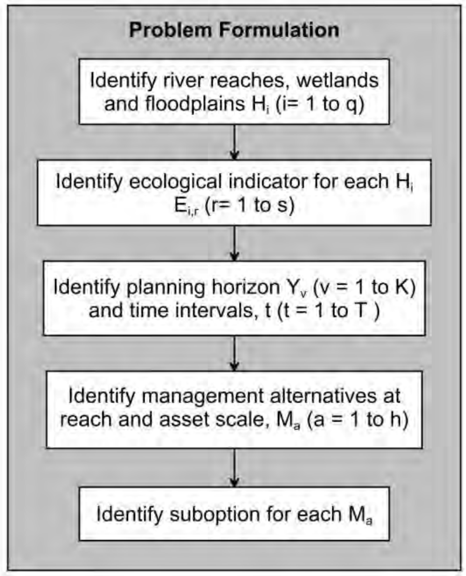

Figure 2.2: Steps in formulation of environmental flow management schedule optimization problem. The river reaches, wetlands, and floodplains are defined as H_i, and i ranges from 1 to q. The ecological indicators, $E_{i,r}$, where r ranges from 1 to s, are specified for each H_i. The planning horizon is defined as Y_v, where v ranges from 1 to v years, while the time interval, t, ranges from 1 to the final time interval, T. The number of management alternatives, M_a, ranges from 1 to h

Next, appropriate ecological indicators $E_{i,r}$, are specified for each wetland, floodplain and river reach, H_i, in order to assess the performance of each potential management schedule in terms of ecological response. For example, the r ecological indicator/s (ranging from 1 to s) can be used to assess the ability to simulate the natural flow regime (*Richter et al.*, 1996), assess processes that govern the life cycle of different types of flora and fauna species (*Young et al.*, 2003), or measure the succession and retrogression of vegetation (*Benjankar et al.*, 2011). The choice of the number and types of indicators is case study dependent. It should be noted that there are other ecological responses that can be taken into account, such as the fact that lower peak flows can increase ecological response through terrestrialization of riparian areas or the encroachment of the river channel by riparian communities (*Poff and Zimmerman*, 2010). However, such ecological responses can only be incorporated if they can be represented in the form of an ecological indicator, which is a limitation of the proposed optimization framework.

Once the wetlands, floodplains, river reaches and ecological indicators have been identified, the planning horizon over which the schedules need to be developed, Y_v, where v ranges from 1 to K years, and the time intervals between potential management actions during the period, t, which ranges from 1 to T time intervals, should be selected. Selection of appropriate values for these variables is also problem dependent.

The next step in the problem formulation procedure is the specification of the management alternatives, which can be divided into two groups. The first category includes reach-scale management alternatives, which affect the hydrological regime of the entire river system. These include reservoir releases or weir operations that govern the flow within the entire river reach and affect wetland and floodplain inundation. The second type includes management alternatives that manipulate hydrological regimes for individual wetlands and floodplains. An example is the manipulation of water levels using individual gates and/or pumps at the entrances or exits of wetlands, which could prevent, allow, or force water from entering or leaving. The combination of reach, wetland, and floodplain scale management options constitutes the final set of management alternatives, M_a, where a ranges from 1 to h.

The final stage of the problem formulation step involves the specification of the suboptions for each management alternative, that is, the magnitude, duration and timing of the proposed management interventions described in section 2.1. All of the available suboptions need to be specified for each of the management alternatives in order to define the decision space in its entirety.

2.2.2 Selection of Objective Function and Constraints

The second stage of the proposed optimization framework involves definition of the objectives and constraints. It is important to select an appropriate objective function, as this characterizes how well different management schedules perform. The constraints, on the other hand, ensure that infeasible schedules are not considered.

The objective function used to assess the performance of the proposed management schedules should consider all of the wetlands, floodplains and river reaches, as well as the selected ecological indicator(s). Since there are generally multiple, and at times competing, indicators, the values of individual indicators need to be summed over all ecological assets (e.g., river reaches, wetlands, floodplains) in order to obtain an estimate of the ecological response of the entire system under investigation for a given management schedule. In order to account for differences in the relative importance of various ecological assets, indicators, and time periods, user defined weights are included. Consequently, the proposed objective function takes the following form:

$$F = \sum_{i=1}^{q} w_{1i} \sum_{r=1}^{s} w_{2r} \sum_{v=1}^{K} \frac{w_{3v} E_{i,r,v}}{Y_K} \tag{2.1}$$

where $E_{i,r,v}$ is the indicator value for asset i, for indicator type r in the vth yearly time interval. In equation (2.1), the overall objective function value is obtained by summing (1) values of each ecological indicator over the q wetlands, floodplains and river reaches considered, (2) values of the s indicators used for each wetland, floodplain, and river reach, and (3) ecological indicator values over the number of years (Y_K) over which the schedule of EFMAs has been developed (i.e., the planning horizon). Weights, w_{1i}, w_{2r} and w_{3v} place emphasis on the qth wetlands, floodplains or river reaches, rth ecological indicator and Y_Kth year, respectively. Consequently, the proposed objective function is sufficiently flexible to cater to particular aspects of the problem (e.g., favoring an endangered species), while also ensuring that an overall ecological score is obtained for the river system.

Once the objective function has been defined, the constraints need to be specified to ensure infeasible schedules of EFMAs are not developed. Since the aim of the research is to develop EFMA schedules that optimize the environmental benefit associated with a given amount of environmental water, constraints have to be placed on the total amount of water that is available for environmental purposes, which is likely to vary over the planning horizon (e.g., on a seasonal basis), as given by

$$\sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \leq A_{\max\_ni(pd)} \tag{2.2}$$

where, *pd* is the number of periods of constrained environmental water allocations, ranging from 1 to *np*, while the number of increments in each period, *ni(p)* ranges from 1 to *Vp*, and *i_ni(pd)* and *f_ni(pd)* are the corresponding initial and final time steps for *pd*, over which a particular water allocation is released. The duration of each increment is defined as $d_{ni(p)}$, and the summation of all duration increments for each period must equal the total duration interval, T_d. Being able to have different allocation constraints for different time periods during the planning horizon provides the ability to account for situations such as hydrograph inversion, or physical constraints on water release infrastructure.

Constraints also have to be placed on the magnitude and duration of the sub-options for a particular management alternative, M_a, as given in Equations 2.3 and 2.4:

$$M_{a,m\_\min} \leq M_{a,m} < M_{a,m\_\max}, \qquad m = 1 \text{ to } n \tag{2.3}$$

$$M_{a,d\_\min} \leq M_{a,d} < M_{a,d\_\max}, \qquad d = 1 \text{ to } p \tag{2.4}$$

where the magnitude sub-options for wetlands, floodplains, and river reaches are $M_{a,m}$, which are constrained by minimum and maximum values of M_{a,m_min} and M_{a,m_max}, respectively, and the duration sub-options are $M_{a,d}$, which are constrained by minimum and maximum values of M_{a,d_min} and M_{a,d_max}, respectively, for each management alternative. The m possible magnitude sub-options, $M_{a,m}$, range from 1 to n and $M_{a,d}$ is the number of duration sub-options available, where d is between 1 and p. Each management alternative must therefore be assessed individually in order to determine appropriate values for the above constraints. These ranges may depend on the characteristics of the wetlands and floodplains, or the chosen ecological indicator.

If a yearly time step is chosen, then an additional timing constraint is required to determine during which month a particular management alternative should be implemented. However, such a constraint is not required if a monthly time step is adopted. Other constraints that must taken into account are mass balance constraints, for instance the overall water entering the system must equal the water leaving system (through either water allocated to the wetlands and floodplains or evaporation).

2.2.3 Environmental Flow Management Schedules Development

Once the problem has been formulated, management schedules can be constructed by first selecting a management alternative, as shown in Figure 2.3. Next, a schedule needs to be constructed for all T time intervals. In order to do this, the magnitude suboptions for M_a should be selected, followed by an assessment of the number of available duration suboptions, $M_{a,d}$. The second step is necessary, as the number of duration suboptions can change during the generation of a schedule. For example, if a monthly time step were used, there would be a maximum of twelve duration options at the beginning of a year, which would reduce to six halfway through the year. Consequently, the conditional dependencies associated with the selection of $M_{a,d}$ need to be taken into account during the schedule generation process, as shown by the loops in Figure 2.3. Once all suboptions have been selected at each time step for a particular management alternative, this process has to be repeated for all of the remaining management alternatives until a complete EFMA schedule has been developed.

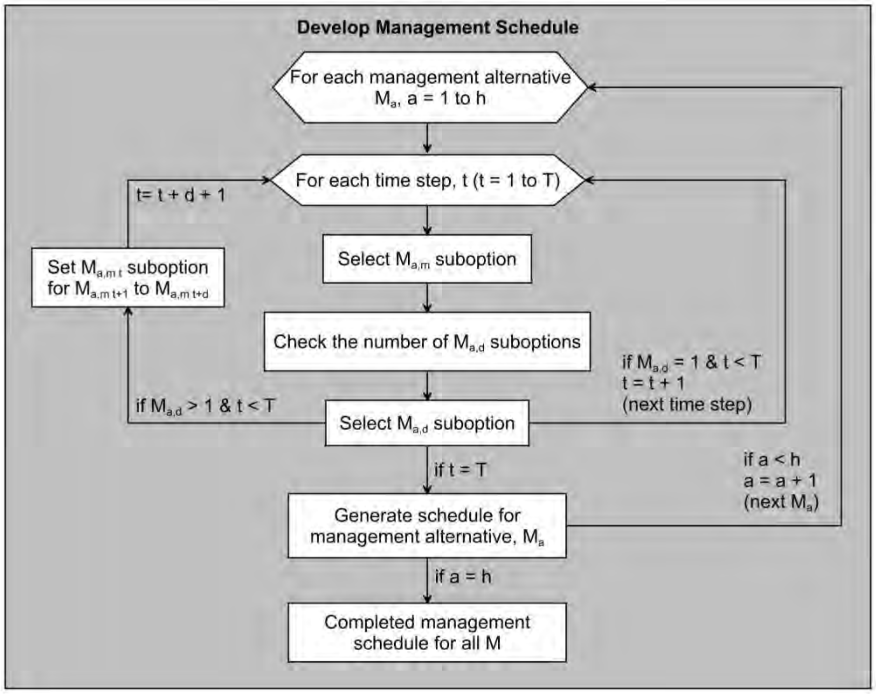

Figure 2.3: Environmental flow management schedule development, where the number of management alternative, M_a, ranges from 1 to h. The time step, t, ranges from 1 to T months, while $M_{a,m}$ and $M_{a,d}$ are the magnitude and duration suboptions for each M_a and d corresponds to the duration of $M_{a,d}$

This procedure demonstrates the sequential nature and dependencies of the optimal scheduling problem, where decision made at certain time steps affect the choices that are available at subsequent time steps. It is vital that such information be taken into account, as it can affect the quality of the management schedule developed, as well as the efficiency with which it is generated.

2.2.4 Calculation of Objective Function and Optimization

Once an EFMA schedule has been developed, its utility needs to be assessed, which is done via the objective function (equation (2.1)). In order to calculate the objective function, a simulation model, such as a hydrological model of the river system, is generally used in order to determine the flow regime within each river reach, floodplain and wetland, as well as the resulting ecological indicator score. Once the objective function has been calculated, its value is used during the optimization procedure in order to develop better solutions (i.e., schedules of EFMAs), as shown in Figure 2.1. The cycle of development, simulation and assessment of EFMA schedules using optimization continues, until the selected termination criteria are met. A discussion of the proposed optimization method for solving the optimal scheduling problem is presented in the next section

2.3 Proposed Ant Colony Optimization for the Scheduling of Environmental Flow Management Alternatives

There are a number of candidate optimization algorithms for solving the optimal scheduling problem formulated in section 2.2, including traditional forms of optimization, such as linear and dynamic programming (*Taha*, 1997) and metaheuristics, for instance, genetic algorithms (GA) (*Goldberg*, 1989) and ant colony optimization (ACO) algorithms (*Dorigo et al.*, 1996). Linear programming only works for linear objective functions and constraints (*Taha*, 1997), resulting in the inability to solve complex nonlinear problem, such as the optimal scheduling problem presented here. Dynamic programming, on the other hand, overcomes this problem by using the principle of optimality to determine optimal solutions (*Taha*, 1997), while genetic and ACO algorithms achieve this by using the principle of survival of the fittest (*Goldberg*, 1989) and the foraging behavior of ants (*Dorigo et al.*, 1996), respectively. However, dynamic programming suffers from the 'curse of dimensionality', which means that it has difficultly solving problems with large search spaces, as the computational requirements grow exponentially with increased complexity

(*Madej et al.*, 2006). Both GAs and ACO algorithms overcome this problem to a large extent by searching for near-optimum solutions using the search principles mentioned above, thereby only exploring a small fraction of the search space. Consequently, they sacrifice "the guarantee of finding the optimal solution for obtaining good solutions in a significantly reduced time" (*Blum and Roli*, 2003). Despite this shortcoming, in tests of problems with known theoretically optimal solutions, GAs and ACO algorithms have been found to produce globally optimal or near-optimal solutions for a range of applications (*Back et al.*, 1997; *Blum*, 2005).

GAs are probably the most widely used heuristic optimization method. However, as they represent solutions as strings of genes, which are modified from one generation to the next as the algorithm attempts to find the globally optimal solution, it is difficult to account for the sequential nature and conditional dependencies of the optimal scheduling problem outlined in section 2.2.3. In other words, as values of all decision variables are generated simultaneously in a particular population, there is no mechanism for adjusting the value of one decision variable based on the selected value of another. This increases the size of the search space unnecessarily and introduces a larger proportion of infeasible solutions, making it more difficult to find globally optimal or near-optimal solutions. In contrast, ACO algorithms are able to account for the sequential nature and conditional dependencies of the optimal scheduling problem explicitly, as the solution space is represented by a graph structure that can be adjusted dynamically based on the choices made at previous points in the decision graph during the constructions of solutions, thereby reducing the size of the decision space and increasing the proportion of feasible solutions (*Afshar*, 2010; *Foong et al.*, 2007; 2008a; *Maier et al.*, 2003). In other words, as solutions in ACO are constructed incrementally by stepping through a decision graph, rather than generating the entire solution simultaneously, as is the case with GAs, the options that are available at subsequent steps in the decision graph can be altered during the construction of a trial solution, based on the choices that were made at previous steps. This is because in ACO, solutions are generated based on changes in the decision space, rather than by modifying solutions themselves.

ACO algorithms have been applied successfully to the traveling salesman problem (*Dorigo and Gambardella*, 1997a) and found to outperform other optimization algorithms, such as genetic algorithms, in terms of computational efficiency and solution quality (*Dorigo and Gambardella*, 1997b). Other successful ACO applications include the quadratic assignment problem (*Mainiezzo and Colorni*, 1999), shop scheduling problems (*Blum and Sampels*, 2004), water distribution systems optimization problems (*Maier et al.*, 2003; *Zecchin et al.*, 2007), reservoir operation problems (*Jalali et al.*, 2007) and power plant maintenance scheduling problems (*Foong et al.*, 2007).. The sections 2.3.1–2.3.3 discuss the problem representation and steps in the ACO algorithm, as well as the implementation of dynamic constraints to account for the conditional dependencies of the EFMA scheduling problem discussed previously.

2.3.1 Problem Representation

Before ACO can be used to develop an optimal or near-optimal schedule as per section 2.2.3, each management alternative must be first mapped onto a graph, which consists of a number of discrete time steps and a set of suboptions at each of these. An example EFMA schedule graph for flow releases is shown in Figure 2.4. As can be seen, there are two suboptions that are considered at each time step, magnitude and duration. The magnitude suboption for this case ranges from a minimum allocation of zero to a maximum allocation of 1000 gigaliters (GL), which is independent of time, and as such remains in a closed loop. However, the next suboption, duration, branches into 12 paths after each magnitude suboption, one for each month, thereby generating multiple possible solutions. The number of possible solutions begins to expand until the final time step, T, is reached. Other suboptions, such as timing, can be also be accounted for in the graph structure. Once the graph has been defined, it can be used to develop a trial schedule using the ACO algorithm, which will be discussed in the following section.

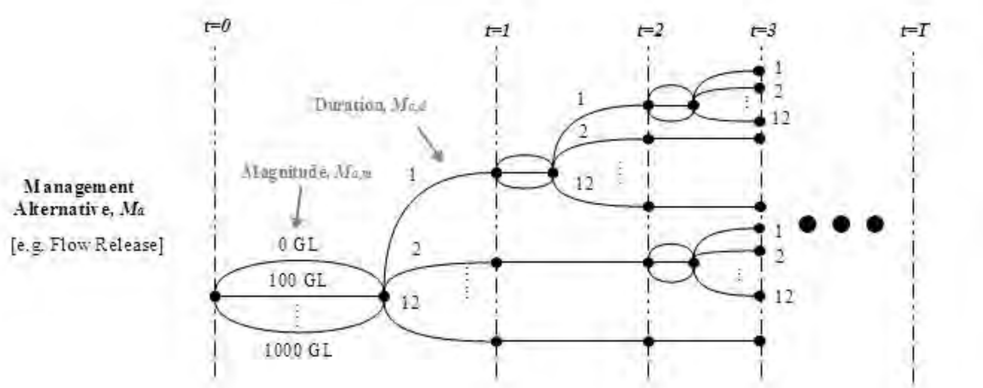

Figure 2.4: Example of an EFMA schedule graph for flow releases (in gigaliters (GL))

2.3.2 Ant Colony Optimization Algorithm

The steps involved in the ACO algorithm are given in Figure 2.5. The process of generating a trial EFMA schedule begins with the initialization of the ACO control parameters. Next, the optimization process takes place, where b ants construct trial schedules during each iteration (its). An ant achieves this by traveling to each time step and selecting magnitude and duration suboptions (Figure 2.4), until it reaches the final time step, T. At each time step, the suboptions are selected probabilistically based on a pheromone intensity (τ)

and heuristic information (η), as well as decision policy control parameters, α and β, that determine the relative importance of pheromone intensity and heuristic information, respectively (*Zecchin et al.*, 2005). The pheromone intensity for a suboption is first initialized to a random value while for subsequent iterations, pheromone is added based on the initial pheromone (τ_o), a pheromone persistence factor (ρ) and a reward factor (Q) that is used to scale the pheromone addition (*Zecchin et al.*, 2005). The heuristic value of a suboption, on the other hand, represents the quality of that suboption based on prior information.

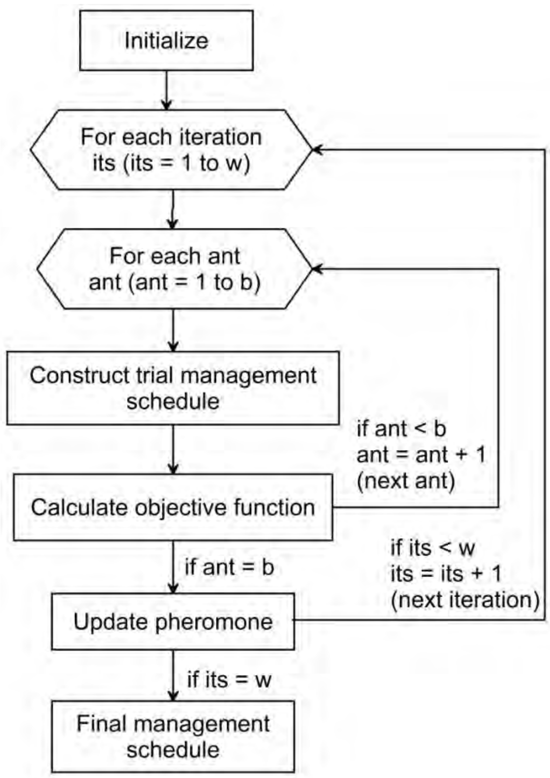

Figure 2.5: Steps in ant colony optimization algorithm

Once a complete trial schedule has been generated by an ant, the plan is evaluated using an objective function (see equation (2.1)). As discussed in section 2.2, a simulation model, such as a hydrological model for the river system under investigation, is used in the calculation of the objective function and any constraint violations (e.g., equation (2.2)). An iteration is completed once b ants have developed and evaluated a trial schedule.

At the end of each iteration, the quality of the EFMA schedules generated by the ants is evaluated and pheromone values are modified accordingly (i.e., the better the solution, the higher the pheromone that is added to the "paths" that made up that solution). The pheromone intensity for a suboption thus reflects the quality of trial schedules developed in previous iterations that contained that particular suboption, which creates bias for ants in future iterations to develop solutions of high quality. Additionally, pheromone evaporation is applied to components of schedules that do not perform well, which in turn deters the ACO algorithm from choosing those paths again. In this manner, the environment is modified to guide the artificial ants to regions of the search space that contain attractive solutions. For an ACO algorithm to be effective in generating optimal or near-optimal solutions, it is important that the correct balance of exploration (i.e., exploring the search space widely) and exploitation (i.e., converging to an optimal solution as quickly as possible) is struck. A number of ACO variants that use different pheromone updating schemes have been developed to achieve this. Some of these include: Ant Systems (*Dorigo et al.*, 1996), Ranked-Based Ant System (*Bullnheimer et al.*, 1999) and MAX-MIN Ant Systems (*Stutzle and Hoos*, 2000).

The process of developing, assessing and updating the pheromone trails to guide the ACO algorithm to near-optimal schedules continues until the specified stopping criteria have been met. For a detailed description of the ACO algorithm and equations used, readers are referred *Dorigo and Stützle* (2004).

2.3.3 Dynamic Constraint Adjustment

As discussed above, ACO algorithms have the ability to cater to the sequential nature and conditional dependencies involved in the development of EFMA schedules (see section 2.2.3). This is achieved by dynamically adjusting the number of available suboptions as ants construct a trial schedule. An example decision tree graph that incorporates dynamic constraints for a flow release management alternative is shown in Figure 2.6. The example is for four time steps and considers magnitude and four duration suboptions

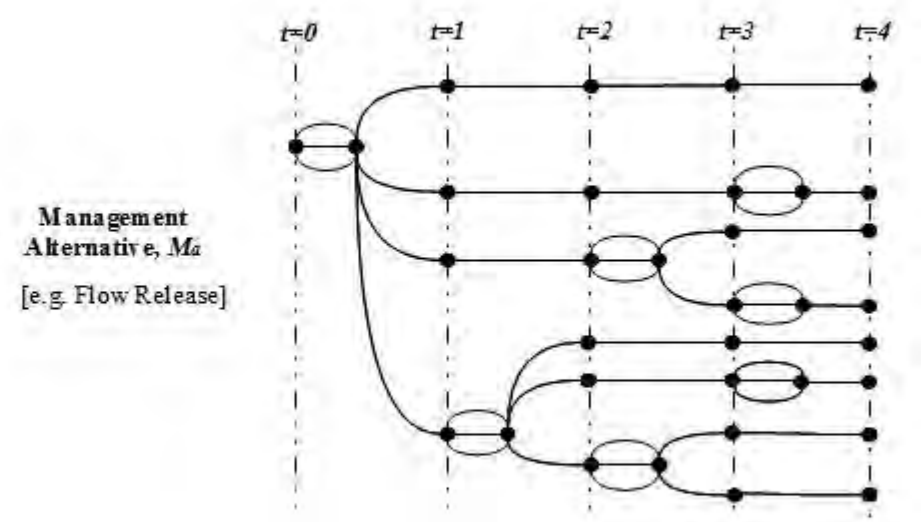

Figure 2.6: Example of an environmental flow management schedule decision tree graph using dynamic constraints

If the maximum duration, which is assumed to be greater than four time steps for the example in Figure 2.6, is selected by an ant at the first time step (decision point), then no other decision paths need to be made available at subsequent time steps (decision points), as shown by the top path in Figure 2.6. In this way, the decision tree is adjusted based on the choice made at the first decision point, thereby reducing the size of the search space and increasing the likelihood that globally or near globally optimal solutions will be found. On the other hand, if a duration option of one is chosen by an ant at the first time step (bottom path), then the potential duration suboptions are considered again at the following time step. However, the number of available options decreases from four to three, as there are only three more time steps remaining. If the number of available duration suboptions was not adjusted dynamically, four duration options would be considered after each magnitude suboption, which would result in a significantly larger search space. Therefore, this form of dynamically constraining the decision tree graph ensures that feasible EFMA schedules are developed, as well as ensuring that the ACO algorithm is able to find optimal solutions more efficiently.

2.4 Case Study

In order to test and demonstrate the utility of the proposed optimization framework, it has been applied to a quasi-hypothetical case study based on the Murray-Darling river system in South Eastern Australia. The majority of this river system experiences arid or semiarid climate and incorporates a large array of connected wetlands and floodplains, which are mainly flooded during high streamflows (*Maheshwari et al.*, 1995). However, due to the regulation of flow and over allocation of water to other users (e.g., irrigation), the flow regime has been changed, which has had significant negative impacts on the ecology of the river and adjacent wetlands and floodplains. In recent years, it has been recognized that the environment is a legitimate user of water and water allocations have been made available for environmental purposes. However, how this environmental flow allocation should be used in order to achieve the best ecological response remains a challenge.

Figure 2.7 shows the layout of the case study used to meet the objectives outlined in the Introduction. It consists of a river reach, three wetlands and two floodplains that contain a variety of different flora and fauna species found in the River Murray. To quantify the ecological response of the species within the river reach, wetlands and floodplains, the Murray Flow Assessment Tool (MFAT) was used (*Young et al.*, 2003). The minimum monthly river flows were based on entitlement flows used in the River Murray (*MDBA*, 2010) and it was assumed that there were only gates (no pumps) to regulate flows into and out of the wetlands. Reservoir releases were taken as given and not considered part of the decision set. Details of how the proposed framework and solution approach, introduced in sections 2.2 and 2.3, respectively, have been applied to the case study are given in sections 2.4.1–2.4.4

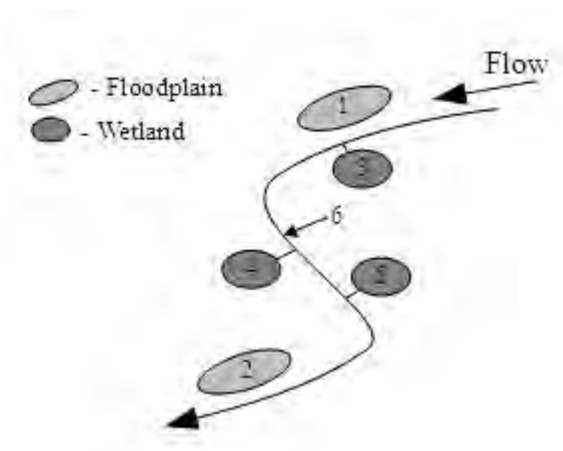

Figure 2.7: Layout of case study

2.4.1 Problem Formulation

2.4.1.1 Identification of Ecological Assets and Indicators

In this case study, there are two floodplains and three wetlands (Figure 2.7). The key flora and fauna species for each asset are given in Table 2.1, which were selected to represent the diversity and complexity that would occur in the

River Murray, Australia, as presented by *Rogers* (2011b). The wetland and floodplain fill values, which relate to the minimum river flow required to inundate the assets, are also presented in Table 4.1. To delineate the flora and fauna species within each wetland and floodplain, a number of assumptions were made (R. Oliver, personal communication, 2009). First, it was assumed that the floodplain species lie on the same elevation plane, therefore once the river flow was above the fill value, all species were inundated at a specific depth, depending on the water level in the river. Second, wetland species were assumed to lie along a nonlinear gradient, resulting in a wetland depth range at which the species would be inundated, for instance, Cumbungi rushland would lie lower on the wetland gradient than Lignum shurbland. Therefore, if the wetland water depth (which is dependent on the river flow and regulator settings) was above the minimum species depth, then that species would be inundated.

In order to obtain the required ecological flow requirements for the species of flora and fauna considered, the Murray Flow Assessment Tool (MFAT), developed by *Young et al.* (2003), was used. MFAT is a habitat simulation model that was developed specifically for the River Murray and can be used to assess the impact of different flow scenarios on vegetation and wildlife (*Young et al.*, 2003). This is done using a set of response curves, which are based on important flow components, such as duration, timing and magnitude (which is represented in terms of depth), as well as the interdry period.

Table 2.1: Wetland and Floodplain Specifications

Asset	Type	Dominant Species	Fill Value (GL/month)
1	Floodplain	Black box woodland (*Eucalyptus largiflorens*)	1200
2	Floodplain	River red gum forest (*Eucalyptus camaldulensis*) Lignum shrubland (*Muehlenbeckia florulenta*) Colonial nesting waterbird (e.g. ibis) Flood spawners (e.g. golden perch)	800
3	Wetland	Common reed *(Phragmites australis*)	300
		Cumbungi rushland (*Typha* sp.)	400
		Lignum shrubland (*Muehlenbeckia florulenta*) Waterfowl and grebes	500
4	Wetland	Ribbon weed herbland (*Vallisneria americana*)	400
		Giant rush rushland (*Juncus ingens*)	450
		Rats tail couch grassland (*Sporobolus mitchelli*)	500
5	Wetland	Spiny mudgrass grassland (*Pseudoraphis spinescens*)	300
		River red gum forest (*Eucalyptus camaldulensis*)	400
		River red gum woodland (*Eucalyptus camaldulensis*)	550
6	River	Main channel specialists (e.g. Murray cod)	450

The MFAT response curves for ten different species of vegetation used in this study are shown in Figure 2.8 for illustration purposes. As can be seen, a score between 0 and 1 is given for each flow component, where 0 corresponds to a poor and 1 to a good ecological response. It should be noted that the curves take into account different flow requirements for recruitment (i.e., promotion of seed growth) and maintenance (i.e., maintenance of adult habitat). As can be seen in Figure 2.8, there are curves for twelve different flow components, which can be divided into timing, frequency, duration and various inundation depth groups. It should be noted that there is an additional water depth response curve (in terms of maximum mean depth percent) for the wetland vegetation species ribbon weed herbland, which has not been presented here, as well as the flooding memory response curves for the various floodplain species. Other flow factors, such as the rate of rise and fall, have also not been presented in Figure 2.8. In total, there are approximately 48 curves for the vegetation species that, at times, have competing requirements, which highlights the complexity of the EFMA scheduling problem and the difficulties in developing optimal management schedules.

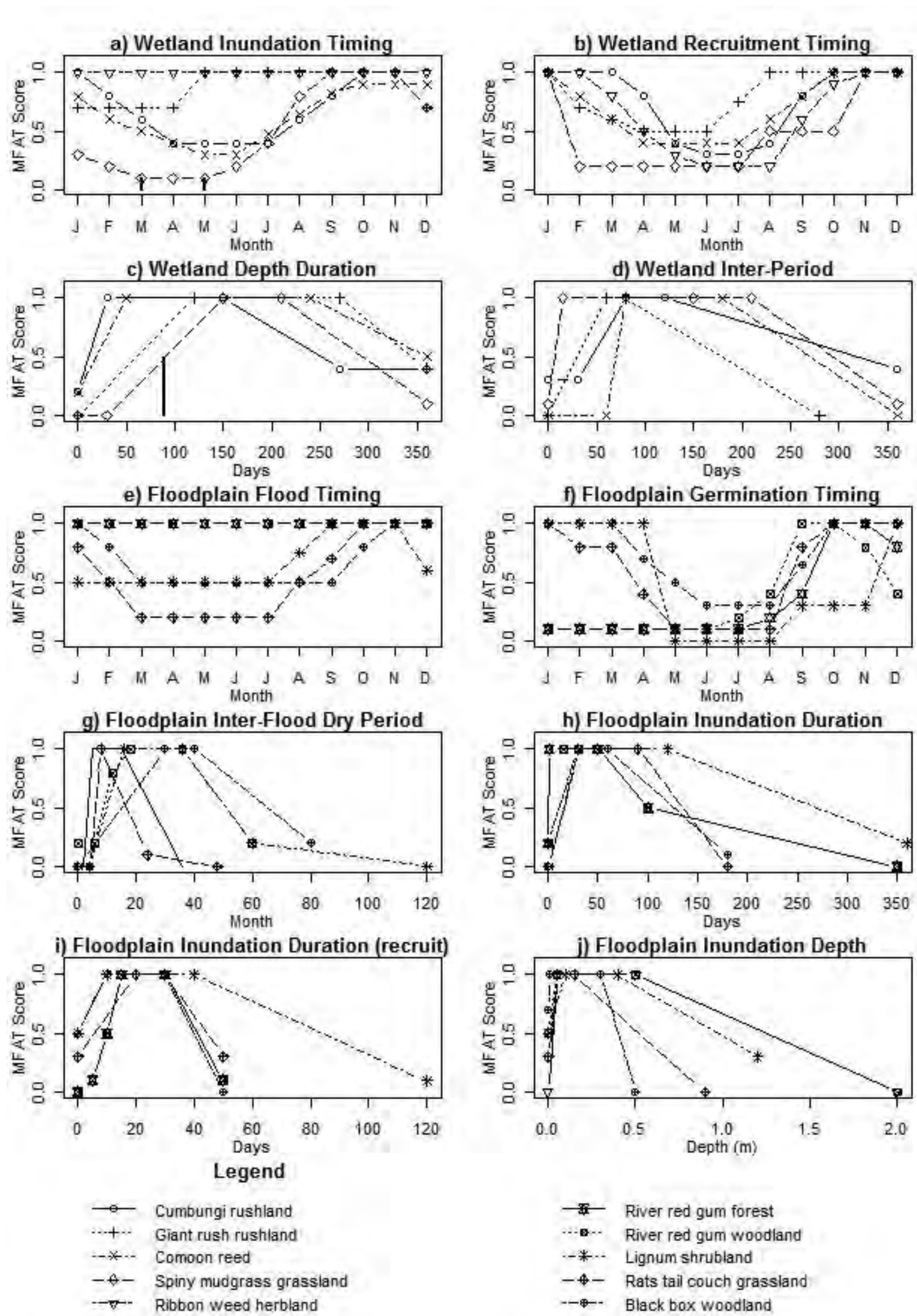

Figure 2.8: MFAT response curves adapted from *Young et al.* (2003)and the Inside MFAT website (http://www2.mdbc.gov.au/livingmurray/mfat/index.htm)

The top four response curve graphs in Figure 2.8 are associated with wetlands, while the bottom six are for floodplains species. To determine the response from the wetland inundation and the floodplain flood timing and inundation depth curves, the median value of the ‘best flood event’ was used, where the ‘best flood event’ was the event that produces the highest overall ecological scores. For example, if the spiny mudgrass grassland was inundated from the beginning of March until the end of May, it would receive a wetland inundation score of 0.1, as this was the median value for that event. This region is depicted by the two bold lines in Figure 2.8a, where from March to May, the curve remains at a constant score of 0.1. On the other hand, inundation duration, recruitment and germination timing, and interperiod scores are based on a single value for the “best flood event.” Therefore, the inundation duration for spiny mudgrass grassland is approximately 90 days, giving a score 0.5. This is represented by the bold line in Figure 2.8c. Additionally, it was assumed that a draw down and rewetting sequence must occur within a year, so that the interperiod could be calculated. Once all the scores have been obtained from Figure 2.8, they are used in equations to calculate an overall ecological response for each vegetation species in the MFAT (*Young et al.*, 2003). It should be noted that there are weights x_1 and x_2 that emphasize, for example, the recruitment of vegetation seedlings and maintenance of adult plant species, respectively.

There are an additional 12 response curves, not depicted in this paper, for assessing the health of the fauna species (i.e., fish and water birds). For waterbird responses, only the flood duration and dry period were taken into account, while for fish responses, the flood and spawning timing, inundation duration and dry period were considered. Other factors, such as thermal pollution (1.0), woody debris (1.0), the level of fish barrier (1.0), and channel straightening (0.78) were set to MFAT default values. For further details on the fauna and flora response curves and the equations used, readers are referred to *Young et al.* (2003) and the Inside MFAT Web site (http://www2.-mdbc.gov.au/livingmurray/mfat/index.htm)

2.4.1.2 Planning Horizon and Time Interval

A planning horizon of 5 years was chosen, as this (1) is the time period selected for the development of wetland management plans in the River Murray (*Schultz*, 2007; *Turner*, 2007), and (2) ensures that there is sufficient time to achieve the maximum ideal flooding frequency for the species of flora and fauna considered (see Figure 2.8g). A monthly time interval was selected, as this provides sufficient resolution for the hypothetical case study. This meant that the "rate of change" flow component in MFAT for flora and fauna species was not considered. Therefore, there are 60 time steps where an option has to be selected for each management alternative. This is discussed in section 2.5.

2.4.1.3 Management Alternatives and Suboptions

There was one reach-scale management alternative (i.e., releases) for this case study and the associated suboptions include the magnitude and duration of the releases. An example of the resulting problem graph structure is shown in Figure 2.6. The number of magnitude options depends on the minimum and maximum fill values of the whole system. In this case, this could be anywhere between 100 GL/month, which was the minimum flow that needed to be added to the minimum river flows in order to inundate the wetland with the lowest fill value, and 1500 GL/month, which ensures that all of the wetlands and floodplains can be inundated simultaneously. An increment of 50 GL/month between these limits was chosen for the available suboptions to provide sufficient resolution to ensure that the ideal depth could be achieved for the different flora and fauna species considered. An additional zero allocation was defined to ensure that a "no release option" was available. Consequently, a maximum of 29 magnitude decision values are available (i.e., n = 29 for management alternative M_1). The number of duration options, p, available at each time step (i.e., month) varies throughout the year from 12 in January to 1 in December. The wetlands also have gates that can regulate flow into the wetlands, while floodplains do not. This leads to three additional management alternatives, which control the flow into and out of the wetlands via gates (thus for M_2, M_3, and M_4, $n = 2$ and $p = 12$). Therefore, there are a total of four decision tree graphs similar to the one in Figure 2.6 that control the flow releases and flow via gates to the three wetlands. This produces a total search space size of 10^{141} discrete combinations of decision variable values, highlighting the potential benefit of using a formal optimization approach to solve this problem.

2.4.2 Objective Function and Constraints

The ecological score for each species per asset was calculated using MFAT, which was described in section 2.4.1.1. The equation used to calculate an average MFAT score was based on the formulation presented in equation (2.1):

$$F = \sum_{i=1}^{6} \frac{w_{1i}}{6} \sum_{r=1}^{16} \frac{w_{2r}}{16} \sum_{v=1}^{5} \frac{w_{3v} E_{i,r,v}}{Y_5} \tag{2.5}$$

where the number of assets is 6, the number of ecological indicators is 16 for each flora and fauna species (see Table 2.1), and finally, the score, $E_{i,r,v}$ for each asset and indicator is calculated per year, with the total number of years equaling 5. To obtain an average score and an indication of the overall health of all the species and assets, $E_{i,r,v}$ was divided by the total number of assets and indicators. The weights (w_{1i}, w_{2r}, w_{3v}) were varied for the different investigations conducted in order to examine various trade-offs between competing objectives (see section 2.5 for details). In order to maximize F in equation (2.5), an objective function most appropriate for this case study needs to be selected, bearing in mind that the ACO algorithm minimizes the selected objective function and cannot accommodate constraints on environmental flow allocations explicitly. A number of different objective function formulations were assessed and the following form of the objective function (Y) was found to perform best and was hence used in this study:

$$Y = \frac{10}{10 + F} + Penalty \tag{2.6}$$

where F is the MFAT ecological score calculated using equation (2.5), and Penalty is a penalty function that was developed to ensure that the water allocation constraints for each period were adhered to and is given by

$$Penalty = \begin{cases} 0 & \text{if} \quad \sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \leq A_{\max\_ni(pd)} \\ \left\{ \sum_{t=i\_ni(pd)}^{f\_ni(pd)} (A_t) - A_{\max\_ni(pd)} \right\} \times 100{,}000 & \text{if} \quad \sum_{\mathrm{t=i\_ni(pd)}}^{f\_ni(pd)} A_t > A_{\max\_ni(pd)} \\ 100{,}000 & \text{if} \quad F = 0.0 \end{cases} \tag{2.7}$$

where the variables in equation (2.7) have been defined in equations (2.1) and (2.2).

2.4.3 Calculate Objective Function

In order to calculate the objective function specified in section 2.4.2, the wetland and floodplain hydrology must be simulated for each management schedule. The following sections discuss the equations and assumptions used to achieve this.

2.4.3.1 Wetland Hydrology Model

To ensure that the model adequately accounts for wetland hydrology, whereby wetlands fill quickly once the river level breaches the fill value and when gates are opened but then drain slowly either when the gates are closed or when the river level drops below the fill value, equations (2.8) and (2.9) have been utilized. A simple water balance relationship is

$$I_t - O_t = S_{t+1} - S_t \tag{2.8}$$

where I_t refers to the wetland inflows, O_t are the wetland outflows, while S are the wetland storages at time t. The outflows O_t are the summation of the flows out of the wetland (O_w) and evaporation (E_t). To calculate the evaporation loss from the wetlands, it was assumed that the wetland is rectangular with the longer sides parallel to the river, and that the bank slope remained constant. Consequently, the surface area versus depth relationship is linear. A simple relationship of 0.7 × (pan evaporation) was used to determine the evaporation from the wetland, in meters/month. The value of 0.7 was chosen as it is a common value used to determine evaporation within the Murray Darling Basin (*Gippel*, 2006).

To simulate the gate operations at the wetlands, logic (If-Then) statements were used to adjust the components of the water balance equations. If the gate was closed, the inflow at that time step was zero (i.e., $I_t = 0.0$) and if there was water in the wetland, wetland storage was only affected by evaporation:

$$S_{t+1} = S_t - E_t \tag{2.9}$$

If there was water remaining in the wetland and the gate was opened at the next time step, water would flow out until the fill value was reached, after which water would remain in the wetland and only be affected by evaporation (i.e., equation (2.9)). It should be noted that the mass balance constraints associated with the problem were also satisfied within this wetland hydrology model.

Assumptions made include that water seepage, the effect of rainfall and the fill and drainage rate of the wetlands were negligible. This was considered reasonable, since a monthly time step was used. Additionally the storage capacity of the wetlands was set to be very small in comparison to the streamflows, thus having negligible effect on downstream flows as a result of upstream wetlands storage.

2.4.3.2 Floodplain Hydrology Model

The floodplain hydrology model used the same equations and assumptions as the wetland model, with the exceptions of (1) being only affected by the river level (i.e., if the river level is above the fill value then the floodplain would be inundated at a depth dependent on the river level or if the river level is below the fill value then the floodplain would not be inundated) and (2) not including gates to regulate the flow, and as such the gate operational equations were not used.

2.4.4 ACO Algorithm

As discussed in section 2.3.2, there are various types of ACO algorithm, which generally differ in the pheromone updating methods used (*Dorigo and Blum*, 2005). In this study, the MMAS algorithm was used, as it has been found to outperform other ACO variants in a variety of studies (*Foong et al.*, 2007; *Zecchin et al.*, 2007). Details relating to the procedure and equations used by the MMAS are given by *Stützle and Hoos* (2000).

An extensive sensitivity analysis was undertaken to determine the optimal values of the parameters that control the searching behavior of the MMAS algorithm. The range of parameter values tried and the final parameter values chosen are shown in Table 2.2. It should be noted that each sensitivity run was performed with 10 different random numbers (i.e., starting positions in the decision space) to minimize the impact of the random starting position in decision variable space on the results obtained.

Table 2.2: MAX-MIN Ant Systems Parameters

ACO Parameter	Range Investigated	Final Value
Alpha (α)	0.5,1.0,1.5.2.0	1.0
Beta (β)	0.5,1.0,1.5.2.0	1.0
Initial pheromone (τ_o)	0.5, 1.0, 2.0, 5.0, 10.0	5.0
Pheromone persistence (ρ)	0.1,0.2,0.6,0.8,0.9,1.0	0.6
Pheromone reward factor (Q)	0.5, 1.0, 2.0, 5.0, 10.0	5.0
Number of ants (*ant*)	50-1500	500 and 1200

2.5 Analysis Conducted

In order to meet the objectives stated in the Introduction, a number of studies were conducted, which demonstrate how the proposed framework and optimization approach are applied in practice in different settings (objective iiia). In the first study (section 2.5.1), the proposed optimization approach was compared with and tested against a heuristic scheduling approach by analyzing whether it performed adequately on problems of varying complexity (objective iiib). In the second and third studies (sections 2.5.2 and 2.5.3, respectively), it is demonstrated that the proposed approach can account for the competing requirements of individual species (objective iiic) and the competing requirements of species of flora and fauna (objective iiid) (section 2.5.3), respectively. In the final study (section 2.5.4), it is illustrated that the proposed framework and solution approach can deal with environmental water allocations of varying magnitude and timing (objective iiie). Details of the various studies and the specific investigations conducted as part of each these are given in Tables 2.3 and 2.4, and described in detail below.

Table 2.3: Details of Each Study and Corresponding Objective

Study	Objective	Investigations	Species	Planning Horizon
Section 2.5.1	iiib	1 - 6	Flora	5 years
Section 2.5.2	iiic	7 - 9	Flora	
Section 2.5.3	iiid	10 - 11	Flora and fauna	
Section 2.5.4	iiie	12 - 13	Flora and fauna	

Table 2.4: Details of the Investigations used in each Study

Investigation	Allocation Constraint Period/s	Allocation Constraint/s (GL)	Weight preferences
1	5 years	5000	Equal preference
2		1750	
3		3500	
4		4750	
5		10,000	
6		10,000	
7	5 years	500 – 12,000	Recruitment favored
8			Processes equally favored
9			Maintenance favored
10	5 years	10,000	Flora favored
11			Fauna favored
12	5 years and 3 months	10,000 and Table 6	Equal preference
13	5 years	10,000	

2.5.1 Validation of Optimization Framework

In order to provide some degree of validation, and to assess the potential benefits, of the proposed optimization framework, it was compared with a heuristic EFMA scheduling approach for six investigations of varying complexity. It was recognized that the proposed ACO-based optimization approach should outperform a heuristic scheduling approach due its greater degree of sophistication. However, simply because an algorithm is highly advanced does not guarantee that it will perform well and it was therefore considered important to evaluate it against a benchmark approach that is representative of current practice in the River Murray before it was applied to more complex problems (sections 2.5.2 to 2.5.4). In addition, it highlights the complexity of the problem being addressed and the benefits of the approach introduced in this paper.

The six investigations considered in this study only considered flora (Table 2.3), as this provided a sufficient level of complexity (i.e., 48 different MFAT response curves) to validate the optimization framework. The allocation constraint period was set to 5 years (Table 2.4), indicating that there were no constraints on the time periods during which the water available for environmental purposes was used over the planning horizon of 5 years (Table 2.3), as long as the total environmental water allocation was not exceeded. The total amount of water available for environmental flow purposes varied between investigations (Table 2.4) based on the outcomes of the heuristic scheduling procedure, as explained below, and equal preference was given to all components of the overall ecological score in equation (2.5) (i.e., species, assets and time period) (Table 2.4), such that $w_{1i} = 0.2$, $w_{2r} = 0.08$ and $w_{3v} = 0.2$ for i, r and v. Additionally, the recruitment and maintenance MFAT weights, x_1, and x_2, were both set to equal 0.5. The degree of complexity of the investigations was variable, both in terms of the number of species and the spatial extent considered (Table 2.5).

Table 2.5: Details of the 6 Investigations used for Developing Heuristic and Optimization Based Management Schedules

Investigation	Total number of flora species	Plant species
1	1	River red gum forest in Asset 5
2	1	Rats tail couch grassland in Asset 4
3	1	Spiny mudgrass grassland in Asset 5
4	3	All flora species in Asset 3*
5	7	All flora species in Assets 1,3 and 5*
6	12	All flora species in Assets 1 to 5*

* Please see Table 2.1 for details

Details of the heuristic approach are given in Figure 2.9. The first step is the identification of species groups with similar MFAT flow requirements for each management alternative (M_a). These species groups are defined as $G_{a,c}$, where c ranges from 1 to nc number of species and a ranges from 1 to h (i.e., number of M_a). The groups are ordered so that the first group, $G_{1,1}$, has the largest number of species with similar MFAT requirements that is affected by M_1, $G_{1,2}$ the second largest number of species, and so on.

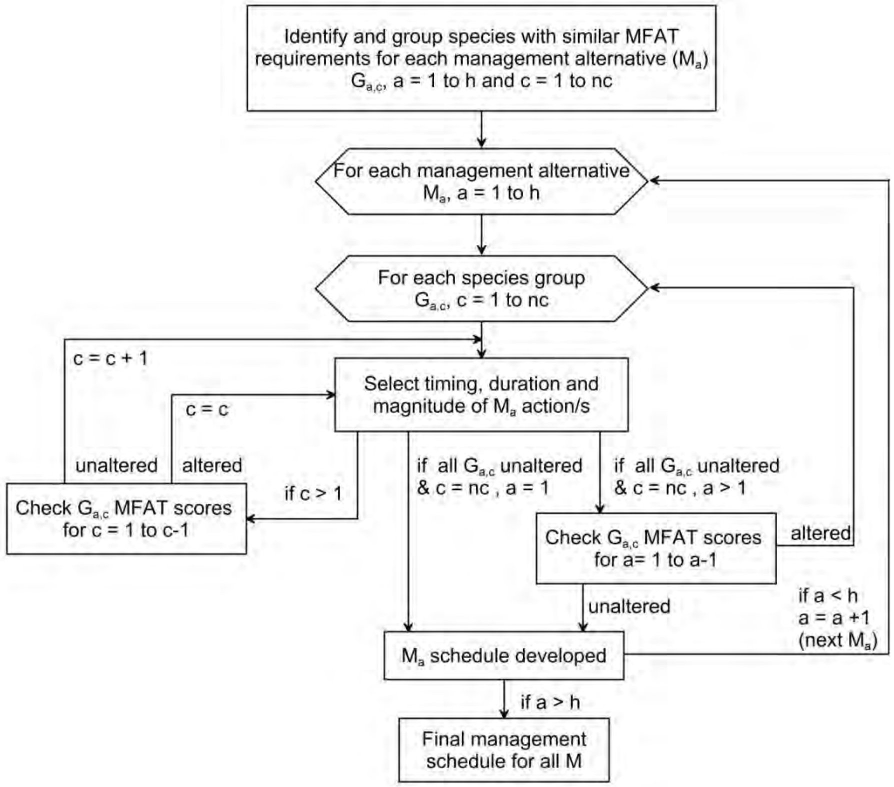

Figure 2.9: Environmental flow management schedule development using the heuristic approach

For each management alternative, M_a, duration, timing and magnitude values are selected based on the MFAT flow requirements of the species in the largest group. $G_{a,c}$. The selection of these values may be repeated several times to ensure that the highest possible MFAT score is achieved for all species. Next, the selection process is repeated for the remaining $G_{a,c}$ species that are affected by the M_a under consideration, starting with the group with the second largest number of species. A check is then undertaken to ensure that the M_a values chosen (i.e., duration, timing and magnitude) for a particular $G_{a,c}$ do not negatively impact the MFAT scores of the species groups considered previously. This cycle continues until a complete schedule has been produced for management action M_a, after which the process is repeated for the next M_a until schedules have been developed for all M.

It should be noted that this scheduling approach does not take into account any constraints on the amount of water that is available for environmental flow allocation purposes. Addressing the constrained scheduling problem would add another level of complexity, which was not considered warranted for the purposes of illustrating the complexity of this problem and validating the proposed optimization approach. Consequently, in order to provide a fair comparison between the heuristic and ACO-based approaches, the constraints in relation to the total water allocation used when developing the ACO-based schedules corresponded to the volumes found in the corresponding management schedules obtained using the heuristic approach. Additionally, for each investigation, all ACO optimization runs were repeated ten times with different random starting positions in decision variable space in order to minimize any effects of the probabilistic nature of the searching behavior of the ACO algorithm.

2.5.2 Determination of Optimal Trade-Offs Between Recruitment and Maintenance Scores for Different Flow Allocations

As discussed in section 2.4.1.2, MFAT considers both recruitment (i.e., promoting and ensuring seedling growth) and maintenance (i.e., maintaining and ensuring the good condition of current adult habitat) of flora species. These factors have differing and, at times, competing flow requirements and, as such, must be considered separately. In order to investigate the trade-offs between recruitment and maintenance, optimal management schedules for maintenance and recruitment of the flora species over a 5 year management period were generated (Investigations 7 to 9, Table 2.3). Further details of each investigation are presented in Table 2.4, with schedules that favor recruitment considered in Investigation 7, schedules that emphasize recruitment and maintenances equally in Investigation 8, and schedules that favor maintenance in Investigation 9. This was achieved by specifying additional weights as part of the calculation of MFAT scores that either emphasize recruitment (x_1, = 1.0 and x_2 = 0.0), maintenance (x_1, = 0.0 and x_2 = 1.0), or both (x_1, = 0.5 and x_2 = 0.5). The weights that control asset, flora type and release year (i.e., w_{1i}, w_{2r}, w_{3v}), were set to have equal preference, using the same values as in section 2.5.1. The planning horizon for this study was five years and seven different environmental water allocation constraints (i.e., different amounts of water available for environmental flow purposes), ranging from 500 to 12,000 GL (i.e., 500, 2000, 4000, 6000, 8000, 10,000 and 12,000 GL) were examined (Table 2.4), in order to investigate the impact of a number of different water policies (i.e., different amounts of water set aside for environmental flow purposes, as opposed to consumptive uses (e.g., irrigation, water supply)) on ecological response and the trade-off between maintenance and recruitment. Each optimization run for the 21 schedules developed was repeated ten times with different starting positions in the solution space in order to minimize the impact of the random starting position on the results obtained.

2.5.3 Determination of Optimal Trade-Off Between Flora and Fauna Ecological Response

In order to investigate the trade-offs between the requirements of flora and fauna, the flow requirements of four fish and waterbird species (see section 2.4.1.1) were added to those of the flora species used in Investigation 6 of section 2.5.1 (Table 2.5), and optimal EFMA schedules generated using the proposed ACO-based approach. Details of this study are given in Tables 2.3 and 2.4, where a single environmental water allocation constraint of 10,000

GL was used over the adopted planning horizon of 5 years and different weightings were used to either favor fauna (Investigation 10) or flora (Investigation 11). The fauna species weights in Investigation 10 equaled 0.25 and the flora weights equaled 0.0, while in Investigation 11, the flora species weights equaled 0.08 and the fauna weights were set to 0.0. The other weights (i.e., w_{1i}, w_{3v}, x_1 and x_2) were set to provide equal preference. As was the case in section 2.5.1, each optimization run was repeated ten times from different starting positions in the solution space.

2.5.4 Determination of Optimal EFMA Schedules as a Result of Hydrograph Inversion

Many regulated river systems, such as the Murray River, have reversed flow regimes with major flows now occurring in summer–autumn (i.e., December to May) to sustain human needs, instead of winter–spring (i.e., June to November). In order to assess the impact of the hydrograph inversion case, two investigations were developed, including Investigation 12, which considered an additional seasonal flow constraint, and Investigation 13, which had no such constraint. Details of these investigations are given in Tables 2.3 and 2.4. As can be seen, both flora and fauna species and a 5 year management period were considered, as well as a 10,000 GL total water allocation constraint. Additionally, equal weight values were used for all the weight groups, as was the case in the previous study (section 2.5.1). Table 2.6 presents the environmental flow allocations that were available in each season. As with the previous studies, each optimization run was repeated 10 times.

Table 2.6: Seasonal Environmental Flow Allocation used in Investigation 12

Season	Environmental flow allocation (GL)
Summer (Dec.-Feb.)	1500
Autumn (Mar.-May.)	1000
Winter (Aug.-Jul.)	500
Spring (Sept.-Nov.)	200

2.6 Results and Discussion

2.6.1 Validation of Optimization Framework

The MFAT scores obtained using the ACO and heuristic approaches are given in Table 2.7. As can be seen, the ecological scores obtained using both approaches were the same for the first three investigations. This indicates that there do not appear to be any problems with the formulation and implementation of the proposed optimization framework. Additionally, the ACO-based approach was able to determine management schedules that use less water, with the exception of Investigation 2, which had identical allocations and scores. Once the number of species was increased to three in Investigation 4, the benefit of using the optimization framework was demonstrated clearly. The MFAT score of the management schedule obtained using the ACO approach was higher than that of the management schedule developed using the heuristic approach, with a significantly smaller amount of water (i.e., 600 GL less). This demonstrates the ability of the optimization approach to search effectively through the large number of potential management schedules using the ACO process described in section 2.3.2. This results in management schedules that use the available environmental water allocation in an efficient manner, as expected, which would be especially beneficial during times when water resources are limited and must be allocated effectively between competing stakeholders.

Table 2.7: Heuristic and ACO Management Schedule Results for Investigations 1 to 6

Investigations	Heuristic		ACO	
	Allocation (GL)	**MFAT Score**	**Allocation (GL)**	**MFAT Score**
1	5000	1.00	4650	1.00
2	1750	0.91	1750	0.91
3	3500	1.00	3100	1.00
4	4750	0.86	4150	0.91
5	10,000	0.67	10,000	0.78
6	10,000	0.67	9850	0.83

The results for Investigations 5 and 6 (Table 2.7), which were significantly more complex since they considered a larger number of plant species (7 and 12, respectively), provided further evidence of the benefit of the proposed optimization approach. For instance, in Investigation 6, the management schedules developed using the ACO-based method resulted in an increase in MFAT scores of approximately 0.2 for all wetlands and floodplains, despite using less water. The corresponding flow releases obtained using the heuristic and ACO-based approaches are shown in Figure 2.10. It can be seen that there was more variability in the flows in the ACO-based management schedule, which ensured that all of the flow components in Figure 2.8 were accounted for. Generally, the larger flow releases obtained using both approaches occurred at similar times, except for year 2, where the flow releases obtained using the ACO-based approach occurred midyear instead of at the end of the year. These differences in flow releases contributed to a better MFAT score. In particular, there was significant improvement of approximately 0.4 in the MFAT score for assets 4 and 5, as shown in Table 2.8

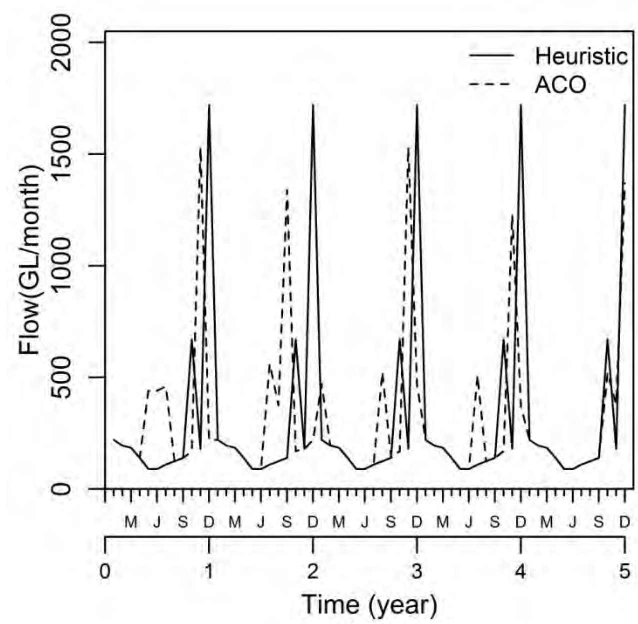

Figure 2.10: Monthly flow releases for heuristic and ACO management schedule for Investigation 6.

Table 2.8: Difference in Annual MFAT Scores between Management Schedules obtained using ACO and Heuristic Approaches for Investigation 6

Asset	Species	Difference ACO and Heuristic MFAT Scores				
		Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
4	Ribbon weed herbland	0.0	0.0	0.0	0.0	0.0
	Giant rush rushland	0.5	0.6	0.5	0.5	0.5
	Rats tail couch grassland	0.0	0.2	0.4	0.3	0.5
5	Spiny mudgrass grassland	0.3	0.5	0.4	0.4	0.5
	River red gum forest	-0.1	0.5	0.6	0.4	0.5
	River red gum woodland	0.0	0.3	0.3	0.2	0.1

It was found that this increase in MFAT score was because some species, such as giant rush rushland and spiny mudgrass grassland, were inundated for longer than one month. Ideally, giant rush rushland requires inundation for 120–270 days, while spiny mudgrass grassland requires 150–210 days of inundation. This was clearly not achieved by the management schedule developed using the heuristic approach, resulting in a much lower overall MFAT score, as the inundation requirement for maintenance was not satisfied. Another requirement that was difficult to meet in the development of the management schedule using the heuristic approach was the ideal depth for some of the floodplain species (e.g., river red gum forest, rats tail couch grassland), which corresponds to a certain depth that must be maintained to ensure the recruitment of these species. In contrast, this requirement was able to be satisfied by the management schedule developed using the ACO approach, thereby ensuring that a good recruitment score could be achieved. Overall, this study showed that once the number of wetlands and floodplains is moderately large, developing a management schedule heuristically over multiple years is extremely difficult. This is because there are too many wetlands and floodplains with different and competing water demands that must be considered. However, the optimization method can deal with these complexities with the aid of the searching process outlined in section 2.3.

Another benefit of the ACO approach over the heuristic approach was that it provided a number of possible optimal management schedules for each investigation. For example, the releases and corresponding MFAT scores from three different management schedules for asset 3 in Investigation 4 generated using the ACO approach are shown in Figure 2.11. As can be seen, water was allocated to asset 3 twice in the first year in management schedules 1 and 2, while this was not the case in schedule 3. This resulted in a lower MFAT score of 0.74 in year 1 for schedule 3, while the corresponding score for schedules 1 and 2 is 0.8. This was because the interperiod for lignum shrubland (Figure 2.8d) was not achieved for schedule 3. The releases for the three management schedules then followed a similar pattern in the second year, where, initially, there was a dry period until the end of the year, when asset 3 was inundated. In the third year, there was some variability between the management schedules, but generally flows were allocated at the end of the year in each of the schedules. Consequently, for years 2 and 3, the MFAT scores were similar for all management schedules. In the fourth year, a gate was used as part of management schedule 3, the effect of which was shown by the gradual change in flow (Figure 2.11). This contributed to a significantly lower maintenance score, as a longer duration of flooding negatively affected the wetland response. A gate was closed in the fourth year as part of management schedule 1; however, this did not negatively affect the final MFAT score. Finally, all three assets were inundated at the end of the fifth year, indicating that the species within this asset prefer to be flooded at the end of the year. This comparison can aid in the understanding of how sensitive the assets are to the flow regime. By knowing this sensitivity, managers have the ability to develop much more effective management schedules that efficiently use the water allocated for environmental flow management purposes, while achieving a high ecological response. Additionally, it provides wetland managers with a variety of different optimal management schedules that could be implemented, depending on prevailing social and economic factors, for example. This discussion further highlights the complexity of EFMA scheduling, as there are many different solutions that result in similar MFAT scores.

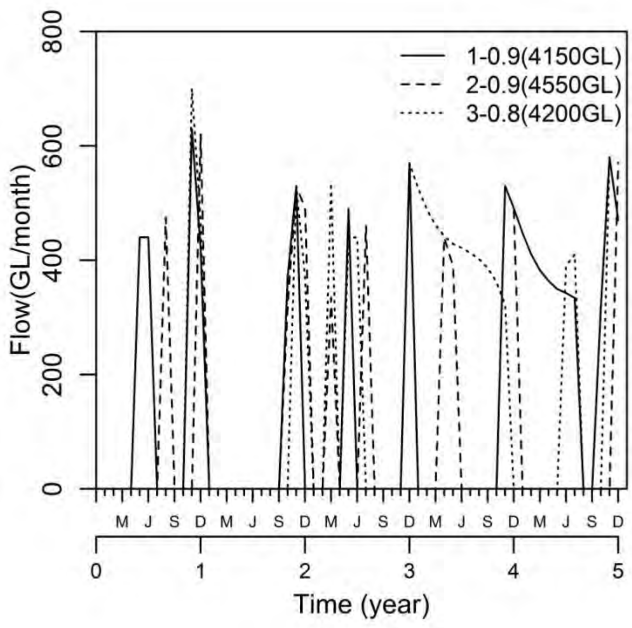

Figure 2.11: ACO management schedule for Investigation 3.

2.6.2 Determination of Optimal Trade-Offs Between Recruitment and Maintenance Scores for Different Flow Allocations

The optimal trade-offs between recruitment and maintenance scores for total environmental water allocations ranging from 500 to 12,000 GL obtained using the ACO-based approach are shown in Figure 2.12. As can be seen, at an allocation of 500 GL, there was a small recruitment and maintenance response of approximately 0.2. However, this increased significantly to an average of 0.5 when the water allocation was increased to 2000 GL. The lower MFAT scores for the 500 GL allocation were due to insufficient water to inundate all of the wetlands and floodplains over the 5 year planning horizon. Only the wetlands with lower fill values were inundated. As the allocation increases from 2000 to 12,000 GL, more wetlands and floodplains were flooded and began to contribute to the overall score. Additional water was shown to have a decreasing marginal benefit and reached an asymptote of approximately 0.9, beyond which, further environmental flow allocations would not increase the overall MFAT scores.

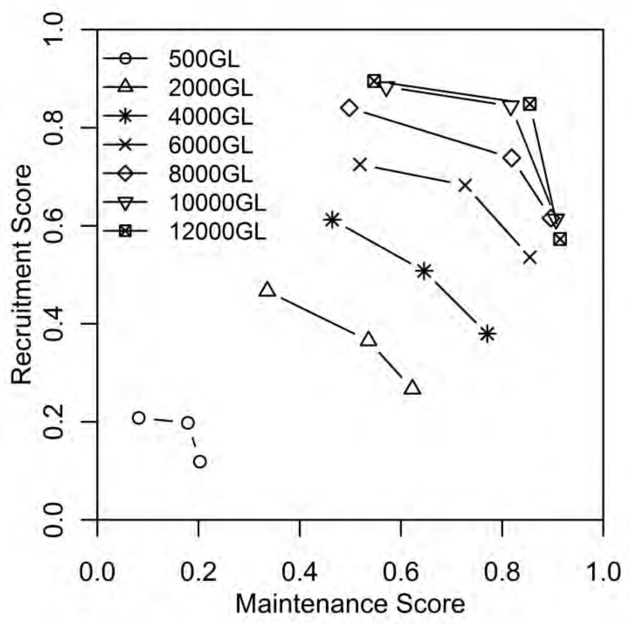

Figure 2.12: Optimal trade-offs between MFAT recruitment and maintenance scores for 500–12,000 GL allocations.

The maximum score obtained by either favoring maintenance or recruitment was approximately 0.9, which was shown by the outer two points for the 10,000 and 12,000 GL water allocations in Figure 2.12. The maximum value of 1.0 could not be achieved for a number of reasons. First, each wetland and floodplain had different flow requirements. Second, the maintenance and recruitment flow components for particular species were different, for instance favoring the maintenance and survival of a plant species such as, river red gum, could in turn limit its recruitment and regeneration capacity (*George et al.*, 2005; *Rogers*, 2011b), thus resulting in the inability to achieve the maximum response for all ecological processes, simultaneously. Finally, there were particular flood factors, such as the interdry flood period, which were difficult to satisfy. For example, the interflood dry period response curve was the only one that accounted for flooding over multiple years, while the remaining response curves were determined annually. Therefore, it had less impact on the objective function (and in turn the resulting management schedule), as only one graph governed the flooding over several years.

Gate operations have the ability to increase significantly the efficiency of water use in the management schedule. Changes in gate settings were used extensively in the optimal schedules for the 500 and 2000 GL allocations. This was expected, since there is significant benefit in using gates to prolong inundation when a limited amount of water is available. Gate operations featured less prominently in the optimal schedules once allocations increased to 8000 GL, particularly if the aim was to favor recruitment or to balance recruitment and maintenance. As the flow allocations increased to 10,000 and 12,000 GL, gates were used to prevent inflows into wetlands, rather than prolonging inundation. It was evident from the optimal management schedules that the use of gates has the potential to improve MFAT scores, especially at times when water is limited and to prevent water flowing into the wetlands during flood events. This enables the ecological integrity of wetlands to be maintained over a wider range of flow conditions.

In order to understand better the impact of the flow releases on recruitment and maintenance scores, the optimal releases obtained for the 10,000 GL allocation for Investigations 7, 8 and 9 were analyzed and are given in Figure 2.13. Generally, larger releases were scheduled at times that favored the timing of the processes that were emphasized by the weight preferences. For example, in Investigation 7, larger releases were scheduled between October and December (spring to summer), with the majority of the releases being allocated in November. This was a reasonable selection of releases for this investigation, as nine out of the ten MFAT plant species preferred recruitment inundation in November, with inundation in October and December being preferred by seven and eight of the ten species, respectively. In all three investigations, most of the releases occurred in November, as the majority of the MFAT vegetation species preferred spring inundation for both recruitment and maintenance. However, the difficulty in the development of a management schedule arises in the determination of the magnitude and duration of releases, as these components vary from species to species (see Figure 4.8), which the optimization approach was able to account for. The maintenance and recruitment scores for each investigation and year are given in Table 2.9. It can be seen that, generally, when the preference is to ensure recruitment, the scores were approximately 0.95, with the exception of the first year. This was because recruitment timing for some species was based on the inundation from the previous year. When both recruitment and maintenance were favored, the scores were generally similar (see Table 2.9). On the whole, it seemed that the recruitment scores were higher than the maintenance scores. This was due to the difficulty associated with achieving the required interflood dry periods for maintenance, as discussed previously. The investigation favoring maintenance achieved an average score of approximately 0.9, while the recruitment score was not as high, at 0.6. This suggests that the optimization approach was able to ensure that the ideal maintenance flow components were met.

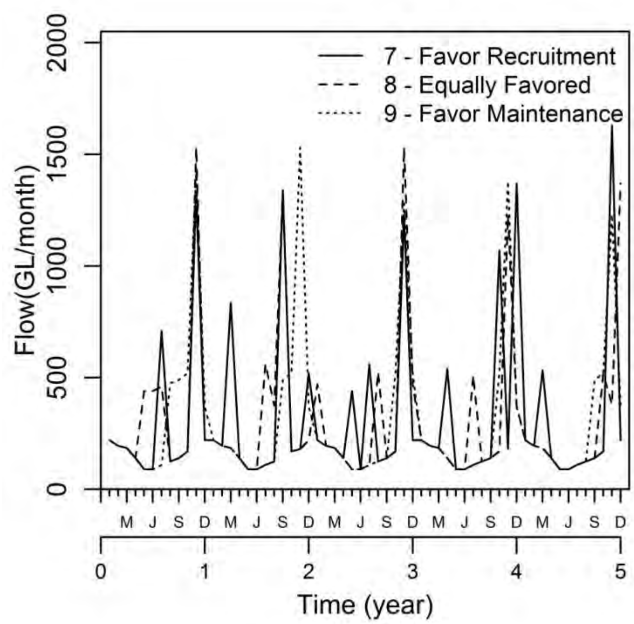

Figure 2.13: Monthly flow releases for the three points along the 10,000 GL allocation trade-off

Table 2.9: Annual Recruitment and Maintenance Scores for the Three 10,000 Water Allocation Investigations

Investigation	Score	Year				
		1	2	3	4	5
7 – Favor recruitment	Maintenance	0.47	0.48	0.70	0.59	0.62
	Recruitment	0.58	0.97	0.96	0.95	0.95
8 – Equally favored	Maintenance	0.80	0.80	0.84	0.79	0.85
	Recruitment	0.55	0.89	0.93	0.93	0.93
9 – Favor maintenance	Maintenance	0.91	0.91	0.88	0.91	0.92
	Recruitment	0.53	0.66	0.63	0.63	0.62

Overall, the ACO-based approach was able to be guided by the preferences of either maintenance, recruitment, or even both, quite successfully. Even though the management schedules had similar major release timings, the magnitudes for the smaller allocations were different, thus introducing the required flow variability to incorporate the ideal recruitment and maintenance flow components shown in Figure 2.8 into the schedule. There was however a limitation with the use of MFAT as the ecological indicator, as it was unable to account for vegetation encroachment. According to *Dolores Bejarano and Sordo-Ward* (2011) altered flow regimes as a result of dams influence tree and shrub establishment patterns along the river and as such should be taken into account. Even with this limitation, the approach was able to be used to develop near-optimal management schedules based on preferences chosen by managers. This is not only restricted to maintenance and recruitment scores, but can also incorporate emphases on different types of species or river reaches, wetlands and floodplains, as shown in the following subsections.

2.6.3 Determination of the Optimal Trade-Off Between Flora and Fauna Ecological Response

Table 2.10 shows the overall maintenance and recruitment scores for Investigations 10 and 11 (i.e., favoring flora and fauna, respectively). As can be seen, the overall maintenance and recruitment scores were significantly lower for Investigation 11, where fauna was favored, as only four species were considered within the objective function and therefore used to guide the ACO algorithm. Assets 1 and 5 were particularly affected, achieving a zero recruitment score, as there were no fauna species present in these assets, and there was therefore no contribution from these assets to the objective function. However, the fauna ecological scores in Investigation 10 were high, ranging from 0.8 to 1.0, which indicated that the optimization framework could be used to successfully find a management schedule that only focused on the fauna ecological response.

Table 2.10: Maintenance and Recruitment Scores for Investigations 10 and11

Investigation	Maintenance Score	Recruitment Score
10	0.80	0.86
11	0.68	0.57

On the other hand, higher recruitment and maintenance scores of 0.86 and 0.8, respectively, were obtained in Investigation 10. This was because, first, there were more species governing the development of the management schedule and second, the flora response curves were more difficult to satisfy and needed to be incorporated in the objective function, so that the resulting management schedules had higher overall MFAT scores. Although the flora species were preferred in Investigation 10, the fauna species also achieved high MFAT scores. This was because some of the fauna response curves were similar to the flora curves. For example, the ideal flood and spawning timing for main channel specialist fish, such as Murray Cod, is in late spring (*Ralph et al.*, 2011), which is within the range required for the ideal timing for the maintenance and recruitment of the majority of plant species (i.e., November). This suggests that ensuring major flows in late spring not only enhances the vegetation within the wetlands and floodplains, but also promotes the spawning and of recruitment of fish. Additionally, by flooding wetland/floodplain vegetation, habitat productivity is encouraged, resulting in an abundance of waterbird prey (*Rogers*, 2011a) and an ideal environment for waterbirds to forage and reproduce. Therefore, by ensuring flora species are of good health, the health of waterbird and fish species is also taken into account, indicating that in this particular case study, it is best to favor flora over fauna, as an overall better MFAT score can be achieved.

The optimal flow releases for both investigations are presented in Figure 2.14, and it can be seen that the larger releases occurred between October and December in Investigation 10, which corresponded to the preferred timing (i.e., spring–early summer) for all the vegetation types in the case study. On the other hand, in Investigation 11, major releases of lower magnitude were scheduled in December, since the fish species preferred that timing and the fauna species did not require such high flow releases during that time. Additionally, longer inundation times of approximately 6 months in years 1 and 4 ensured that the waterbird species in asset 3 could achieve the ideal inundation duration. In doing so, there was not enough water to support the surrounding biota, resulting in a lower overall MFAT score, and in turn, a poorer ecological state.

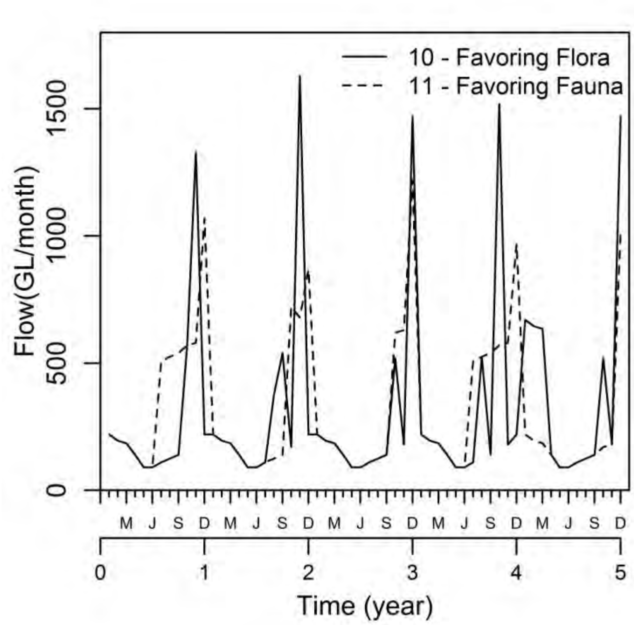

Figure 2.14: Flow releases for Investigations 10 and 11

This study demonstrates the development of management schedules that favor specific species and the impact this might have on the remaining species. The results suggest that the proposed framework can be applied to cases when particular species (e.g., endangered species) need to be favored in the development of EFMA schedules, thereby providing wetland managers with valuable information about the trade-offs in ecological outcomes between different species for different management schedules. Finally, the study demonstrates the flexibility and versatility of the proposed optimization framework, as the additional fauna species could be incorporated into the study with ease.

2.6.4 Determination of Optimal EFMA Schedules as a Result of Hydrograph Inversion

The average MFAT scores obtained for Investigations 12 and 13 are given in Table 2.11. The scores achieved when the seasonal constraints (i.e., Investigation 12) were included were lower compared with those produced when an overall constraint was applied over the entire 5 year planning horizon (i.e., 0.75 and 0.84, respectively). This was because the majority of environmental water allocation in the seasonal constraint case was available in summer and autumn (i.e., December–May), which was not ideal for the flora and fauna species in the case study. For instance, a total release of 200 GL was scheduled in spring (with the majority scheduled in summer) when a seasonal constraint was applied, while a release of 5450 GL of the 10,000 GL allocation was scheduled in the spring months (i.e., September–November) in Investigation 13, resulting in a higher MFAT score, as the majority of the biota prefer to be inundated at this time. On the other hand the hydrograph inversion case score was higher than expected, which may have been due to the assumptions made, such as setting the MFAT water temperature score to 1.0 (see section 2.4.1.1). In reality, river thermal regimes are altered by reservoir operations and can have a significant impact on fish species spawning (*Clarkson and Childs*, 2000) and the overall integrity of the ecosystem (*Olden and Naiman*, 2010). Even though, the hydrograph inversion scores were relatively high, the seasonal restrictions had an impact on the overall ecological health of the river and associated wetlands and floodplains, since the required flow was not provided to the biota. However, by using the optimization approach introduced in this paper, the best possible ecological outcome, given the constraints on the water available for ecological purposes at different times of the year, can still be achieved.

Table 2.11: MFAT Scores for each Asset and overall MFAT score for Investigation 12 and 13

Asset	MFAT Scores	
	Investigation 12	Investigation 13
1	0.72	0.79
2	0.76	0.90
3	0.82	0.86
4	0.71	0.78
5	0.58	0.77
6	0.95	0.95
AVERAGE SCORE	0.75	0.84

The individual MFAT scores for each asset are also given in Table 2.11. As can be seen, the scores were generally lower when the seasonal constraint was applied, with the exception of the fish species at asset 6, which had the same score. This was because, first, the ideal inundation duration of one month, as well as the ideal dry period of between 6 and 12 months, could be met, and, second, the preferred timing for spawning and flooding could both be achieved in spring and summer. This means that a high MFAT score for main channel specialists can be achieved in cases when the majority of environmental water is available in summer or spring.

In comparison, there was a significant drop in MFAT scores for assets 2 and 5 of 0.14 and 0.19, respectively, when the seasonal constraints were applied. This was mainly due to lower recruitment and maintenance scores for river red gums. Both assets contain this species of vegetation and both had lower MFAT scores. This was because the ideal flow requirements were not met, particularly the ideal timing for maintenance of current adult habitat and germination of seedlings, as both prefer inundation in spring. This indicates that for the hydrograph inversion case, there is significant impact on river red gums, which might threaten their survival. This impact would be worse if the available total environmental water allocation over the 5 year period was reduced. In the River Murray, the health and growth of river red gum areas have declined as a result of river regulation (*Bren*, 1988) and for this reason wetland management plans in this region focus on maintaining this particular species (*Tucker et al.*, 2002).

Overall, the optimization framework was able to cater to the hydrograph inversion case and show that a particular plant species (i.e., river red gum) was particularly susceptible to seasonal constraints. It can therefore be used to identify species under threat and provide wetland and water resource managers with a better understanding of the management schedule that will ensure the ecological health of the entire river system, even if the river is regulated. Furthermore, the study demonstrated that the optimization framework can incorporate other constraints (e.g., seasonal, monthly or yearly), which managers may need to employ in other investigations.

2.7 Summary and Conclusion

This paper provides a detailed formulation of the EFMA schedule optimization problem (section 2.2) and presents a novel and robust optimization framework for solving it (section 2.3). In order to be able to account for the sequential nature of the EFMA problem, it has been suggested to use ant colony optimization (ACO), as it uses a graph structure to represent the problem, which is able to be adjusted dynamically during the construction of trial solutions, thereby reducing the size of the search space and increasing the chances of finding globally optimal solutions. In order to demonstrate the utility of the proposed optimization framework, a case study based on the Murray River, Australia, was used, which consists of a river reach, three wetlands and two floodplains. In order to evaluate the effectiveness of the management schedules developed, the Murray Flow Assessment Tool, MFAT (*Young et al.*, 2003) was used.

To validate the management schedules developed using the ACO-based optimization framework, the schedules obtained using the framework were initially compared with those developed using a heuristic approach. Although it is recognized that the use of a heuristic approach as a basis of comparison has its limitations, it provides some degree of validation of the proposed optimization approach, as well as illustrating its potential benefits. Six investigations of varying complexity were used as part of the validation process, with Investigations 1–3 having only one plant species, while the number of plant species ranged from 3 to 12 in the remaining three investigations. Identical MFAT scores were obtained for the first three investigations using both techniques, while for the more complex investigations, the management schedules constructed using the optimization approach were able to save water and achieve higher MFAT scores than the management schedules obtained using the heuristic approach. Based on these results, the optimization approach was considered successful in developing management schedules for both simple and complex circumstances.

The optimization framework was then applied to a range of different studies that include (1) the development of optimal trade-offs between recruitment and maintenance for 12 species of flora for different 5 yearly flow allocations ranging from 500 to 12,000 GL, (2) the development of an optimal trade-off in ecological response between flora and fauna species, and (3) the development of EFMA schedules for a hydrograph inversion case. The results of the first study indicated that allocations greater than 10,000 GL did not change the final MFAT ecological scores for the wetlands and floodplains. Additionally, a maximum score of approximately 1.0 for both recruitment and maintenance could not be achieved, as there were competing flow components, where an increase in the score for a particular flow component decreased the score of another component, and vice versa. The second study indicated that favoring fauna species resulted in the surrounding biota having a lower score, while prioritizing flora achieved an overall higher score. Finally, the third study showed that the hydroinversion case could be easily incorporated within the optimization framework, as well as providing information on which species were particularly threatened. Overall, these studies were able to provide further understanding regarding when recruitment, maintenance, or a particular species are favored, the water allocation necessary to improve the ecological integrity of biota, as well as developing optimal flow management schedules in a regulated river system. This suggests that the proposed approach is a valuable tool in achieving the best possible ecological outcomes, given particular environmental flow allocations.

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Chapter 3

3 A multi-objective ant colony optimization approach for scheduling environmental flow management alternatives with application to the River Murray, Australia (Paper 2)

Statement of Authorship

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Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Joanna Szemis		
Contribution to the Paper	Conceptual and algorithm development, analysis of results, manuscript preparation and corresponding author.		
Signature		Date	11/06/2014

Name of Co-Author	Graeme Dandy		
Contribution to the Paper	Research supervision and review of manuscript		
Signature		Date	11/06/2014

Name of Co-Author	Holger Maier		
Contribution to the Paper	Research supervision and review of manuscript		
Signature		Date	06/06/2014

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Abstract

In regulated river systems, such as the River Murray in Australia, the efficient use of water to preserve and restore biota in the river, wetlands and floodplains is of concern for water managers. Available management options include the timing of river flow releases and operation of wetland flow control structures. However, the optimal scheduling of these environmental flow management alternatives is a difficult task, since there are generally multiple wetlands and floodplains with a range of species, as well as a large number of management options that need to be considered. Consequently, this problem is a multi-objective optimization problem aimed at maximizing ecological benefit while minimizing water allocations within the infrastructure constraints of the system under consideration. This paper presents a multi-objective optimization framework, which is based on a multi-objective ant colony optimization approach, for developing optimal trade-offs between water allocation and ecological benefit. The framework is applied to a reach of the River Murray in South Australia. Two studies are formulated to assess the impact of (i) upstream system flow constraints and (ii) additional regulators on this trade-off. The results indicate that unless the system flow constraints are relaxed, there is limited additional ecological benefit as allocation increases. Furthermore the use of regulators can increase ecological benefits while using less water. The results illustrate the utility of the framework since the impact of flow control infrastructure on the trade-offs between water allocation and ecological benefit can be investigated, thereby providing valuable insight to managers.

3.1 Introduction

River basin development, including land conversion, over-allocation of water and the construction of barriers (e.g. dams) has altered many rivers and their adjacent wetlands and floodplains worldwide (*Kingsford*, 2000; *MEA*, 2005). To preserve and restore these systems, much focus has been given to environmental flow management (*Arthington and Pusey*, 2003; *Arthington et al.*, 2010; *Kingsford and Auld*, 2005; *Tharme*, 2003), which aims to follow the 'natural flow paradigm' developed by *Poff et al.* (1997) and "mimic components of natural flow variability", in terms of flow frequency, duration, timing, rate of change and magnitude (*Arthington et al.*, 2006). These flow components are integral to maintaining and preserving biota within river-floodplain system (*Junk et al.*, 1989).

The management and delivery of environmental flows (in terms of the five important flow components) is not an easy task, since (i) there are generally large numbers of wetlands and floodplains containing a variety of flora and fauna with different flow requirements that need to be taken into account, for instance, lignum shrubland (*Muehlenbeckia florulenta*) prefer an inundation duration of 1-6 months while great crested grebes prefer 2-5 months (*Rogers and Ralph*, 2011); (ii) there is generally limited water available for environmental purposes, given that there are a number of users (e.g. irrigation, domestic and industrial supply) all vying for the same water resource (*Wallace et al.*, 2003); and (iii) there might be flow restrictions as a result of constraints in the system (e.g. upstream flows are limited to particular values in particular months) (*MDBA*, 2011a). Therefore, in order to use environmental water effectively and efficiently so as to maximize the ecological integrity of rivers, wetlands and floodplains, a number of environmental flow management alternatives (EFMAs) can be utilized, including upstream flow releases or the operation of gates and pumps to regulate water entering and leaving wetlands. Since decisions in relation to EFMAs (e.g. reservoir flow releases or gate operations) are made at discrete timesteps over a specific planning horizon (e.g. a number of years) and at numerous locations (e.g. different wetlands), the search space for this scheduling problem generally becomes very large, especially when extended spatial and temporal scales are considered (*Szemis et al.*, 2012). Due to this complexity, there is potential benefit in employing optimization approaches to schedule EFMAs to maximize ecological integrity, given a particular environmental flow allocation.

Optimization studies in this area have mainly focused on the development of optimal reservoir/weir operating rule parameters or monthly reservoir releases, while attempting to maintain an appropriate balance between the environment and other potential water users (e.g. irrigators), rather than how to schedule a given environmental water allocation in order to maximize ecological outcomes (e.g. (*Chang et al.*, 2010; *Chaves et al.*, 2003; *Higgins et al.*, 2011; *Homa et al.*, 2005; *Shiau and Wu*, 2004; 2007; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2011; *Yin et al.*, 2010)). Consequently, ecological objectives have been generally treated in a rather simplistic fashion. In order to overcome this shortcoming, *Szemis et al.*(2012) introduced an optimization framework for the development of environmental flow management schedules for maximizing the ecological response of rivers, wetlands and floodplains that incorporates different EFMAs (i.e. wetland gate operations, reservoir releases), flow components (i.e. flood timing, flood duration, dry period, depth), and water allocation constraints. The framework is also able to cater for the relative importance of different ecological assets, species and processes. However, the approach has only been tested on a hypothetical case study thus far. In addition, the optimization framework is single objective, whereas in practice, there is significant interest in the optimal trade-offs between the amount of water allocated to the environment and the corresponding optimal ecological responses of affected wetlands and floodplains or particular species.

In order to address the shortcomings in existing literature identified above, the objectives of this paper are (i) to extend the single-objective optimization approach developed by *Szemis et al.*(2012) to include multiple objectives and compare the performance of three multi-objective algorithms in order to determine which is most suitable for the EFMA optimization problem, so that the optimal trade-offs between ecological response and environmental flow allocations can be obtained, and (ii) to apply the approach to a real case study in the South Australian reaches of the River Murray. This case study is well suited to testing the multi-objective EFMA approach, as flow in the River Murray is over-allocated and a number of options are being considered for increasing the ecological health of the many wetlands and floodplains in the region. These include different environmental flow allocations and infrastructure options for maximizing the benefit of these allocations. One of these infrastructure options is the utilization of wetland regulators to enable direct control over the flow regime in the wetlands (e.g. introducing a drying phase to wetlands that are permanently inundated) and to reduce evaporation losses (*Higgins et al.*, 2011). However, where these regulators should be located and how they should be operated, as well as their effect on the optimal trade-offs between the amount of water allocated to the environment and the corresponding optimal ecological response, is unknown. The second infrastructure option considered is the potential increase in the maximum rate of upstream environmental flow releases, thereby enabling the magnitude of flow events, and hence levels of inundation, to be increased. However, the impact of these system constraints on the optimal trade-offs between environmental flow allocations and ecological response is currently unknown.

The remainder of this paper is organized as follows. The case study area, problem formulation and multi-objective optimization approach used to develop the environmental flow management schedules, including the comparative study of three multi-objective algorithms, are described in Sections 3.2 and 3.3. The analyses conducted are described in Section 3.4, while the results, discussion and limitations are discussed in Section 3.5. Finally, the conclusions of the study are given in Section 3.6.

3.2 Case Study: River Murray in South Australia

The South Australian reaches of the River Murray are part of the Murray-Darling river system, which is located in south eastern Australia and spans a number of Australian States, including Victoria, New South Wales, Queensland and South Australia (see Figure 3.1) (*Reid and Brooks*, 2000). Since the 1920s, the South Australian reaches of the River Murray have become significantly regulated with the construction of six locks along the river channel and a number of upstream structures in New South Wales and Victoria (*George et al.*, 2005). An annual water entitlement of 1,850 GL has been allocated to South Australia by the Murray-Darling Basin Authority (MBDA). This is predominantly for main channel flows, irrigation and water supply for Adelaide, the capital of South Australia, which has a population of 1.21 million (*ABS*, 2012), with only 38.7 GL of this entitlement being used for wetlands, and recreational and environmental use (*SAMDBNRM*, 2009).

The increase in river regulation and over-allocation of water (due to an expansion of irrigation), and the effect of drought over a long period of time, have reduced the flow variability within the river system and highly stressed and altered the biota in the river and adjacent wetlands and floodplains (*Overton et al.*, 2010). In response, the Commonwealth Government of Australia approved a basin wide plan developed by the MDBA that determined the water allocation for each user and intends to increase the annual environmental water for the entire basin by 3,200 GL/yr, taking it to a total volume of 4,023 GL/yr (*MDBA*, 2012c). In addition, the MBDA modeled and recommended the relaxation of system constraints, such as increasing the maximum flow releases from Hume Dam (an upstream dam) from 25,000 to 40,000 ML/day in order to allow higher flows to reach the South Australian River Murray and inundate mid to high elevation floodplains (*MDBA*, 2012d). However, many scientists recommend that further investigations should be conducted to assess the impact of an increase in the environmental water allocation to 4,000 GL/yr, ensuring that high-elevation floodplains are inundated periodically (*GSA*, 2012).

The case study area under investigation is a reach of the River Murray between Locks 1 and 2, shown in Figure 3.1. This reach spans 89.0 kilometers (*Overton et al.*, 2006) and accommodates eight wetlands and a large number of high lying floodplains along the river channel. Due to the construction of the locks, the wetlands closer to Lock 1 have become permanently inundated (i.e. continual connection to the river) and experience no drying, which has reduced the ecological health of the biota, such as Lignum (*Muehlenbeckia florulenta*), which dies when inundated for a prolonged period of time (*Kingsford*, 2000; *Smith and Smith*, 1990; *Walker and Thoms*, 1993). In contrast, wetlands closer to Lock 2 are temporary and rarely inundated due to upstream system constraints. Each wetland and surrounding floodplain houses a variety of flora and fauna, ranging from high-lying river red gums (*Eucalyptus camaldulensis*) to water birds and fish (e.g. ibis and carp gudgeon) (*Turner*, 2007).

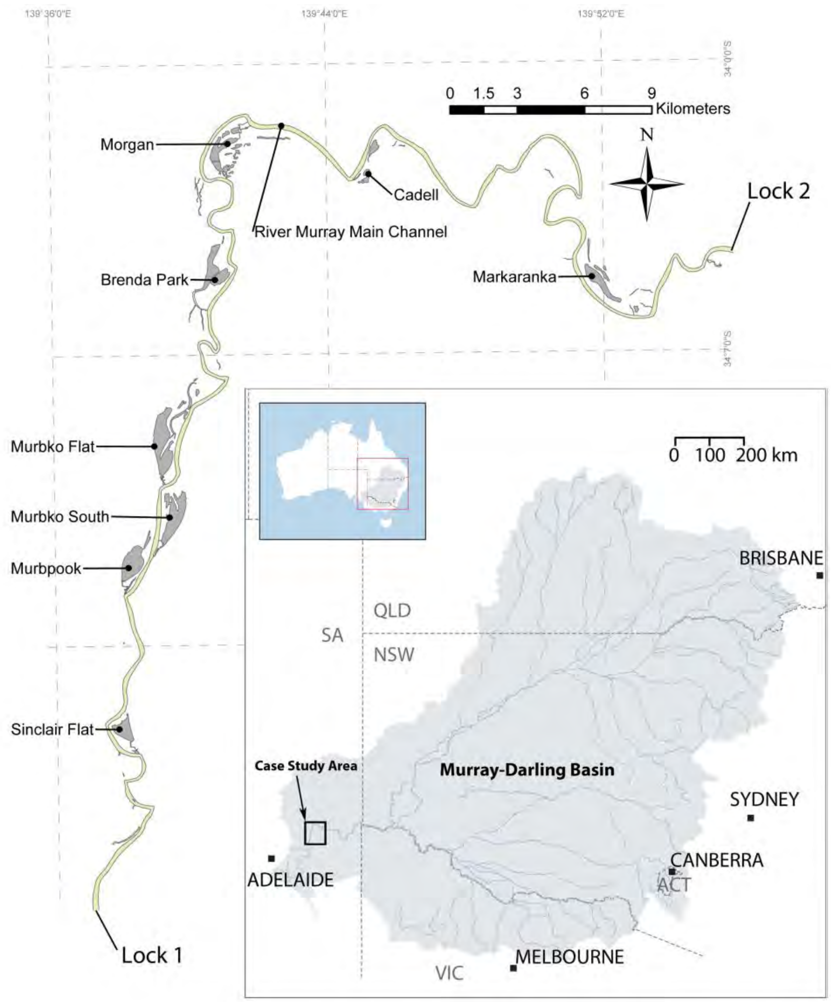

Figure 3.1: Map of case study area adapted from Murray-Darling Basin Authority website (http://www.mdba.gov.au/river-data/spatial-data-services/spatial-information).

As discussed in Section 3.1, the use of wetland regulators has been suggested in the case study area. Currently there are two wetlands with gates (*Schultz*, 2007; *Turner*, 2007), with a proposal to add flow regulation systems to a further three (*EA*, 2007; *Overton et al.*, 2010). In addition to the manipulation of regulators, ecological response can also be influenced by upstream flow releases from the South Australian border. As stated in the Introduction, the objectives of this paper are to investigate the effect system constraints and regulator locations and settings have on the optimal trade-off between environmental flow allocations and different aspects of ecological integrity within the case study area. The methodology for achieving this is given in the next section.

3.3 Methodology

In order to investigate the optimal trade-offs between environmental flow allocations and ecological response(s) for the case study area under a range of scenarios, optimal EFMA schedules (i.e. flow releases and regulator settings) have to be identified over the selected planning horizon. This is achieved by modifying the optimization framework presented by *Szemis et al.* (2012) to incorporate a multi-objective optimization approach. The steps in the framework are shown in Figure 3.2 and include problem formulation, which includes the identification of the river reaches, wetlands and floodplains to be managed, as well as the indicator(s) for measuring ecological response, and potential management alternatives and associated suboptions (Section 3.3.1). The objective function and constraints are then identified (Section 3.3.2), after which a trial schedule of flow releases and regulator settings can be developed over the adopted planning horizon, and assessed by calculating the objective functions using a hydrological model (Section 3.3.3).

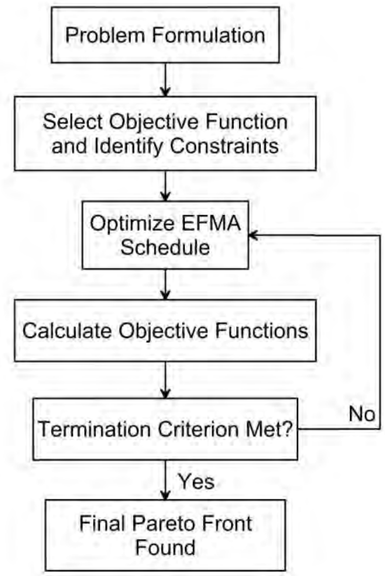

Figure 3.2: Steps in optimization framework

This process of developing and evaluating management schedules is repeated multiple times and guided by a multi-objective optimization algorithm in order to develop the final Pareto front, which contains EFMAs that represent the optimal trade-offs between the total environmental flow allocation and the corresponding ecological response(s). Based on the rationale presented in *Szemis et al.*(2012), Ant Colony Optimization (ACO) is used as the optimization algorithm, since (i) it can solve complex non-linear problems, in contrast to traditional optimization methods, such as linear programming, which can only solve linear problems (*Taha*, 1997), and dynamic programming, which suffers from the 'curse of dimensionality' (*Madej et al.*, 2006), and (ii) unlike other metaheuristics, such as Genetic Algorithms (*Goldberg*, 1989), it can accommodate the sequential nature and the conditional dependencies of the EFMA scheduling problem by using a decision tree graph to represent the problem (*Szemis et al.*, 2012), and is capable of adjusting constraints dynamically during the optimization process in order to reduce the size of the search space (*Afshar*, 2010; *Foong et al.*, 2007; 2008a; *Szemis et al.*, 2012). In order to ensure that the most appropriate multi-objective ACO algorithm is selected, a comparison between three multi-objective ACO algorithms is conducted, as discussed in Section 3.3.5.

3.3.1 Problem Formulation

3.3.1.1 Identification of assets and ecological indicators

The first step of the Problem Formulation stage involves the identification of the ecological assets to be managed, H_i, where i ranges from 1 to q. In this case study, the management of eight wetland areas is considered (i.e. q=8) (Step 1, Table 3.1), which include the wetlands themselves, the high-lying floodplain areas surrounding the wetlands, and the adjacent main river channel. Baseline surveys and wetland management plans have been used to delineate areas of vegetation within the wetland and floodplain areas, as well as to identify the location of certain fish and waterbirds (*EA*, 2007; *Marsland and Nicol*, 2008; *Schultz*, 2007; *SKM*, 2004; *Smith and Fleer*, 2006; *Turner*, 2007; *Waanders*, 2007; *Watkins et al.*, 2007).

The Murray Flow Assessment Tool (MFAT) developed by *Young et al.*, (2003) is used as the ecological indicator ($E_{i,r}$, where r is the number of species per wetland or floodplain) in order to quantify the ecological response of each species (i.e. vegetation, waterbird and fish) within the river, and adjacent wetlands and floodplains (Step 2, Table 3.1). MFAT is a habitat simulation model that was developed specifically for the River Murray and can be used to determine the impact of different flow scenarios on the ecological response of biota in terms of two ecological processes, that is, recruitment (e.g. promoting seed germination) and maintenance (e.g.

preserving adult habitat) (*Young et al.*, 2003). This is achieved by using a number of response curves that are based on the five flow components discussed previously (i.e. frequency, duration, timing, rate of change and magnitude) and include factors such as depth, dry period, flood timing, rate of depth change, inundation area and flow magnitude. The response curves used for the case study area are those given in *CRCFW* (2003) and *Overton et al* (2010), and include species such as river red gum (*Eucalyptus camaldulensis*), black box woodland (*Eucalyptus largiflorens*), ribbon weed herbland (*Vallisneria americana*), main channel specialists (e.g. Murray cod) and colonial nesting waterbirds. It should be noted that as part of the MFAT score calculation, weights need to be placed on the recruitment and maintenance processes, which are chosen based on literature or expert opinion. A total of 211 species have been defined for the case study area and the proportions of each species type per wetland are given in Table 3.2. As can be seen, approximately 60% of the species are floodplain flora, followed by waterbirds, fish and a small proportion of wetland flora.

Table 3.1:: Details of Problem Formulation for Case Study

Problem Formulation Steps		Specification
1	Managed Ecological Assets H_i, i=1 to q	$q = 8$
2	Ecological Indicator $E_{i,r}$ r=1 to $s(i)$	Murray Flow Assessment Tool (MFAT) (*Young et al.*, 2003) Total number of species = 211
3	Planning Horizon Yv, v=1 to K	Y_K = 5 years
	Time Interval t, t=1 to T	Monthly, T = 60 months
4	Management Alternatives M_a , a=1 to h	$h = 6$ (1 reach and 5 asset scale)
5	Management Alternative Suboption $M_{a,m}$ and/or $M_{a,d}$	Reach – magnitude & duration Asset – duration

Table 3.2: Species composition in case study area

Asset	Wetland Name	Species Composition (% per asset)				Regulator
		Floodplain Flora	Wetland Flora	Waterbird	Fish	
1	Markaranka	50.0	0.0	42.0	8.0	-
2	Cadell	73.0	0.0	18.0	18.0	-
3	Morgan	50.0	11.0	25.0	14.0	Current
4	Brenda Park	53.0	0.0	29.0	18.0	Current
5	Murbko Flat	64.0	13.0	17.0	6.0	Proposed
6	Murbko South	85.0	4.0	0.0	11.0	-
7	Murbpook	52.0	7.0	30.0	11.0	Proposed
8	Sinclair	61.0	22.0	0.0	17.0	Proposed

3.3.1.2 Selection of Planning Horizon and Time Interval

The third step of the problem formulation includes the selection of the planning horizon, Yv (v=1, K years) and time interval, t, where t ranges from 1 to the final interval, T (Table 3.1). A planning horizon of five years has been selected, as environmental water management plans in the study area are generally developed over five years (*EA*, 2007; *Schultz*, 2007), while a monthly timestep has been chosen, since wetland gate operations are set on a month by month basis (*Schultz*, 2007; *Turner*, 2007). This meant that the final interval, T, equals 60.

3.3.1.3 Determination of Management Alternatives and Suboptions

The identification of the management alternatives M_a, (where a ranges from 1 to h) and suboptions constitute the final two steps of the problem formulation process. The environmental flow release at the South Australian border has been selected as the sole reach scale management alternative, while the asset scale management alternatives include the operations of gates at selected wetlands. Currently, flow at two wetlands (i.e. Morgan and Brenda Park, see Figure 3.1) can be regulated, with another three being proposed, as shown in

Table 3.2. Consequently, there are six management alternatives (i.e. h=6) that can be considered in the development of environmental flow management schedules (Table 3.1). Next, the suboptions for each of the management alternatives, M_a are defined. Duration, $M_{a,d}$, and magnitude, $M_{a,m}$, suboptions have been selected as the only reach scale management suboptions, while duration suboptions have been selected for all asset scale management alternatives (see Table 3.1.). The number of possible duration suboptions ($M_{a,d}$) available at each monthly timestep ranges from 1 to p, with p varying from 12 in January to 1 in December. On the other hand, the number of magnitude suboptions ranges from 1 to n, with the selection of the maximum number of magnitude suboptions (n) dependent on the case study area and system constraints. This is discussed detail in the next Section.

3.3.2 Identification of Objective Functions and Constraints

Once the problem has been formulated, the objective functions and constraints need to be defined (Figure 3.1). As discussed previously, the two broad objectives that need to be considered in the problem being addressed are the maximization of ecological response and the minimization of environmental water allocation. However, as ecological response is comprised of a number of different components (e.g. different types of ecological assets such as wetlands, and floodplains, different species, different ecological processes), the objective of optimizing ecological response can be represented by one or more objective functions, corresponding to different levels of aggregation of these components. In order to account for this, the single ecological response objective introduced by *Szemis et al,* (2012) has been modified to enable consideration of multiple ecological objectives. To develop the multi-ecological response objective, the number of assets, species and years considered in the case study area need to be defined as sets. Consequently, the number of assets ranging from 1 to q is defined in set H, while the number of species per *ith* asset (e.g. wetland) is identified as the R_i set, with each *ith* asset housing $s(i)$ species. Finally, the total year set, V, ranging from 1 to a maximum year of Y_K is also defined, with the sets shown below.

$$i \in H = \{1,2,\ldots,q\}$$

$$R_i = \{1,2,\ldots,s(i)\}$$

$$V = \{1,2,\ldots,Y_K\}$$

Once the asset, species and year sets have been defined, the ecological components that are of interest (e.g. specific area of wetlands or vegetation species) as part of the *gth* ecological response objective, where g ranges from 1 to fg, are defined in the form of g subsets, which also range from 1 to fg. When $fg = 1$, a single objective function is used, in which the ecological responses of all components are aggregated, when $fg = 2$, two ecological objective functions are used in which different sub-sets of ecological components are considered and so on. The subsets are given below.

$$i \in H_g \subseteq H$$

$$R_{i,g} \subseteq R_i, \qquad g = 1 \text{ to } fg$$

$$V_g \subseteq V$$

where H_g is the *gth* subset of H and contains ecological components related to the assets and enables examination of the ecological response of wetlands and floodplains at different locations, while $R_{i,g}$ is the *gth* subset of R_i and contains information about which species (e.g. fish) are included in the *gth* ecological response objective. Lastly, V_g is the *gth* subset of V, which defines the years considered and allows for the investigation of ecological responses at a specific year or over a number of years.

Once the *fg* subsets are defined, each of the *g* ecological response objectives can be determined using Equation 3.1. It should be noted that each objective function includes weights in order to account for the relative importance of various aspects of the problem, such as favoring certain species or wetlands.

$$
\begin{aligned}
F_{E,1} &= \sum_{i \in I_1} w_{1i} \sum_{r \in R_{i,1}} w_{2r} \sum_{v \in V_1} \frac{w_{3v} E_{i,r,v}}{Y_{K,1}}, && g = 1 \\
F_{E,2} &= \sum_{i \in I_2} w_{1i} \sum_{r \in R_{i,2}} w_{2r} \sum_{v \in V_2} \frac{w_{3v} E_{i,r,v}}{Y_{K,2}}, && g = 2 \\
&\vdots \\
F_{E,fg} &= \sum_{i \in I_{fg}} w_{1i} \sum_{r \in R_{i,fg}} w_{2r} \sum_{v \in V_{fg}} \frac{w_{3v} E_{i,r,v}}{Y_{K,fg}}, && g = fg
\end{aligned}
\tag{3.1}
$$

where $E_{i,v,r}$ is the MFAT value for asset *i*, for indicator type *r* in the *vth* yearly time interval for each of the *g* objective functions corresponding to *g* separate ecological components. In Equation 1, each of the *g* objective function values is obtained by summing (i) values of each ecological indicator used in the particular objective function over the wetland areas (including the floodplain areas surrounding the wetlands and the adjacent river reach) defined in subset I_g(ii) values of the species indicators identified in $R_{i,g}$ to be aggregated in the *gth* objective function, and (iii) ecological indicator values used in the particular objective function over the years defined in subset V_g, over which the schedule of EFMAs has been developed (i.e. the planning horizon, which is five years in this instance), with the total number of years considered in the gth ecological response function defined as $Y_{K,g}$. Weights, w_{1i}, w_{2r} and , w_{3v} place emphasis on the *ith* wetlands, floodplains or river reaches, *rth* ecological indicator and $Y_K th$ year, respectively, and are defined by the user before commencement of the optimization process. Consequently, each objective function is sufficiently flexible to cater for particular aspects of the problem (e.g. favoring sensitive or endangered species).

Another component of the extension from the single to the multi-objective optimization framework presented in this paper is the addition of an environmental water allocation objective, F_W, which accounts for the total amount of environmental water that is allocated over the five year planning horizon and is given below:

$$F_W = \sum_{t=1}^{T} A_t \tag{3.2}$$

where A_t is the environmental water allocation in month *t,* which is calculated using the reach scale management alternative magnitude suboptions selected at each *tth* timestep.

In addition, constraints are defined on the magnitude and duration of the suboptions for a particular management alternative, M_a, as given in Equations 3.3 and 3.4:

$$M_{a,m\_\min} \leq M_{a,m} < M_{a,m\_\max}, \qquad m = 1 \text{ to } n \tag{3.3}$$

$$M_{a,d\_\min} \leq M_{a,d} < M_{a,d\_\max}, \qquad d = 1 \text{ to } p \tag{3.4}$$

where the magnitude suboptions ($M_{a,m}$) are constrained by minimum and maximum values of M_{a,m_min} and M_{a,m_max}, respectively, and the duration suboptions ($M_{a,d}$) are constrained by minimum and maximum values of M_{a,d_min} and M_{a,d_max}, respectively, for each management alternative. Each management alternative must therefore be assessed individually in order to determine appropriate values for the above constraints. The specification of M_{a,m_min}, M_{a,m_max}, M_{a,d_min} and M_{a,d_max} is user-defined, based on the requirements of the case study area under consideration (e.g. M_{a,m_max} could be selected based on a maximum achievable flow in the case study area).

A further constraint relates to the maximum allowable monthly flow at the South Australian border, which permits the assessment of the impact of system flow constraints, and is given as follows:

$$Q_t \leq Q_{t\max} , \qquad t = 1 \text{ to } T \tag{3.5}$$

The monthly flow has been defined as Q_t, while Q_{tmax} is the maximum flow at the South Australian border each *tth* month. The selection of Q_{tmax} is user-defined and is generally based on system constraints within the case study area.

3.3.3 Development of Management Schedules

After the objectives and constraints have been defined, management schedules are developed (as shown in Figure 3.2), which is done by selecting values for each of the suboptions. Based on the framework developed by *Szemis et al.* (2012), the management alternatives and suboptions are represented in the form of a decision tree graph, which is able take into account the sequential nature and temporal dependencies associated with the EFMA scheduling problem (e.g. the fact that the values of decision variables selected at one time period, such as the duration of a particular flow release, have an effect on the options that are available at subsequent time periods). Using this graph, a management schedule is developed by selecting one of the available alternatives at each of the nodes. Determination of the management schedules that provide the best possible trade-offs between the competing objectives of minimizing the environmental water allocation and maximizing the ecological response(s) is achieved over a number of iterations with the aid of the multi-objective ant colony optimization algorithm, details of which are given in Section 3.3.5.

An example decision tree graph that incorporates magnitude and duration suboptions, as well as the conditional dependencies associated with the duration suboptions via dynamic constraints, is given in Figure 3.3. The example considers four magnitude options (i.e. 0, 200, 400 and 800 gigalitres (GL)) and three duration suboptions, and is constructed over three time steps.

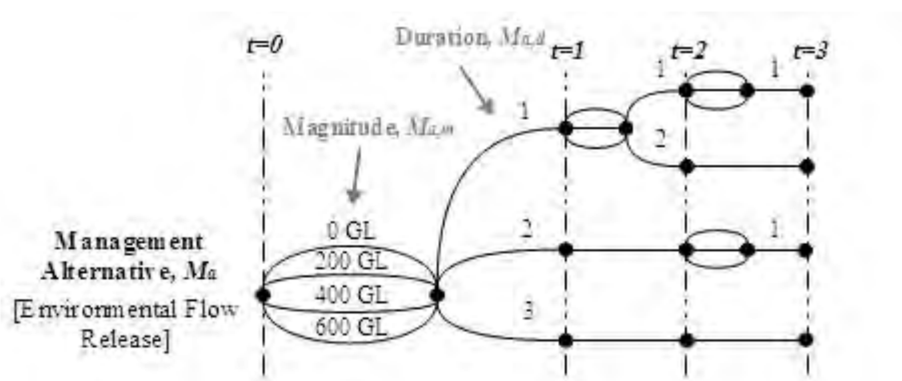

Figure 3.3: Example of an EFMA schedule graph for environmental flow releases (In Gigalitres (GL)) incorporating dynamic constraints

If the maximum duration has been selected at the first time step, then no other decision paths need to be made available at subsequent time steps (decision points), as shown by the bottom path in Figure 3.3. In this way, the decision tree is adjusted based on the selection made at the first decision point, thereby reducing the size of the search space and increasing the likelihood that global or near globally optimal solutions are identified. On the other hand, if a duration option of one is chosen at the first time step (top path), then the potential duration suboptions are considered again at the following timestep. However, the number of available options decreases from three to two, as there are only two more time steps remaining. If the number of available duration suboptions is not adjusted dynamically then three duration options would be considered after each magnitude suboption, which results in a significantly larger search space. Therefore, this form of dynamically constraining the decision tree graph ensures that feasible EFMA schedules are developed, as well as ensuring that the optimization algorithm is able to find optimal solutions more efficiently and cater for the conditional dependencies associated with the EFMA problem (*Szemis et al.*, 2012).

3.3.4 Calculation of Objective Functions

In order to evaluate the objective functions defined in Section 3.3.2 for the selected management schedules, a hydrological simulation model is developed for the river reach under investigation. This is achieved with the aid of backwater curves (T. Bjornsson, personal communication, 2010) that relate river height to river flows at the South Australia border (e.g. 5,000ML/day, 10,000ML/day). This allows a relationship between flow and river height along the length of the main channel to be developed, such that for a certain flow release at the South Australian border, the corresponding river height at the eight wetland locations can be determined. In addition to this, fill values (i.e. the river level at which the wetland or floodplain is flooded) at the eight wetland locations, as well as area vs. average depth curves for each of the specified areas of floodplain and wetland flora and fauna, have been determined using ArcGIS and a range of data sources, including a Digital Elevation Model (DEM) obtained from the Department of Environmental, Water and Natural Resources baseline surveys (*Marsland and Nicol*, 2008; *SKM*, 2004; *Smith and Fleer*, 2006; *Waanders*, 2007) and wetland management plans (*EA*, 2007; *Schultz*, 2007; *Turner*, 2007). Once the flow vs. river height relationships have been developed and the fill values obtained, the hydrological models can be developed using the equations employed in *Szemis et al.* (2012), as detailed below.

To ensure that the model adequately simulates the hydrology, whereby wetlands fill quickly once the river level breaches the fill value and when gates are opened, Equation 3.6 is used, while Equation 3.7 is utilized to simulate the slow draining of a wetland when the gates are closed, or when the river level drops below the fill value. Equation 3.6 represents the water balance for a wetland as follows:

$$I_t - O_t = S_{t+1} - S_t \tag{3.6}$$

where I_t are the inflows, O_t are the outflows, and S_t are the storages at time t. The outflows O_t are the sum of the flows out of the wetland (O_w) and evaporation (E_t), while the inflows are the sum of rainfall (R_t) and flows into the wetland. A simple relationship of $0.7 \times$(pan evaporation) is used to determine the evaporation from wetlands, in meters/month, with average monthly evaporation sourced from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/). The value of 0.7 is chosen as it is a common value used to determine evaporation within the Murray Darling Basin (*Gippel*, 2006).

To simulate gate operation, logic (If-Then) statements are used to adjust the appropriate components of the water balance equations. If a gate is closed, the inflow at that timestep is set to zero (i.e. I_t = 0.0) and if there is water in the wetland at that time, wetland storage at subsequent timesteps is only affected by rainfall and evaporation for the duration of the gate closure, as follows:

$$S_{t+1} = S_t - E_t + R_t \tag{3.7}$$

If there is water remaining in the wetland at the timestep the gate is opened, water is allowed to flow out of the wetland until the fill value is reached, after which water remains in the wetland and only is affected by evaporation and rainfall (i.e. Equation 3.10). It should be noted that average monthly rainfall data in the case study area have been used. These were obtained from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/).

Once the river level is above the fill value or maximum gate height (i.e. the maximum river level at which the gate can operate), the floodplain hydrological model is used. This model utilizes Equation 3.6, whereby floodplain hydrology is only dependent on the river level (i.e. if the river level is above the fill value, the floodplain is inundated and the area of flooding is dependent on the height of the river. For example, as the river level increases, so does the area and depth of inundation). It should be noted that the mass balance constraints associated with the problem are also satisfied within each hydrological model.

A number of assumptions have also been made for both models, including, (i) water seepage is negligible since it is small compared to the evaporation loss, and (ii) the rate of river level rise and fall occurs over each month. Additionally, the storage capacity of the wetlands has been examined and it has been determined that this is very small compared with the magnitude of the streamflows, and thus has a negligible effect on downstream flows.

3.3.5 Multi-objective Optimization

As mentioned in Section 3.3, a multi-objective ACO algorithm is used to iteratively determine management schedules that improve all objective functions with the aim of finding schedules that represent globally optimal or near globally optimal trade-offs between all objectives (i.e. schedules that are on the Pareto front – see Figure 3.2). The traditional multi-objective ACO procedure for determining optimal or near optimal trade-offs is shown in Figure 3.4, where a trial EFMA schedule is initialized, after which the optimization process takes place. This firstly involves the construction of a trial schedule for each b ants during each iteration. Ants achieve this by traveling to each timestep and selecting magnitude and duration suboptions until they reach the final timestep, T. The selection of these suboptions is done probabilistically based on the j pheromone matrices (τ^j) associated with each suboption, with the number of pheromone matrices used dependent on the multi-objective ACO algorithm used, as discussed below. As part of the optimization process, the j pheromone matrices are manipulated to increase pheromone levels for suboptions that have contributed to good overall solutions, so that they are more likely to be selected in subsequent iterations. Additionally, pheromone evaporation is applied to suboptions of schedules that do not perform well, which in turn deters the algorithm from choosing these paths again.

Once an iteration has been completed by an ant, the resulting schedule is evaluated using fitness functions, which are the objective functions (i.e. Equations 3.1 and 3.2) transformed in order to efficiently guide the search of the algorithms. Further details regarding the fitness functions are given in Section 3.3.5.4. The calculation of the fitness functions is achieved with the aid of the hydrological model of the case study area (see Section 3.3.4). This model is also used to assess whether there are any constraint violations (see Section 3.3.5.4). The process of selecting an EFMA schedule and evaluating it against the fitness functions is repeated for each ant. The pheromone levels are then updated and this process continues until the maximum iteration, *w*, is reached. It should be noted, that once the final iteration is complete, the convergence of the Pareto front is checked using the hypervolume, which measures the volume of area dominated by the approximated Pareto front set (*Zitzler and Thiele*, 1999). This has been selected to indicate the point at which there is no further reduction in the volume of the Pareto front, thereby suggesting convergence has been reached.

As part of this study, the performance of three multi-objective ACO algorithms that utilize the traditional ACO procedure (shown in Figure 3.4) has been compared to determine the most suitable algorithm for the case study area. The algorithms considered include the Pareto Ant Colony Optimization Algorithm (PACOA) (*Doerner et al.*, 2004), COMPETants (*Doerner et al.*, 2003) and m-ACO variant 3 (m-ACO_3) (*Alaya et al.*, 2007). These algorithms have been selected because they use different pheromone updating approaches in determining the optimal or near optimal trade-off. PACOA uses multiple pheromone matrices, as well as the best and second best solution during the pheromone update process, COMPETants uses multiple colonies and pheromone matrices, while m-ACO_3 employs a single pheromone matrix and updates the pheromone level using the non-dominated solutions determined after each iteration. It should be noted that other ACO algorithms, such as the population based ACO (*Guntsch and Middendorf*, 2003), have not been considered in this comparison, as they do not follow the traditional ACO process shown in Figure 3.4. A description of the three algorithms used, and the pheromone update process utilized in each, is presented in the following sections.

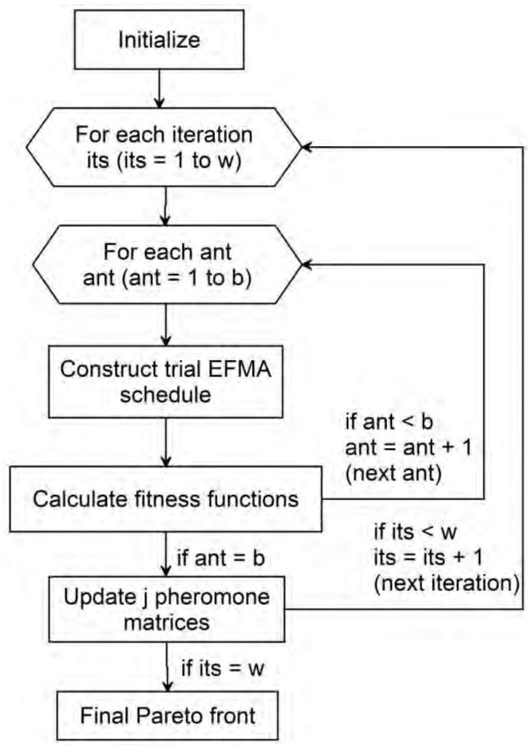

Figure 3.4: Traditional Ant Colony Optimization Procedure

3.3.5.1 Pareto Ant Colony Optimization

The PACOA developed by *Doerner et al.* (2004) utilizes Ant Colony Systems (*Dorigo and Gambardella*, 1997a) as the underlying ACO algorithm, however, unlike Ant Colony Systems, it uses both the first and second best solutions during the global pheromone update (*García-Martínez et al.*, 2007). In addition, the algorithm employs multiple pheromone matrices, one for each objective considered. The pheromone update process is given by the following equation:

$$\tau_t^j = (1-\rho)\cdot\tau_t^j + \rho\cdot\Delta\tau_t^j \tau_t^j = (1\text{-}\rho)\cdot\tau_t^j + \rho\cdot\Delta\tau_t^j \qquad (3.8)$$

$$\Delta\tau_t^j = \begin{cases} 15 & \text{if suboption is in best and second best solution,} \\ 10 & \text{if suboption is in best solution,} \\ 5 & \text{if suboption is in second best solution,} \\ 0 & \text{otherwise.} \end{cases}$$

where the pheromone level on all suboptions is reduced at a rate that is controlled by the pheromone evaporation factor (ρ), while an increase in pheromone levels for each j-th fitness function ($\Delta\tau^j$) is based on whether that particular suboption is part of the best or second best solution. The b trial schedules generated by the b ants then undergo a non-dominated sorting process in order to determine the schedules that are on the Pareto front for that particular iteration and are subsequently stored in an offline storage matrix. Readers are referred to *Doerner et al.* (2004) for a detailed description and the equations used in the PACOA.

3.3.5.2 COMPETants

The COMPETants algorithm proposed by *Doerner et al.* (2003) utilizes multiple colonies and pheromone matrices to determine the optimal or near-optimal Pareto front. Each colony focuses on one objective and constructs solutions independently from each other, with the exception of a group of ants, called spies, that use a weighted sum approach that aggregates the pheromone matrices for each objective.

As was done by *López-Ibáñez and Stützle* (2012), the COMPETants algorithm is formulated using a single-colony algorithm in which the ants are divided into subgroups that either focus on a given objective or act as spies. The pheromone levels for each subgroup are then updated using Equation 3.8, with the level of pheromone increase for each j^{th} objective, $\Delta\tau_t^j$, given in Equation 3.9 as follows:

$$\Delta\tau_t^j = \begin{cases} 10 & \text{if suboption is in best solution for the jth objective,} \\ 0 & \text{otherwise.} \end{cases} \tag{3.9}$$

The update process is independent for each subgroup, such that ants from each subgroup update their own pheromone matrix using the best solution.

As was done by *López-Ibáñez and Stützle* (2012), the COMPETants algorithm employed in this study equally portioned the number of ants used between the *j* objectives and spy subgroups. For further information regarding the COMPETants algorithm, readers are referred to *Doerner et al.* (2003) and *López-Ibáñez and Stützle* (2012).

3.3.5.3 m-ACO variant 3 (m-ACO$_3$)

The ACO variant suggested by *Alaya et al.* (2007) proposes the use of a single pheromone matrix, which is updated using the non-dominated solution determined in the current iteration set. The pheromone values, τ_t^j, are updated using Equation 3.8 (with $j=1.0$) and the increase in pheromone level ($\Delta\tau_t^j$) during the pheromone update process is based on whether a sub-option is in the non-dominated solution set for the current iterations, *P*, which is shown in Equation 3.10.

$$\Delta\tau_t^j = \begin{cases} 10 & \text{if suboption is in P,} \\ 0 & \text{otherwise.} \end{cases} \tag{3.10}$$

This is different to the two previous algorithms, which use the best solutions to update pheromone levels after each iteration.

3.3.5.4 Fitness Function

Before the performance of the multi-objective ACO algorithms can be compared, the objectives defined in Equations 3.1 and 3.2 need to be transformed to fitness functions (i.e. Equations 3.11 and 3.12) in order to effectively guide the search of the algorithms, as the algorithms (i) attempt to minimize all objectives, whereas the aim of this study involves the minimization of the environmental water allocation objective and the maximization of the *fg* ecological response objectives (i.e. MFAT score), and (ii) like other evolutionary algorithms, are unable to explicitly take into account the constraints that are not directly related to the decision variables, necessitating the inclusion of penalties in the fitness functions. Therefore, the following fitness function/s ($Y_{E,fg}$) have been developed, such that $F_{E,fg}$ would be maximized:

$$Y_{E,g} = \begin{cases} 1/F_{E,g} + Penalty_{E,g} & \text{if } F_{E,g} > 0 \\ Penalty_{E,g} & \text{if } F_{E,g} = 0 \end{cases}, \quad g = 1 \text{ to } fg \tag{3.11}$$

$$Penalty_{E,g} = \begin{cases} 0 & \text{if no constraint violation} \\ 1{,}000 & \text{if system constraint violation} \end{cases}, \qquad g = 1 \text{ to } fg$$

As can be seen, a penalty of 1,000 is used if the system flow constraints at the South Australia border are violated for the *fg* ecological response objectives considered. This value was found to produce good results as part of preliminary trials.

The fitness function corresponding to the objective of minimizing the total environmental water allocation (F_W, Equation 3.2), Y_W, is shown below.

$$Y_W = F_W + Penalty_W \tag{3.12}$$

$$Penalty_W = \begin{cases} 0 & \text{if no constraint violation} \\ \sum_{t=1}^{T} (Q_t - Q_{\max}) \cdot 1{,}000 & \text{if system constraint violation} \end{cases}$$

In order to take into account the system flow constraints, the fitness function above also includes a penalty to deter the algorithms from selecting infeasible solutions and instead encourage the determination of optimal schedules within the given constraints. The optimal form of the penalty was determined as part of preliminary trials and has been selected since it is able to severely penalize solutions that include flows that significantly exceed system constraints, while marginally penalizing solutions that include only slight violations of system constraints. This deters the algorithm from developing infeasible solutions, while simultaneously encouraging the search for good solutions and quicker convergence.

3.3.5.5 Comparison of Performance of Multi-objective Optimisation Algorithms

Before the performance of the multi-objective ACO algorithms can be compared, a comprehensive sensitivity analysis is required to determine the optimal values of the parameters that control the searching behavior of each algorithm. The range of values tested, as well as the final values selected, are given in Tables 3.3 and 4. As can be seen in Table 3.4, two different sets of optimal parameter sets are selected, depending on the size of the search space, as dictated by the number of management alternatives (h) considered within the EFMA schedule development. It should be noted that each sensitivity run was repeated ten times (i.e. with 10 random starting positions in decision space) so as to minimize the impact of the starting position on the results obtained.

Table 3.3: Range of ACO parameters investigated for each algorithm

ACO Parameter	Range of Values Tested
Number of ants (*ant*)	30,300,510,1200
Initial pheromone (τ_o^j)	1.0, 10.0
Evaporation rate (ρ)	0.02, 0.1, 0.5, 0.9, 0.98
Evaluations	102,000, 240,000

Table 3.4: Adopted ACO parameters for each algorithm

PACOA Parameter	Adopted Value(s)					
	h<4			*h*=6		
	PACOA	*COMPETants*	*m-ACO₃*	*PACOA*	*COMPETants*	*m-ACO₃*
Number of ants (*ant*)	300	510	30	510	1,200	300
Initial pheromone (τ_o^j)	1.0	1.0	1.0	1.0	1.0	1.0
Evaporation rate (ρ)	0.1	0.1	0.1	0.1	0.1	0.5
Evaluations	102,000			240,000		

Finally, to ensure that the Pareto fronts generated by each algorithm have converged when the optimal ACO parameters in Table 3.4 are used, the hypervolume of the Pareto front, as described in Section 3.3.5, has been assessed. The hypervolume convergence for each algorithm when the number of management alternatives is less than 4 is given in Figure 3.5. As can be seen, all algorithms have converged, with the PACOA converging to a hypervolume of approximately 3.0×10^5 at 160 iterations, COMPETants converging to a hypervolume of approximately 2.9×10^5 at 140 iterations, and m-ACO_3 converging to a hypervolume of 2.7×10^5 at 700 iterations. This indicates that the number of evaluations selected is sufficiently large for each of the algorithms to converge to a given Pareto front. It should be noted that hypervolume convergence has also been assessed for the case of six management alternatives, with the results obtained similar to those shown in Figure 3.5.

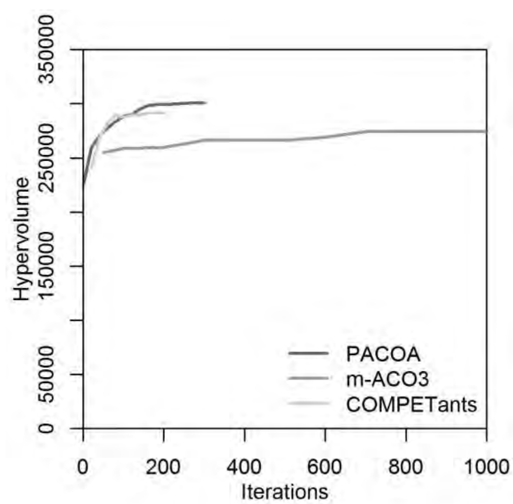

Figure 3.5: Hypervolume convergence for each multi-objective ACO algorithm when h<4

In order to assess the quality of the Pareto fronts obtained, the empirical attainment function (EAF) developed by *da Fonseca et al* (2001) is used. This is because it enables Pareto fronts obtained by two algorithms to be compared, which is not the case for other measures, such as the chi-square-like deviation developed by Srinivas and Deb (*Srinivas and Deb*, 1994) (*López-Ibáñez and Stützle*, 2012). Use of the EAF involves determining the probability that each point in the objective space is attained by an algorithm in a single run (*López-Ibáñez and Stützle*, 2012). To assess two Pareto fronts, the difference in EAFs of each point in the objective space is determined. In this study, a graphical technique (*López-Ibánez et al.*, 2006; 2010; *López-Ibáñez and Stützle*, 2012) is utilized in order to achieve this, with plots generated using the `eaf` R package, which is available at http://cran.r-project.org/package=eaf.

In order to compare the performance of the three multi-objective algorithms, one of the studies (i.e. Investigation 3) described in Section 3.4 is used, which considers two objectives (i.e. total ecological response and environmental water allocation), three management alternatives (h) (i.e. flow releases and the operation of two wetland regulators) and an upstream flow constraint of 1,800 GL/month. The number of flow magnitude suboptions (n) equals 28, while the number of duration suboptions equals 12 at the beginning of the year, but changes depending on selections made during the investigation. Further details, such as the asset (H), species (R_i) and year (V) sets for this investigation are given in Section 3.4.1 and Tables 3.5 and 3.6. The graphs comparing the Pareto fronts developed by PACOA, COMPETants and m-ACO_3 for Investigation 3 in terms of EAF difference are given in Figure 3.6. As can be seen, PACOA performs better than both COMPETants and m-ACO_3 (top and middle plots). This is shown by the black region in the

PACOA graphs (i.e. left graphs), indicating that the PACOA algorithm attained the points in the objective space at least 80% more than COMPETants and m-ACO_3, whereas the regions of white in the m-ACO_3 and COMPETants plots (i.e. right graphs) suggest that the same probability of attaining these points is achieved by all algorithms. On the other hand, the graph that compares the performance of COMPETants and m-ACO_3 (bottom plot) indicates that COMPETants performs better for solutions that minimize environmental water allocation, as indicated by the black region in the top left corner (see left graph), while m-ACO_3 finds solutions that maximize the MFAT score and, in turn, the ecological response of the wetlands and floodplains in the case study area.

The results of the comparison study indicate that the PACOA performs best, given that it is able to develop Pareto fronts with solutions that favor the objectives investigated (i.e. water allocation and ecological response), as indicated by the spread of the black region in the upper EAF difference plots in Figure 3.6. It should be noted that additional analyses have been conducted for the case where the number of management alternatives, h, equaled 6, with results obtained following a similar a trend as those shown in Figure 3.6. Based on these findings, the PACOA is used for the analysis for the case study area, with details of the analysis conducted and results given in Sections 3.4 and 3.5, respectively.

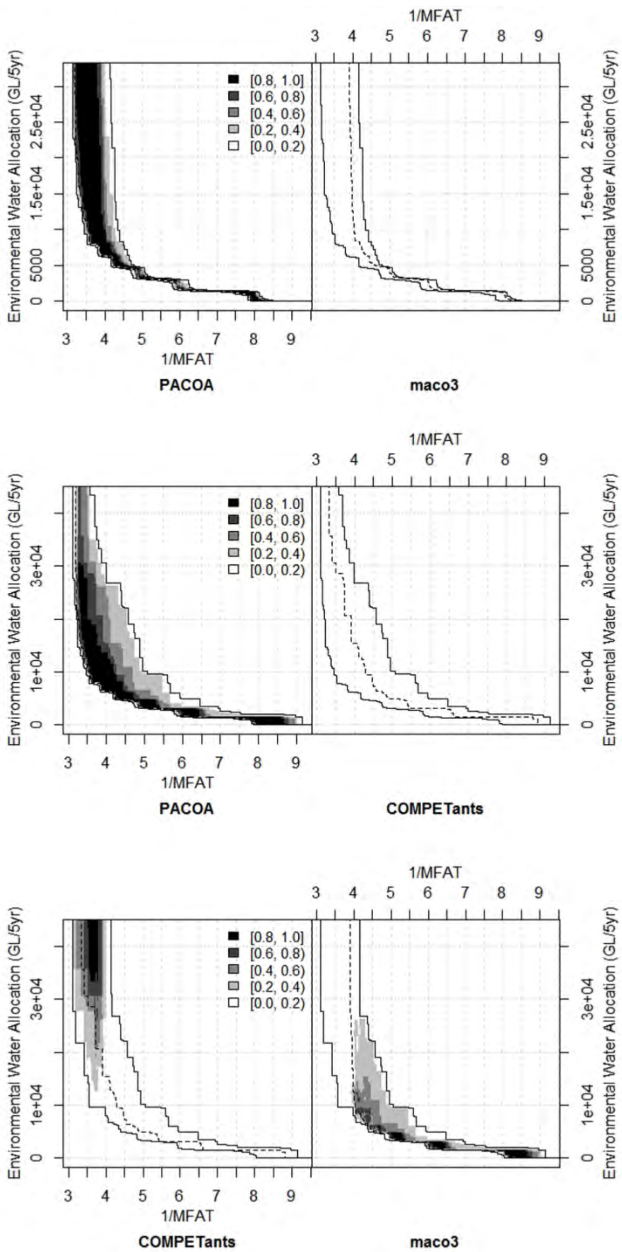

Figure 3.6: Comparison of PACOA, COMPETants and m-ACO_3 using EAF differences plots

3.4 Analyses Conducted

In order to meet the objectives stated in the Introduction, two studies have been formulated. The first of these (Section 3.4.1) focuses on the impact of upstream flow constraints on the optimal trade-offs between environmental flow and ecological response. Two analyses have been conducted as part of this study. The first examines the trade-offs between environmental flow and the total ecological response of the case study area for a range of upstream system constraints, while the second investigates the trade-offs between environmental flow, the wetland ecological response and the floodplain ecological response. The second study (Section 3.4.2) examines the impact of the number of regulators on the optimal trade-offs between environmental water allocation and resulting ecological score in the case study area. Details of the two studies and corresponding investigations are given in Tables 3.5-3.7, and are discussed in detail in the following subsections. It should be noted that minimum monthly flows within the river channel have been set to South Australian entitlement flows (*MDBA*, 2012a), while weights for recruitment and maintenance within MFAT have been set to 0.5 each, with the exception of the weight for the wetland flora species, which has been set to 0.25 for recruitment and 0.75 for maintenance (*CRCFW*, 2003). An equal preference has been given to all species and assets, and each optimization run has been repeated 10 times with different starting positions in the solution space.

Table 3.5: Details of investigations for trade-offs between environmental allocation and total ecological response

Investigation	Upstream System Flow Constraint, Q_{tmax} (GL/month)	Magnitude Suboptions (n)	Ecological Response Objectives (fg)	Management Alternatives (h)	Regulators
1	1,200	20	1	3	2
2	1,650	26			
3	1,800	28			
4	2,400	37			
5	3,000	45			

Table 3.6: Details of number of species per asset and number of years considered in total ecological response objective (g=1) for Investigations 1-5 and 7-10

Asset Set $i \in H$	Number of species ($s(i)$) in $R_{i,1}$ (g=1)	Number of years ($Y_{K,1}$)
1	26	5
2	15	
3	28	
4	17	
5	53	
6	27	
7	27	
8	18	

Table 3.7: Details of investigations conducted as part of examining the trade-offs between environmental flow, wetland ecological response and floodplain ecological response

Investigation	Upstream System Flow Constraint, Q_{tmax} (GL/month)	Magnitude Suboptions (n)	Ecological Response Objectives (fg)	Management Alternatives (h)	Regulators
6	1,800	28	2	3	2

3.4.1 Impact of upstream flow constraints

3.4.1.1 Trade-offs between environmental flow allocation and total ecological response

As discussed in Section 3.2, the Murray-Darling Basin (MDB) is a highly regulated system with many users, resulting in a number of system constraints. Five investigations (i.e. Investigations 1-5 in Table 3.5) have been conducted in order to assess the effect different upstream flow constraints, including maximum upstream releases of 1,200, 1,650, 1,800, 2,400 and 3,000 GL/month, have on the optimal trade-off between total environmental flow allocation and total ecological response. These constraints have been selected based on the current situation in the MDB, where flows less than or equal to 1,200 GL/month (or 40,000ML/day) at the South Australian border can be achieved relatively easily, whereas flows of 1,200-2,400 GL/month (or 40,000 and 80,000 ML/day) are much more difficult to achieve due to upstream system constraints (*Heneker and Higham*, 2012), while flows equal to or greater than 3,000GL/month (or 100,000 ML/day) are not deliverable unless these constraints are relaxed by altering existing upstream flood mitigation constraints at times when there are large inflow events at a number of upstream tributaries (*MDBA*, 2011b; 2012b).

It should be noted that for each investigation, the number of flow magnitude suboptions (n) differs, as shown in Table 3.5, while the duration suboptions for each investigation begin with 12 months at the beginning of each year, but are then dynamically changed depending on prior selections made during a particular iteration. As part of these investigations, only one ecological response objective is considered (i.e. g=1), that is, the total ecological response of the case study area, with the number of assets (i.e. i) in the H set equal to 8, while the number of species considered in each R_i set ($s(i)$) and the number of years (Y_K) are shown in Table 3.6. In addition, only the two existing regulators at Morgan and Brenda Park wetlands are taken into account resulting in three EFMAs (i.e. h=3), including upstream flow releases and the operation of these two regulators. Consequently, the total search space consists of 10^{135} discrete combinations of decision variable values.

3.4.1.2 Trade-off between environmental flow allocation, wetland ecological response and floodplain ecological response

The final investigation (i.e. Investigation 6) as part of this study examines the trade-off between three objectives, that is, the environmental water allocation, the ecological response of the wetlands and the ecological response of the floodplains for a given upstream flow constraint. This investigation has been conducted because wetlands and floodplains lie on different regions of the flood gradient, each with different flow requirements (*Rogers*, 2011b), and the trade-off between these three aspects is currently unknown. Details of the investigation are given in Table 3.7, with the upstream system flow constraint set to 1,800 GL/month and the number of magnitude options (n) set to 28. The number of ecological objectives, fg, equals two, with one ecological response objective focusing on the wetlands (i.e. g=1), and the other on the floodplains (i.e. g=2). In order to account for the two ecological response objectives, fg subsets needed to be defined, with details of each asset subset (H_g), number of species subset in each asset ($R_{i,g}$) and the number of years subset V (i.e. Y_K) given in Table 3.8. As in Investigations 1-5, two regulators at Brenda and Morgan are in operation resulting in to a total of three EFMAs (i.e. flow releases and 2 regulators), with a total search space of 10^{122} discrete combinations of decision variables.

Table 3.8: Details of number of species per asset and number of years considered in wetland ecological response (g=1) and floodplain ecological response (g=2) objectives for Investigation 6

Asset Set $i \in H$	Number of species ($s(i)$) in $R_{i,1}$ (g=1)	Number of species ($s(i)$) in $R_{i,2}$ (g=2)	Number of years for g=1 and g=2 ($Y_{K,g}$)
1	13	13	5
2	1	10	
3	14	14	
4	8	9	
5	19	34	
6	4	23	
7	13	14	
8	7	11	

3.4.2 Impact of additional regulators

In recent years, it has been suggested that the flow regime within a wetland should be controlled in order to maximize ecological health, while maintaining the same level of water use and reducing evaporation loss (*Overton et al.*, 2010). As mentioned previously, two of the wetlands in the case study area currently have regulators, with an additional three wetlands proposed to have such control structures (see Table 3.2). However, the impact of these control structures on the optimal trade-off between environmental flow allocation and ecological response has not been assessed in previous studies. Consequently, an additional four studies have been formulated, the results of which can be compared with results obtained in Investigations 1 and 3. Thus, the effect of zero and five regulators is examined under the current system constraint of 1,200GL/month in Investigations 7 and 8, respectively, and under an increased system constraint of 1,800GL/month in Investigations 9 and 10, respectively. The number of management alternatives for each Investigation ranges from 1 to 6, depending on the number of regulators considered (Table 3.5 and 3.9), resulting in a search space ranging from 10^{87} to 10^{177}discrete combinations of decision variable values. It should be noted that the total ecological response objective (i.e. g=1) of the case study area is considered in Investigations 7-10 and thus uses the same asset (H), species (R_i) and year (V) sets as defined in Investigations 1-5, which are given in Table 3.6.

Table 3.9: Details of investigations conducted as part of the assessment of the impact of additional regulators

Investigation	Upstream System Flow Constraint, Q_{tmax} (GL/month)	Magnitude Suboptions (n)	Ecological Response Objectives (fg)	Management Alternatives (h)	Regulators
7	1,200	20	1	1	0
8				6	5
9	1,800	28		1	0
10				6	5

3.5 Results and Discussion

The results obtained are in the form of optimal trade-offs between the total amount of water available for environmental purposes and ecological response. In order to assess the impact of different upstream flow constraints , and numbers of regulators on the optimal trade-off between environmental flows and ecological response, as per the stated objectives of the paper, the discussion of the results focuses on the following issues:

1. The impact of different upstream flow constraints and numbers of regulators on various aspects of the optimal trade-off curve between environmental flow and ecological response, such as changes in the rate of increase in ecological response relative to the rate of increase in environmental flow, changes in the presence and location of "break points", at which a change in the relative rate of change in one objective occurs relative to that of the other, and changes in the best possible ecological response (Sections 3.5.1.1 and 3.5.2.1).

2. The impact of different upstream flow constraints and numbers of regulators on the effectiveness of a number of proposed environmental flow allocations (Sections 3.5.1.2 and 3.5.2.2). These include the current (2012) allocation of 2,105 GL/yr (i.e. 10,525 GL over 5 years) (Allocation 1), the allocation of 4,023 GL/yr (i.e. 20,115 GL over 5 years) that the MDBA is trying to achieve by 2019 (*MDBA*, 2012c) (Allocation 2), and the allocation of 4,823 GL/yr (or 24,115 GL over 5 years) (*GSA*, 2012) (Allocation 3), which has been suggested by independent scientists, such that required salt exportation from the Lower Murray Region and adequate water for significant floodplains along the South Australian River Murray can be met (*Bloss et al.*, 2012; *Higham*, 2012).

3.5.1 Impact of upstream flow constraints

3.5.1.1 Impact on Optimal Trade-off Curve

Trade-offs between environmental flow allocation and total ecological response

The optimal trade-offs between environmental water allocation and corresponding MFAT score obtained as part of each investigation described in Section 3.4.1 are shown in Figure 3.7. It can be seen that there is little improvement in MFAT score with increased environmental water allocation at the current upstream flow constraint of 1,200 GL/month. In contrast, as the upstream flow constraint is relaxed to between 1,650 GL/month to 3,000 GL/month (Investigations 2 – 5), there is an almost linear increase in MFAT score with an increase in environmental flow allocation up to a certain point, at which there is an almost negligible increase in MFAT score with increased flow allocation. This point is termed a breakpoint and identifies a solution at which there is a significant change in the ecological benefit obtained per unit allocation of environmental water, as mentioned previously. The locations of the breakpoints are shown in Figure 3.7, with BP1 through to BP5 referring to the breakpoints for Investigations 1-5, respectively.

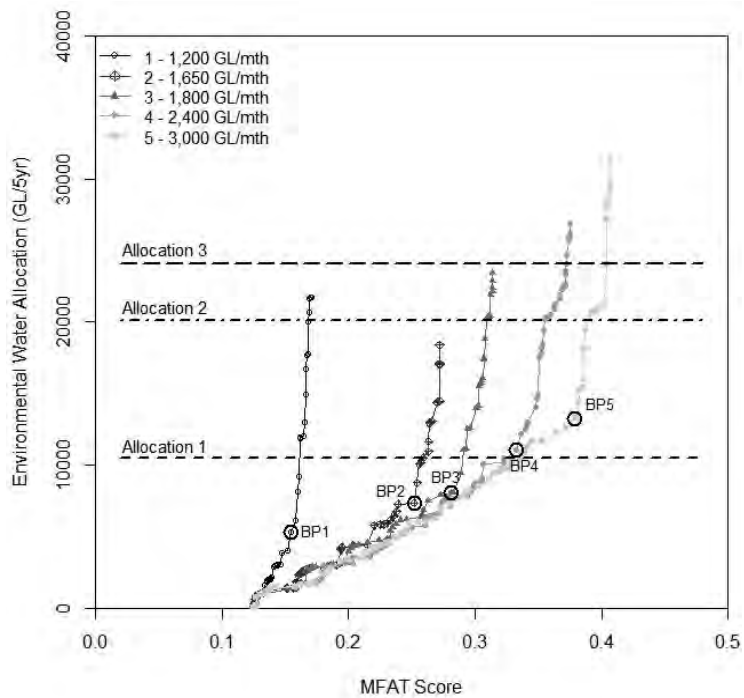

Figure 3.7: Optimal trade-offs between environmental flow allocation (GL/5yr) and MFAT score for Investigations 1-5

The breakpoint values for each of the five investigations are given in Table 10. As can be seen, for Investigation 1, the breakpoint occurs at an MFAT score of 0.15 and an allocation of 5,324 GL/5yr. After this point, there is very little additional benefit in allocating more water, since the rate of MFAT score increase per 1,000GL is only 0.003, whereas the same value is 0.022 before the break point. The break points for the remaining four investigations are much more distinct (Figure 7, Table 10). For Investigations 2 to 5, the increase in MFAT score / 1,000GL of additional upstream release before the break point is approximately the same at around 0.02 (ranging from 0.028 for Investigation 5 to 0.035 for Investigation 3) and reduces significantly to less than 0.004 after the break point (ranging from 0.002 for Investigation 3 to 0.003 for Investigation 4). However, the flow allocation, and hence MFAT score, at which the breakpoints occur increases significantly from Investigation 2 to Investigation 5, indicating the increased benefits of additional environmental flow allocations as the upstream system constraints related to the maximum flow release are relaxed.

Table 3.10: MFAT Score and allocation at the breakpoint for each investigation, as well as the rate at which the MFAT score increases per 1,000GL environmental allocation before and after the breakpoints

Investigation	MFAT Score	Allocation (GL/5yr)	Change in MFAT score/1,000GL in Region before Breakpoint	Change in MFAT score/1,000GL in Region after Breakpoint
1	0.15	5,324	0.022	0.002
2	0.25	7,350	0.034	0.003
3	0.28	8,055	0.035	0.002
4	0.33	11,055	0.030	0.002
5	0.38	13,200	0.028	0.002

The increased benefit of additional environmental flow allocations as upstream system constraints are relaxed can also be seen from the maximum MFAT scores that can be achieved, and the corresponding flow allocations (Table 3.11). The maximum MFAT score that can be achieved with the current system constraint (Investigation 1) is 0.17, which is much lower than those obtained as part of the other Investigations, which ranged from 0.27 for Investigation 2 (i.e. 1,650GL/month upstream flow release constraint) to 0.41 for Investigation 5 (i.e. 3,000GL/month upstream flow release constraint).

Table 3.11: Maximum MFAT Scores and corresponding allocations (GL/5yr) for each Investigation

Investigation	MFAT Score	Allocation (GL/5yr)
1	0.17	12,000
2	0.27	14,400
3	0.31	22,125
4	0.36	26,000
5	0.41	29,500

The reason for the increase in MFAT scores with increasing system constraints is a corresponding increase in the maximum water level that can be achieved. For example, with the current system constraint (Investigation 1), some of the temporary wetlands, such as Cadell, and the higher elevated floodplains containing river red gums (*Eucalyptus camaldulensis*) and black box woodland (*Eucalyptus largiflorens*), which account for the majority of the species in the case study area (see Table 3.2), cannot be inundated. This, and the effect of drought, have resulted in the deterioration of many of the high lying floodplain species in the South Australian River Murray (*GSA*, 2012; *Overton et al.*, 2010). In addition, current system constraints prevent the inundation of 50% or more of the floodplain area, which is a requirement for achieving higher MFAT scores for the floodplain species (*Young et al.*, 2003). As discussed above and illustrated in Figure 3.7, at the current system constraint, MFAT scores are virtually independent of any additional environmental flow allocation, as the occurrence of the larger flow events needed to inundate key ecological assets is prevented.

As the upstream flow constraints are relaxed to 1,650 and 1,800 GL/month, there are significant benefits associated with increased environmental flow allocations (Figure 3.7), as greater areas of the wetlands and floodplains can be inundated and two of the temporary wetlands (Cadell and Markaranka) can be filled, almost doubling the corresponding MFAT scores to 0.27 and 0.31, respectively (Table 3.11). This enables some of the important flora species to be restored or maintained. This trend continues as the constraints are relaxed further to 2,400 and 3,000 GL/month, with increased environmental flow allocations resulting in maximum MFAT scores of 0.36 and 0.41, respectively (Table 3.11).

As can be seen in Figure 3.7, there are a number of step changes in the trade-off curves for Investigations 2 – 5, with points along the step changes for Investigations 2 (i.e. Points A – F) and 5 (i.e. Points 1 – 6) labeled and shown in Figure 3.8. For Investigations 2 and 5, each step change is the result of an additional major flow release (where a major flow release is defined as the largest flow release relative to other monthly flow releases) over the five year planning horizon. For example, for Investigation 2, the region between points A and B included one major flow release, while the regions between points C and D and points E and F, included two and three major flow releases, respectively. Similarly, for Investigation 5, the regions between points 1 and 2 and points 5 and 6 included one and three major flow releases, respectively. For regions of the trade-off curves that included a particular number of major releases (e.g. regions A – B, E – F, 1 – 2, and 3 – 4, Figure 3.8), MFAT scores increased with little additional environmental water allocation as a result of the inundation of the temporary wetlands, Cadell and Markaranka. For example, flows greater than 1,500 GL/month are required to inundate Cadell, which can only be achieved when the environmental allocation is greater than 1,375 GL. Once this allocation is obtained for the planning horizon, Cadell's MFAT score can increase from 0.04 to 0.14, resulting in a significant increase in MFAT score with minimum additional environmental water (i.e. regions A – B).

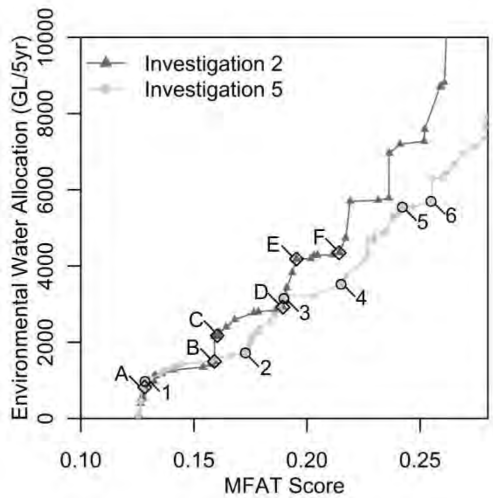

Figure 3.8: Optimal trade-offs between environmental water allocation (GL/5yr) and MFAT score for Investigations 2 (i.e. 1650 GL/month) and 5 (i.e. 3,000GL/month)

Overall, the results highlight the need to assess the impact of a range of upstream system flow constraints on the ecological integrity of the case study area. The limited ecological benefit of increasing environmental flow allocations at the current system constraints and the step changes in the trade-off curves, provide valuable insight to water managers and ensures that optimal EFMA schedules can be developed that use the available water in the most efficient manner, while also maintaining the integrity of the biota.

Trade-off between environmental flow allocation, wetland ecological response and floodplain ecological response

The optimal tradeoffs between environmental water allocation, the ecological response of the wetlands and the ecological response of the floodplains in terms of the MFAT score that have been developed as part of Investigation 6 can be seen in Figure 3.9, where two slices of the three objective trade-off are shown. It can be seen in the graph on the left that the wetland MFAT score ranges from 0.20 to 0.45 as the environmental water allocation increases from 0 to 50,000 GL/5 yr. Additionally, there is an increase of 0.10 in the MFAT score as the allocation increases from 0 to the 10,000 GL/5 yr mark. However, after this point, an additional allocation of 30,000 GL/5 yr is required to achieve the same increase of 0.10 in the wetland MFAT score. This suggests that after the 10,000 GL/5 yr environmental water allocation point, the ecological benefit for the wetlands as more water is added into the case study area is minor.

It can also be seen in the graph on the left that there is very little spread in the points along the wetland MFAT score axis, indicating that the same wetland MFAT score can be achieved at a given environmental allocation, irrespective of the timing, magnitude and duration of the management alternatives selected as part of the development of an EFMA schedule. In contrast, when comparing the trade-off between floodplain MFAT score and environmental water allocation in the graph on the right in Figure 3.9, it can be seen that the spread of points along the floodplain MFAT axis becomes greater at higher allocations. This suggests that at higher allocations, the scheduling of management alternatives (e.g. magnitude, duration) can have a major impact on the overall floodplain MFAT score, with differences in floodplain MFAT scores of 0.1 being obtained for a given allocation and wetland MFAT score. In addition, it can be seen that once the environmental water allocation of 40,000 GL/5 yr has been exceeded, the floodplain MFAT score begins to decrease to 0.10, suggesting that too much environmental water has been released, thereby prolonging inundation of these areas and reducing the overall ecological integrity of the floodplains. Finally, it can be seen that the overall floodplain MFAT score achieved is much less than that achieved for the wetlands. This is because of the system constraint (i.e. 1,800 GL/month) considered in this investigation, which is not high enough to result in inundation of larger portions of the floodplains at higher elevations.

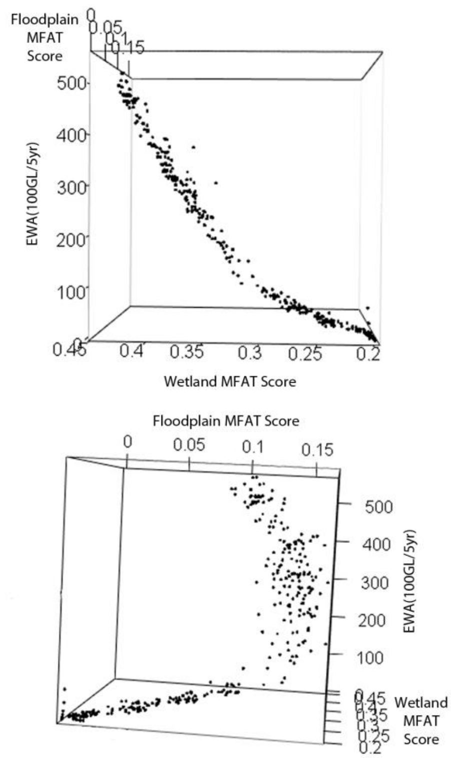

Figure 3.9: Optimal trade-off between environmental water allocation (EWA (100 GL/5yr)) and the wetland and floodplain MFAT score for Investigation 6

Overall, this study highlights the valuable insight that can be obtained when assessing the trade-offs between different components of ecological response (in this case the wetlands and floodplains) and environmental water allocation. In particular, the sensitivity of the floodplain MFAT scores at higher allocations can provide further information to water managers, specifically in the selection of the best EFMA schedule at higher allocations, which will ensure not only the best wetland ecological outcome, but also that for the floodplains.

3.5.1.2 Impact on Effectiveness of Various Environmental Flow Allocations

The MFAT scores at the three suggested environmental flow allocations considered for each investigation are shown in Figure 3.7 and Table 3.12. It can be seen that for Investigation 1, an MFAT score of approximately 0.17 is achieved at each allocation, indicating that at the current system constraint of maximum upstream releases of 1,200 GL/month, the allocation of environmental water above the current allocation in the MDB does not increase the overall ecological benefit within the case study area. As discussed in Section 5.1.1, this is because the maximum possible flows are not sufficient to inundate the temporary wetlands and achieve the 50% floodplain area inundation needed in the MFAT calculation (*Young et al.*, 2003). Similarly, there is very little change in MFAT scores for the different flow allocations for Investigations 2 and 3, with increases ranging from 0.01 to 0.02 when moving from Allocation 1 to Allocation 2, and no further increase in the scores when moving to Allocation 3. On the other hand, there is a slight increase in MFAT scores when moving from flow Allocations 1 to 3 for Investigations 4 and 5, with a maximum increase in MFAT score of 0.04 for Investigation 4 and a maximum increase of 0.06 for Investigation 5, suggesting that there is only a slight ecological benefit associated with increased environmental water allocations if the upstream flow release constraint is increased to 2,400 GL/month or greater.

Table 3.12: Maximum MFAT scores for each Allocation and Investigation

Investigation	Allocation		
	1	2	3
1	0.16	0.17	0.17
2	0.26	0.27	0.27
3	0.29	0.31	0.31
4	0.33	0.36	0.37
5	0.34	0.40	0.40

Overall, the results suggest that there is limited ecological benefit beyond Allocation 1 (i.e. the current environmental allocation), while the upstream flow constraint has a significant impact. As discussed above, this is because the major factor affecting the ecological health of the case study area is whether the high lying wetlands and floodplains can be inundated or not. This requires the occurrence of high-magnitude flows, which simply cannot be achieved unless the upstream flow constraints are relaxed. However, this results in flooding of upstream agricultural and recreational (e.g. holiday houses) areas located adjacent to the Murray River, which can result in other problems, such as the loss of crops and profits. On the other hand, unless the system constraints are relaxed, the required ecological benefits within the case study area can only be achieved if natural major flooding occurs.

3.5.2 Impact of Additional Regulators

3.5.2.1 Impact on Optimal Trade-off Curve

The optimal trade-offs between environmental water allocation and MFAT score developed as part of the investigations discussed in Section 3.4.2 are shown in Figure 3.10. As can be seen, the general shape of the trade-off curves is not affected by the number of regulators (i.e. zero, two or five) for both upstream system flow constraints considered (i.e. 1,200 and 1,800 GL/month). However, there was a distinct advantage in the addition of more regulators, as indicated by a shift in the trade-off curves to the right with an increase in the number of regulators for both of the upstream system constraints.

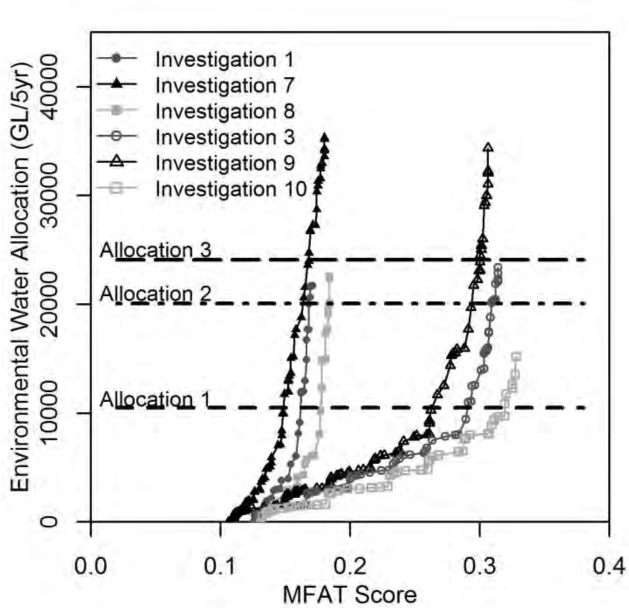

Figure 3.10: Optimal trade-offs between environmental flow allocation and MFAT score for Investigations 1, 3 and 7-10

The maximum MFAT scores and associated environmental flow allocations for each investigation are given in Table 3.13. For Investigations 7 and 9, where no regulators are present, an environmental allocation greater than 29,000 GL/5 yr is required to achieve MFAT scores of 0.18 and 0.30, respectively. Once two regulators are in operation within the case study area (i.e. Investigations 1 and 3), a water saving of 20,000 GL/5 yr is achieved in order to obtain MFAT scores that are similar to those obtained in the corresponding investigations that considered no regulators. As the number of regulators in operation increases to five in Investigations 7 and 9, there is little difference in the scores and allocations obtained compared with those obtained in the investigations where two regulators are used (i.e. Investigations 1 and 3).

Table 3.13: Maximum MFAT Scores and associated allocations achieved for each regulator in operation

Regulators	System Constraint (GL/month)	Investigation	MFAT Score	Allocation (GL/5yr)
0	1,200	7	0.18	32,478
	1,800	9	0.30	29,100
2	1,200	1	0.17	12,000
	1,800	3	0.31	22,125
5	1,200	8	0.18	17,750
	1,800	10	0.34	15,225

Overall, the use of two regulators for both system constraints considered does not alter the maximum MFAT score, but results in a substantial reduction in the environmental water allocation required to achieve this score. This suggests that the regulators are best used as water saving measures and would benefit areas where limited water is available as a result of drought or when multiple users are present, as is the case in the South Australian reaches of the River Murray.

3.5.2.2 Impact on Effectiveness of Various Environmental Flow Allocations

The MFAT scores at the three suggested environmental flow allocations for each investigation are shown in Figure 3.10 and Tables 3.14 and 3.15. It can be seen in Table 3.14 that at the current environmental allocation (i.e. Allocation 1), for the upstream system flow constraint of 1,200 GL/month, the MFAT score increases marginally by 0.01 as the number of regulators increases from two to five. Once the allocation increases to the volume proposed by the MDBA (i.e. Allocation 2), the MFAT score gradually increases from 0.16 to 0.18 as more regulators are considered, while at Allocation 3 (i.e. the allocations proposed by environmental scientists), a 0.01 improvement in MFAT score is obtained when five regulators are taken into account. This indicates that at lower allocations, a marginal ecological benefit is achieved with the operation of two regulators, however, once the allocation increases to Allocation 3, a small improvement in MFAT score is only obtained when five regulators are in operation.

Table 3.14: MFAT scores achieved for each Allocation and Investigation for the 1,200 GL/month system constraint

Regulators	Investigation	Allocations		
		1	2	3
0	7	0.15	0.16	0.17
2	1	0.16	0.17	0.18
5	8	0.17	0.18	0.18

Table 3.15: MFAT scores achieved for each Allocation and Investigation for the 1,800 GL/month system constraint

Regulators	Investigation	Allocations		
		1	2	3
0	9	0.26	0.29	0.31
2	3	0.29	0.31	0.33
5	10	0.30	0.34	0.34

The MFAT scores achieved for a system constraint of 1,800 GL/month are given in Table 3.15 for each of the three environmental water allocations considered. It can be seen that at Allocation 1, there is a marginal increase in MFAT score of 0.03 when two regulators are considered, while the addition of three regulators increases the MFAT score by 0.01. On the other hand, for Allocations 2 – 3, a score of approximately 0.29 is achieved when no regulators are in operation, which increases to 0.31 and 0.34 as the number of regulators increases from two to five, respectively. This suggests that a positive impact can only be achieved at larger allocations when 5 regulators are considered, compared with the use of two regulators, which improved the score for all allocations.

In summary, this study showed the improvement in MFAT scores achieved as additional regulators are introduced in the case study area for different environmental flow allocations. It showed that if five regulators are in operation, an improvement in MFAT score can only be achieved at higher allocations, while the use of two regulators can marginally improve the ecological health at lower allocations.

3.5.3 Limitations

While the results obtained provide valuable insight into the management of environmental water in order to maximize ecological response, there are some limitations with the findings as a result of the uncertainties associated with the ecological scores calculated using the Murray Flow Assessment Tool (MFAT). The MFAT model uses preference curves to develop a relationship between flow and ecological response for species types, however, knowledge of these ecological relationships is imperfect, thereby introducing uncertainty into the model and the final results (*Baihua and Merritt*, 2012). To overcome this shortcoming, a sensitivity analysis, as conducted by *Norton and Andrews* (2006) and *Baihua and Merritt* (2012) on the preference curves and/or aggregation approach, could be performed. Such an analysis would examine the robustness and variance of the likely ecological response that could be obtained for a given EFMA schedule. This would provide detailed information to water managers and further understanding of the likely ecological benefit that could be achieved for a particular EFMA schedule. However, such an analysis is beyond the scope of this study. Finally, it should be noted that the results and conclusions obtained from this analysis are only applicable to the case study area.

3.6 Summary and Conclusion

In this paper, the optimization framework developed by *Szemis et al.*(2012) is extended to incorporate multiple objectives and applied to a real case study in the South Australian River Murray. The aim is to assess the trade-offs between environmental flow allocations and ecological benefits based on the impact of (a) upstream system flow constraints and (b) the number of regulators used to control the flow at wetlands. In order to achieve this, the performance of three multi-objective ACO algorithms (i.e. COMPETants (*Doerner et al.*, 2003) and m-ACO_3 (*Alaya et al.*, 2007) and PACOA (*Doerner et al.*, 2004)) is compared, with the PACO algorithm found to perform best (see Section 3.5.5). The PACOA is coupled with a hydrological model consisting of eight wetlands, five of which can be regulated. Each wetland is composed of a variety of flora and fauna species, obtained using DEM and baseline survey data of the case study area. The management options considered as part of the development of EFMA schedules include the scheduling of environmental flow allocations and regulator operations. The ecological benefit of each EFMA schedule developed is assessed using the Murray Flow Assessment Tool developed by *Young et al.*, (2003), while a hydrological model is used to determine the total environmental water allocation.

Two studies are undertaken to achieve the objectives of the paper. In the first study, the impact of upstream system flow constraints on the optimal trade-off between environmental water allocation and ecological benefit is assessed, while in the second study, the effect of additional regulators on these trade-offs is investigated. The shape of the trade-off curve, the effectiveness of three different environmental water allocations and the impact of flow releases and gate operations on EFMA schedule development are analysed for each study.

The results of the first study indicate that increased environmental water allocations only have a positive ecological impact if the current upstream flow constraints are relaxed, which enables large areas of floodplain flora to be inundated. In addition, results from assessing the trade-offs between environmental flow allocation, floodplain ecological response and wetland ecological response indicate that floodplain scores are more sensitive at higher allocations compared with the wetland ecological response. The results of the second study indicate that the addition of regulators only marginally improves the ecological response in the case study area, but that this can be achieved with significantly smaller volumes of water. In addition, the results obtained indicate that at lower system constraints (e.g. 1,200 – 1,800 GL/month), the allocations recommended by the MDBA and environmental scientists may be too large for the case study area, as only a marginal ecological benefit is achieved for Allocations 1 – 3. However, once the system constraints are relaxed, there is a significant improvement in the MFAT scores as environmental allocations increase from those recommend by the MDBA to those proposed by the environmental scientists.

Overall, the studies provide valuable insight into the EFMA scheduling problem, particularly the ecological benefit gained from an increase in environmental allocation for a range of upstream system flow constraints and numbers of regulators. The approach presented in this study enables water managers to make informed decisions regarding the management of environmental releases, regulator operation, and investment in additional infrastructure, particularly when there is limited water available, as is the case for the South Australian River Murray.

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Chapter 4

4 An adaptive ant colony optimization framework for scheduling environmental flow management alternatives under varied environmental water availability conditions (Paper 3)

Statement of Authorship

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Name of Principal Author (Candidate)	Joanna Szemis		
Contribution to the Paper	Conceptual and algorithm development, analysis of results, manuscript preparation and corresponding author.		
Signature		Date	11/06/2014.

Name of Co-Author	Holger Maier		
Contribution to the Paper	Research supervision and review of manuscript		
Signature		Date	06/06/2014

Name of Co-Author	Graeme Dandy		
Contribution to the Paper	Research supervision and review of manuscript		
Signature		Date	11/06/2014

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Abstract

Human use of water is ever increasing and, as such, water for the environment is limited and needs to be managed efficiently. One method for achieving this is the scheduling of environmental flow management alternatives (EFMAs) (e.g. releases, wetland gate operation), with these schedules generally developed over a number of years. However, availability of environmental water changes from year to year as a result of natural variability (e.g. drought, wet years). To take this variation into account, an adaptive multi-objective optimization approach for the development of EFMA schedules in an operational setting is proposed. As part of this approach, optimal schedules are updated at regular intervals during the planning horizon based on forecasts of future environmental water allocations. In addition, the changes between current and updated schedules are minimized to reduce any disruptions to long-term planning. The utility of the approach is assessed by applying it to an 89km section of the River Murray in South Australia. Results indicate that the proposed approach is beneficial under a range of hydrological conditions and can successfully produce optimal trade-offs between the number of disruptions made to existing schedules and the resulting ecological response. Overall, the results indicate that the information obtained using the proposed approach has the potential to aid managers in the efficient and effective management of environmental.

4.1 Introduction

Environmental flow management aims to ensure that ecological flow requirements of flora and fauna, which can be represented by the timing, duration, rate of change, and magnitude of flow (*Poff et al.*, 1997), are satisfied in regulated river systems (*Junk et al.*, 1989; *Poff et al.*, 1997). However, due to the competing water demands for the environment and for human purposes (e.g. water supply, industrial, agricultural and recreational), the water available for environmental purposes is generally insufficient to meet all ecological flow requirements (*Arthington et al.*, 2006; *Poff and Zimmerman*, 2010). This conflict over water use is exacerbated by the rapid growth of the global population and by climate change (*Arthington et al.*, 2006; *Castelletti et al.*, 2010). Given that there is limited water available for environmental purposes, there is a need to make best use of this water so as to achieve the best possible ecological outcomes.

This is not an easy task because the available environmental water: (i) has to be allocated not only within the river channel but also to the surrounding wetlands and floodplains, which accommodate a range of different species of flora and fauna; (ii) has to be scheduled at various times and released in various volumes and for various durations in order to maintain and restore the ecological integrity of different species, which generally have varying flow requirements (*Rogers*, 2011b); (iii) can be managed using a range of alternatives at different spatial scales, such as at the individual wetland scale (e.g. wetland regulators/pumps) or at a the landscape scale (e.g. flow releases and weir pool manipulation); and (iv) has to be managed over multiple years, since there are species that require dry periods over multiple years, such as the Black Box woodland (*Eucalyptus largiflorens*), or require the maintenance of a flood frequency of 1 in 2 to 5 years (*Rogers*, 2011b), resulting in temporal dependencies between scheduling decisions.

In order to address this problem, optimization approaches have been used extensively to obtain optimal monthly reservoir flow releases or operating rule parameters for reservoirs/weirs (e.g. (*Chang et al.*, 2010; *Chaves et al.*, 2003; *Higgins et al.*, 2011; *Homa et al.*, 2005; *Shiau and Wu*, 2004; 2007; 2013; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2011; *Yin et al.*, 2010)), or monthly schedules of optimal environmental flow management alternatives (EFMAs), such as wetland gate operations and reservoir releases (*Szemis et al.*, 2012; *Szemis et al.*, 2013). However, all of the above approaches rely either on the *historical* natural flow hydrograph or an *assumed known volume* of available environmental water. While optimized schedules developed over extended time periods based on assumed water availabilities are useful for longer-term *planning* purposes (as in *Szemis et al.* (2013)), they are not suitable for use in an *operational* setting (e.g. determining optimal EFMA schedules under actual and predicted flow conditions), in which flows available for environmental purposes are likely to change from year to year as a result of natural hydrologic variability (e.g. droughts, floods). Consequently, there is a need to develop an optimal EFMA scheduling approach that takes changes in actual environmental water availability into account, and can therefore be used for *operational* purposes.

As has been demonstrated successfully in other areas of water resources management, such as irrigation scheduling, this can be achieved by updating schedules as new information becomes available (*Rao et al.*, 1992). Alternatively, the development of optimal schedules can be based on forecasts of future conditions, rather than on historical or assumed future conditions, which can then be updated in an adaptive manner at regular time intervals (e.g. *Gowing and Ejieji*, 2001). However, such approaches have not yet been applied to the optimal scheduling of EFMAs. Consequently, there is a need to develop an *adaptive* optimization approach that can be used for operational purposes, in which optimal EFMA schedules are (i) developed based on *forecasts* of available environmental water and (ii) *updated* at regular intervals throughout the planning horizon in order to take account of updated knowledge of hydrological conditions. However, in order to comply with practical requirements, any changes to existing EFMA schedules should be kept as small as possible during the adaptation process so as to minimize the negative impacts on related operational strategies and resource scheduling (e.g. human resources and equipment). Consequently, there is a need to develop a novel optimization formulation that enables an appropriate trade-off between ecological outcomes and practical considerations to be considered.

In order to address the research needs outlined above, the objectives of this paper are to (i) develop a novel *adaptive* approach to the optimal scheduling of EFMAs for rivers and their associated wetlands and floodplains that (a) is based on *forecasts* of available environmental water over the time period over which optimal EFMA schedules are developed (b) enables *updated* hydrological information to be incorporated at regular intervals and (c) is able to consider optimal trade-offs between the *minimization of changes to existing optimal schedules* and the maximization of ecological response; and (ii) to test the utility of the overall approach and its features for a real case study of a section of the River Murray in South Australia under various hydrological conditions over a 20 year period (1983-2003).

The remainder of this paper is organized as follows. The proposed adaptive optimization approach is introduced in Section 4.2, with details of how the approach was applied to the case study given in Section 4.3. The analyses performed to achieve the objectives are given in Section 4.4, after which the results and discussion are presented in Section 4.5. Concluding remarks are then presented in Section 4.6

4.2 Proposed Adaptive Optimization Approach for the Optimal Scheduling of Environmental Flow Management Alternatives

The main steps in the proposed framework are shown in Figure 4.1, which are based on the approaches introduced by *Szemis et al.* (2012; 2013). The primary differences between this approach and those presented in *Szemis et al.* (2012; 2013) are:

1. Rather than assuming that the water that is available for environmental flow allocation purposes is *known* and *fixed* over the required planning horizon, optimal EFMA schedules over the planning horizon are (i) obtained initially based on *forecasts* of environmental water allocation over the planning horizon (i.e. at timestep ut = 1) and (ii) *updated* at regular intervals (at timesteps ut = 2, 3, …ft), taking into account updated forecasts of environmental water allocation, as highlighted by the grey boxes in Figure 1. The forecast environmental water allocation is defined as $A_{max\_ni(pd)}$, where pd is the number of periods of estimated environmental water allocations, ranging from 1 to np. It should be noted that this general approach is similar to that adopted by *Gowing and Ejieji* (2001) for real-time irrigation scheduling. While the

approach has elements in common with model-predictive control methods used in other areas of water resources management (e.g. *Bakker et al.*, 2013; *Park et al.*, 2009; *Prasad et al.*, 2013; *Xu et al.*, 2013), its aim is not to control the system to achieve a desired output (i.e. to minimize the difference between actual and desired system response), but to optimize system response.

2. In order to ensure that any changes to the EFMA schedules due to the updating process (i.e. from *ut-1* to *ut*) are minimized, while still maximizing ecological response, a novel *multi-objective* optimization *formulation* is introduced. It should be noted that the specific changes that are minimized are case study dependent (e.g. which of the resources affected by potential changes to an EFMA schedule are constrained, what the dependencies between different operational strategies are) and need to be selected by the relevant authorities (e.g. water manager or river operator).

As can be seen in Figure 4.1, the proposed approach begins with the formulation of the problem, which includes identifying: (i) the wetlands, floodplains and river reaches that are to be managed; (ii) appropriate ecological indicators (e.g. vegetation or fish species); (iii) the planning horizon over which the schedule for the EFMAs is to be developed (e.g. 5 years), as well as the planning period (e.g. 20 years); (iv) the time interval, t, at which schedules are to be developed (e.g. monthly), which ranges from 1 to T intervals; and (v) the EFMAs, M_a that are available for achieving the desired ecological response (e.g. flow release options, regulator settings, pumping schedule), where a ranges from 1 to h. EFMAs, as well as the sub-options associated with each of these alternatives (e.g. magnitude, duration), are discussed in *Szemis et al.* (2012; 2013). In order to cater to the adaptive elements of the approach, additional variables that control the number of updates within the planning horizon, *ut* ranging between 1 and *ft*, where *ft* is the maximum number of updates and the update interval, *xu*, (i.e. annual, quarterly), are also defined.

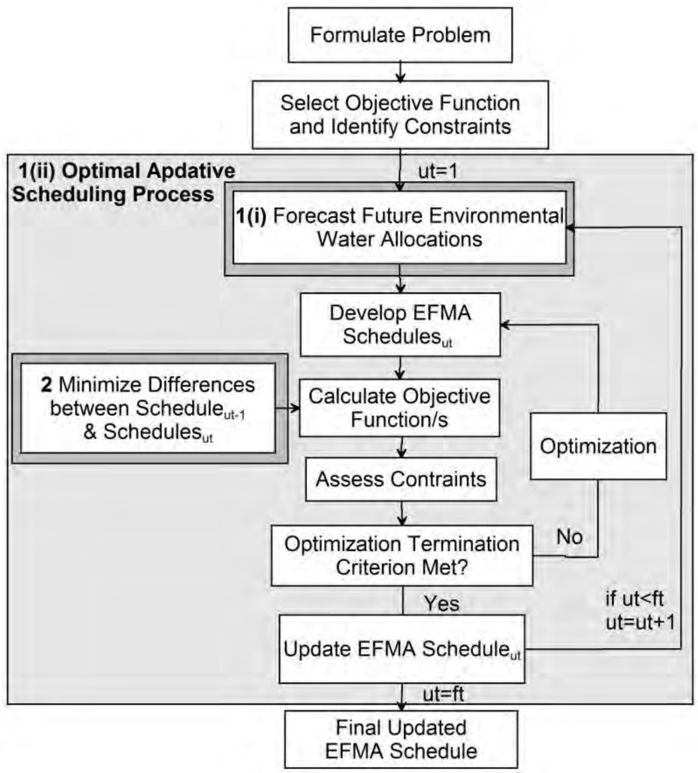

Figure 4.1: Steps in Proposed Adaptive Optimization Framework

Once the problem has been formulated, the objectives (i.e. maximize ecological response and minimize differences between schedules) and constraints (e.g. environmental allocation constraints) need to be defined. Next, the optimal scheduling process can commence. The first step of this process involves the forecasting of the water allocation that will be available for environmental purposes over the planning horizon with the aid of a forecasting model. The selection and development of an appropriate forecasting model is dependent on the problem at hand, as well as the previous and current hydrological data that are available within the case study area.

Next, a number of potential EFMA schedules are developed and their utility is assessed via the objective functions and constraints. This is undertaken by linking a multi-objective ant colony optimization algorithm (ACOA) with appropriate hydrological and ecological models. For a discussion on the justification of the use of the use of ACOAs in preference to other optimization approaches, such as dynamic programming or genetic algorithms, the reader is referred to *Szemis et al.,* (2012). The optimization process continues until certain stopping criteria, such as hypervolume convergence (*Zitzler and Thiele*, 1999), have been met. The outcome of this process is an optimal EFMA schedule over the selected planning horizon at timestep *ut* =1, based on the forecasts of future environmental water allocations at this timestep.

At timestep *ut* = 2, the forecasts of the water allocation that will be available for environmental purposes over the planning horizon are updated based on the latest available information and the process of obtaining optimal EFMA schedules is repeated. In order to minimize the differences between the existing optimal schedule and the new optimal schedule based on updated water availability estimates (Figure 4.1), the following objective, F_D, should be used in addition to the objective of maximizing ecological response:

$$F_D = \sum_{mc=nc(1)}^{nc(f_{nc})} \sum_{v=1}^{K} w_{D,v} \sum_{t=ti(v)}^{tf(v)} D_{mc,t} \tag{4.1}$$

with $D_{mc,t} = 1 \text{ when } M_{mc,ut,t} \neq M_{mc,ut-1,t}$
$D_{mc,t} = 0 \text{ when } M_{mc,ut,t} = M_{mc,ut-1,t}$

where the number of differences between the initial schedule at *ut-1* and the new schedule at *ut* is defined as $D_{mc,t}$ for the *mcth* management alternative scheduled over K years and *ti(v) to tf(v)* time intervals. The number of management alternatives (M_a) that will be compared, *mc* ranges from *nc(1)* to $nc(f_{nc})$, while $w_{D,v}$, specifies the weight value that indicates the relative importance of minimizing the difference between subsequent schedules for year *v*. A value for $D_{mc,t}$ of 1 is given when the option selected for the *mcth* management alternative at timestep *ut* and at time interval *t* is not the same as the corresponding option for the EFMA schedule at *ut*-1. In contrast, a value of 0 is assigned to $D_{mc,t}$ when the selected options are the same. For example, if a regulator is open as part of the optimal schedule developed at *ut-1,* at the *tth* timestep, and the regulator is closed at the *tth* timestep as part of the optimal schedule at *ut*, then the corresponding value of $D_{mc,t}$ is 1. As can be seen from Equation 4.1, the values of D_{mc} are summed over the time intervals at which schedules are to be developed, as well as the f_{nc} user-defined management alternatives for which the minimization of differences between management options is considered important.

The process of updating the forecasts of the available environmental water allocations and re-optimizing the EFMA schedules in light of this information, while ensuring that any changes to updated schedules are limited, is repeated for *ut*=3, 4, …,*ft*.

4.3 Methodology

In this section, the utility of the approach introduced in Section 4.2 is assessed by applying it to a section of the River Murray in South Australia under various hydrological conditions. Details of the case study, which was adapted from *Szemis et al.* (2013), are given in Section 4.3.1, followed by details of how the proposed adaptive optimal EFMA scheduling approach (Figure 4.1) is applied to the case study in Sections 4.3.2 to 4.3.8.

4.3.1 Case Study

The case study area under investigation is a reach of the South Australian River Murray between Locks 1 and 2 (Figure 4.2). In this figure, the River flows from Lock 2 to Lock 1. The South Australian River Murray is part of a larger river system (the Murray-Darling Basin (MDB)) that is located in south eastern Australia and includes portions of four states, namely Victoria, Queensland, New South Wales and South Australia (see Figure 4.2) (*Reid and Brooks*, 2000). Over the years, it has become highly regulated due to the construction of six locks along the river channel, as well as a number of upstream structures, such as Hume Dam, located on the border between Victoria and New South Wales (*George et al.*, 2005). As result of this regulation and the over-allocation of water, the flow variability within the river section in Figure 4.2 has reduced and caused much of the biota in the river and adjacent wetlands and floodplains to be stressed or altered (*Overton et al.*, 2010). In response, a basin-wide plan developed by the Murray Darling Basin Authority and approved by the Government of Australia now recognizes the environment as a key stakeholder within the MDB. However, how any environmental water allocations should be prioritized to maximize ecological response is unclear, particularly given that the environmental allocation is not constant from one year to the next, but is reduced during times of drought and increased during times of flooding (*GSA*, 2013).

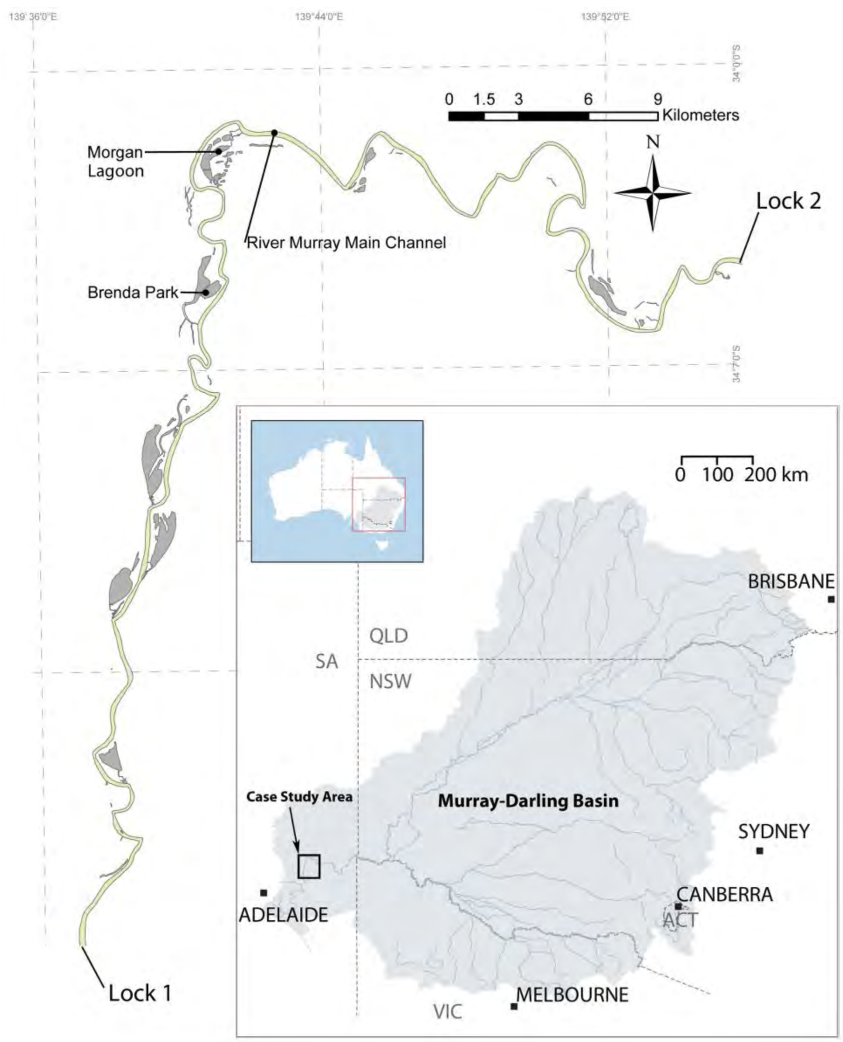

Figure 4.2: Map of case study area (adapted from Murray-Darling Basin Authority website, http://www.mdba.gov.au/river-data/spatial-data-services/spatial-information)

The river reach under investigation spans 89.0 kilometers and currently accommodates two regulated wetlands and a large number of high lying floodplains along the river channel. As a result of the construction of the locks, the wetlands closer to Lock 1 have become permanently inundated (i.e. continual connection to the river) and experience no drying, whereas, wetlands closer to Lock 2 are temporary and rarely inundated due to upstream system constraints (*Overton et al.*, 2010). Each wetland and surrounding floodplain houses a variety of flora and fauna, ranging from high-lying black box woodland (*Eucalyptus largiflorens*) to water birds and fish (e.g. ibis and carp gudgeon) (*Turner*, 2007).

In order to preserve and maintain the ecological integrity of the wetlands within this river section, it has been suggested to not only release environmental water upstream at the South Australian border, but to also operate gates at the wetland inlets, with two wetlands within the case study area currently falling into this category (*Schultz*, 2007; *Turner*, 2007).

4.3.2 Problem Formulation

4.3.2.1 Specification of Ecological Assets and Indicators

The first step of the problem formulation stage involves identifying the ecological assets (i.e. wetlands, floodplains, river) to be managed, H_i, where i ranges from 1 to q. In this case study, the management of two wetlands, Morgan Lagoon and Brenda Park, is considered (i.e. q=2) (Table 4.1). This includes the wetlands themselves, the high-lying floodplain areas surrounding the wetlands, and the adjacent main river channel. These wetlands have been selected because they are the only wetlands within the case study area that currently have operational regulators. The vegetation areas within the wetland and floodplain, as well as the location of the fish and water bird species within the wetlands themselves, are identified with the aid of existing wetland management plans (*Schultz*, 2007; *Turner*, 2007).

Table 4.1: Details of Problem Formulation for Case Study

<table>
<tr><th colspan="2">Problem Formulation Steps</th><th>Specification</th></tr>
<tr><td>1</td><td>Managed Ecological Assets
H_i, i=1 to q</td><td>q = 2
(Morgan Lagoon and Brenda Park)</td></tr>
<tr><td>2</td><td>Ecological Indicator
$E_{i,r}$ r=1 to $s(i)$</td><td>Murray Flow Assessment Tool (MFAT)
(Young et al., 2003)

Total Number of Species Types = 10</td></tr>
<tr><td rowspan="3">3</td><td>Planning Horizon and period
Yv, v=1 to K
Yp =1 to P</td><td>K= 5 years
P= 20 years</td></tr>
<tr><td>Time Interval
t, t=1 to T</td><td>Monthly, T = 60 months</td></tr>
<tr><td>Update Interval, xu
Number of Updates
ut, ut=1 to ft</td><td>xu = 1 (i.e. year), ft = 20</td></tr>
<tr><td>4</td><td>Management Alternatives
M_a , a=1 to h</td><td>h = 3
(1 reach and 2 asset scale)</td></tr>
<tr><td>5</td><td>Management Alternative Suboptions (i.e. magnitude, $M_{a,m}$, and/or duration, $M_{a,d}$)</td><td>Reach – magnitude & duration
Asset – duration</td></tr>
<tr><td>6</td><td>Number of Management Alternatives compared
mc, mc=1 to fn.</td><td>fn = 3</td></tr>
</table>

Next, the ecological response indicator, $E_{i,r}$, is identified, which is the Murray Flow Assessment Tool (MFAT) developed by *Young et al*. (2003). This was also used by *Szemis et al.* (2012; 2013). This indicator quantifies the ecological response of each species (including vegetation, waterbird and fish) within the river, and adjacent wetlands and floodplains (Table 4.1). MFAT was developed specifically for the River Murray and can be used to investigate the impact of different flow scenarios on the ecological response of flora and fauna in terms of two ecological processes, that is, recruitment (e.g. promoting seed germination) and maintenance (e.g. preserving adult habitat) (*Young et al.*, 2003). In order to determine the ecological response using MFAT, response curves are used, which are based on five flow components, that is frequency, duration, timing, rate of change and magnitude. The response curves used for the case study area are those given in *CRCFW* (2003) and *Overton et al* (2010), and include species such as river red gum (*Eucalyptus camaldulensis*), wetland specialists (e.g. carp gudgeons) and waterbirds (e.g. grebes). In addition, weights for the recruitment and maintenance processes need to be selected and are chosen based on literature or expert knowledge. A total of 10 species are defined for the case study area and the proportions of each species type per wetland are given in Table 4.2.

Table 4.2: Species Composition in Case Study Area

Asset	Wetland Name	Species Composition (% per asset)			
		Floodplain Flora	**Wetland Flora**	**Waterbird**	**Fish**
1	Morgan Lagoon	50.0	11.0	25.0	14.0
2	Brenda Park	53.0	0.0	29.0	18.0

4.3.2.2 Identification of Planning Horizon, Time and Update Intervals

The planning horizon, Yv (v=1, K years), time interval, t, where t ranges from 1 to the final interval, T and the variables introduced as part of the proposed adaptive optimization approach, that is, the update interval, xu, and the number of updates, ut, (which ranges from 1 to ft) need to be selected (see Table 4.1). In this case, a planning horizon of five years is chosen, as wetland management plans in the study area are generally developed over five years (*EA*, 2007; *Schultz*, 2007), while a monthly timestep is selected, since wetland gate operations are set on a month by month basis (*Schultz*, 2007; *Turner*, 2007), with the total number of time intervals, T, being 60. Finally, the update interval, xu, is set to one year, while the EFMA schedule will be updated along a 20 year planning period (Y_p) from 1983 to 2003, thus ft, equals 20.

4.3.2.3 Selection of Management Alternatives and Suboptions

This step of the problem formulation stage involves the determination of the management alternatives, M_a, where a is between 1 and h, and the corresponding suboptions. The environmental flow releases at the South Australia border are selected as the only reach scale management alternative, while the operations of gates at the two wetlands (i.e. Morgan and Brenda Park, see Figure 2) constitute the chosen asset scale management alternatives. As a result, there are three management alternatives (i.e. $h = 3$) that can be considered in the development of the optimal EFMA schedules. The suboptions for the reach scale management alternative include magnitude, $M_{a,m}$, and duration $M_{a,d}$ suboptions, while only the duration suboption is required for asset scale management alternatives (i.e. regulators open or closed), as shown in Table 4.1. The selection of the maximum number of magnitude suboptions, n, is dependent on the case study area and system constraints, where the number of potential duration suboptions at each timestep equals p, where p varies between 12 in July and 1 in June the following year.

Finally, the management alternatives for which changes between current (i.e. at $ut-1$) and updated (i.e. at ut) schedules are to be limited, M_{mc}, need to be selected, where mc ranges from 1 to fn management alternatives. For the case study, fn is set to three (Table 4.1), since the differences are compared for all selected management alternatives.

4.3.3 Specification of Objective Function and Constraints

Once the problem has been formulated, the objective functions and constraints are defined (Figure 4.1). As per the methodology introduced in Section 4.2, the two objectives include the maximization of ecological response and the minimization of changes to optimized EFMA schedules. Details of the formulation of these objectives for the case study are given below. As described in *Szemis et al.* (2013), the ecological response can be comprised of a number of different components, including different types of assets (e.g. wetland or floodplain) and different ecological processes (e.g. recruitment or maintenance). As a result, the number of assets, species and years considered need to be defined as sets, where the number of assets in set H ranges from 1 to q, while the number of species per *ith* asset is identified as the R_i set, with each *ith* asset accommodating $s(i)$ species. Finally, the total year set, V, ranging from 1 to a maximum year of Y_K is also defined, with the sets shown below.

$$i \in H = \{1,2,\dots,q\} \tag{4.2}$$

$$R_i = \{1,2,\dots,s(i)\} \tag{4.3}$$

$$V = \{1,2,\dots,Y_K\} \tag{4.4}$$

The ecological components (e.g. fauna species or recruitment process) that are to be investigated as part of the *gth* ecological response objective, where g ranges from 1 to fg, are then defined in the form of g subsets, which also range from 1 to fg. In this study, the aim is to maximize the overall ecological response within the case study area, which results in a single ecological objective ($F_{E,1}$), where fg=1.

The corresponding Equation is as follows:

$$F_{E,1=} \sum_{i \in H_1} w_{1i} \sum_{r \in R_{i,1}} w_{2r} \sum_{v \in V_1} \frac{w_{3v} E_{i,r,v}}{Y_{K,1}}, \qquad g = 1 \qquad (4.5)$$

where $E_{i,v,r}$ is the ecological indicator value for asset i, for indicator type r, in the vth yearly time interval. The subset H_1 contains the number of assets that enable the assessment of the river, wetland and floodplain ecological response, which in this case is three (including two regulated wetlands and their surrounding floodplains, as well as the river channel). On the other hand, $R_{i,1}$ contains information about which species (e.g. waterbirds) are incorporated in the ecological response objective ($F_{E,1}$). The number of species per ith asset can be seen in Table 4.3. Finally, V_1 specifies the number of years for which the ecological response objective is calculated, which is five in this study (i.e. K=5). Weights, w_{1i}, w_{2r} and, w_{3v} place emphasis on the ith wetlands, floodplains or river reaches, rth ecological indicator and $Y_K th$ year, respectively. For this case study, the values of the weights are set equal to one to give equal preference to each asset, species and year.

Table 4.3: Details of the Number of Species per Asset in the Total Ecological Response Objective (g=1) for all Investigations

Asset Set $i \in H$	**Number of species ($s(i)$) in $R_{i,1}$ (g=1)**
1	28
2	17

The objective function used for the minimization of differences between EFMA schedules at subsequent time steps is given in Equation 4.1. Preliminary testing indicated that increasing the weighting for differences in early years produced the best trade-offs between the objectives. Thus, the weight values used in this case study are, $w_{D,1}$ equals 5, $w_{D,2}$ equals 2, and $w_{D,3}$ to $w_{D,5}$ equal 1.

The constraints considered include the number of suboptions available for each management alternative (i.e. Equations 4.6 and 4.7), and the annual environmental water allocation available (i.e. Equation 4.8). The constraints on the number of magnitude and duration suboptions per management alternative, M_a, are as follows:

$$M_{a,m\_\min} \leq M_{a,m} < M_{a,m\_\max}, \qquad m = 1 \text{ to } n \tag{4.6}$$

$$M_{a,d\_\min} \leq M_{a,d} < M_{a,d\_\max}, \qquad d = 1 \text{ to } p \tag{4.7}$$

where the magnitude suboptions ($M_{a,m}$) are constrained by minimum and maximum values of M_{a,m_min} and M_{a,m_max}, respectively, and the duration suboptions ($M_{a,d}$) are constrained by minimum and maximum values of M_{a,d_min} and M_{a,d_max}, respectively, for each management alternative. The specification of M_{a,m_min}, M_{a,m_max}, M_{a,d_min} and M_{a,d_max} is user-defined, based on the requirements of the case study area under consideration (e.g. M_{a,m_max} could be selected based on a maximum achievable flow in the case study area). In this case, the minimum magnitude option for the environmental flow releases at the border, M_{1,m_min}, is set to 0 GL/month, while the maximum value, M_{1,m_max}, is dependent on the forecasted annual environmental water allocation each year. If the asset scale management alternative (i.e. a=2,3), M_{a,m_min}, equals 1, the gate is closed, whereas if M_{a,m_max} equals 2, the gate is open. In addition, M_{a,d_min} is set to 1, while the maximum number of duration sub-options, M_{a,d_max}, is set to 12 to correspond to the number of months in a given water year.

The second constraint considered is associated with the environmental water allocation, which can vary over a set planning horizon (e.g. annually) due to the forecasts of environmental water made each year, $A_{max\_ni(pd)}$ (see Section 4.2). This information is then used to update the schedule at regular times in the planning horizon. The constraint is given as:

$$\sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \leq A_{\max\_ni(pd)} \tag{4.8}$$

where, A_t is the environmental water allocation at the *tth* timestep, *pd* is the number of periods of constrained environmental water allocations, ranging from 1 to *np*, while the number of increments in each period, *ni(p)* ranges from 1 to *Vp*, and *i_ni(pd)* and *f_ni(pd)* are the corresponding initial and final time steps for *pd*, over which a particular water allocation is released. The duration of each increment is defined as $d_{ni(p)}$, and the summation of all duration increments for each period must equal the total duration interval, T_d. In this case, the environmental water allocation varies annually making the number of periods, *pd*, five, whereas the number of increments in each period equals 12, corresponding to the number of months in a year.

4.3.4 Forecasting of Future Environmental Water Allocation

In order to obtain forecasts of environmental water allocations over the planning horizon of five years, five artificial neural networks (ANNs) are developed to obtain forecasts at t+1, t+2, t+3, t+4 and t+5. ANNs are used as they have been used successfully for water resources modeling in a variety of applications (*Abrahart et al.*, 2012; *Maier et al.*, 2010; *Wu et al.*, 2014). The ANNs are developed using the procedure outlined in *Wu et al.*(2014), including input selection, data splitting, architecture selection, structure selection, calibration and validation. In total, 106 years of reconstructed environmental water allocation and inflow storage data from 1897 to 2003 are available for model development (see *MDBA* (2012b)).

Input selection is performed using a combination of system understanding and the partial mutual information (PMI) algorithm, which accounts for both input significance and independence and has been applied successfully in other water resources studies (*Bowden et al.*, 2005; *May et al.*, 2008a; *May et al.*, 2008b). The candidate inputs considered before application of the PMI algorithm are shown in Table 4.4 and have been selected based on the assumption that the past five years of inflows, storages and environmental allocation in the Murray Darling Basin can influence future environmental allocations. The final inputs selected are summarized in Table 4.4, which indicate that future environmental flow allocations are a function of environmental flow allocations, system storage and system inflows in current and previous years.

Table 4.4: Details of Candidate Inputs and Selected Inputs for all five ANNs

Candidate Inputs	Selected Inputs				
	Environmental Allocation (t+1)	**Environmental Allocation (t+2)**	**Environmental Allocation (t+3)**	**Environmental Allocation (t+4)**	**Environmental Allocation (t+5)**
Inflows (t, t-1, t-2, t-3, t-4)	t, t-1	t, t-1, t-2	t	t-4	t-2, t-4
Storage (t, t-1, t-2, t-3,t-4)	t, t-3	t-2	t-1, t-2, t-3	t, t-2, t-4	t-1, t-3, t-4
Environmental Allocations (t, t-1, t-2, t-3, t-4)	t	t	t-1, t-4	t, t-2, t-3	t-2, t-3

The available data are split into training (50%), testing (30%) and validation (20%) subsets using a modified version of the DUPLEX algorithm (see *May et al.*, 2008a). This data splitting algorithm is used as it is deterministic and suitable for data that are skewed and peaked and have low to medium variability (see *May et al.*, 2010; *Wu et al.*, 2013), which is the case here (Table 4.5). Both input selection and data splitting approaches are implemented using a Neural Network Excel Add-in (http://www.ecms.adelaide.edu.au/civeng/research/water/software/).

Table 4.5: Statistical Properties of the Data (Number of Observations = 106)

Variables	Mean	S.D.	Skewness	Kurtosis
Inflows	18348.4	8183.7	1.54	3.69
Storage	11731.2	2803.5	-0.75	0.33
Environmental Allocations	2229.0	288.6	-1.73	4.96

Multilayer perceptrons (MLPs) are used for the model architecture, as they are the most commonly used form of ANN in water resources and have been used successfully in many applications (*Maier et al.*, 2010; *Wu et al.*, 2014). A single hidden layer is used, as MLPs with a single hidden layer have been proven to be universal function approximators. The number of hidden nodes is determined by trial and error based on model performance on the testing set, which has also been used effectively in a large number of studies (*Wu et al.*, 2014). The number of hidden nodes tried varied from 1 to 7 and the optimal number of hidden nodes for each ANN model is given in Table 4.6.

Table 4.6: Parameter Values Ranges Tested and Final Selected Parameters for each ANN

Parameter	Parameter Value Ranges	Selected Parameter Values				
		ANN 1 (t+1)	ANN 2 (t+2)	ANN 3 (t+3)	ANN 4 (t+4)	ANN 5 (t+5)
Number of Hidden Layer Nodes	1 – 7	3	5	4	6	5
Learning Rate	0.05 – 0.75	0.05	0.05	0.05	0.05	0.05
Momentum	0.0 – 0.9	0.0	0.1	0.1	0.0	0.1

The back-propagation (BP) algorithm is employed for calibration, since it is the most frequently used method for calibrating MLPs (*Maier et al.*, 2010; *Wu et al.*, 2014). The optimal values of the parameters controlling BP searching behaviour (i.e. momentum and learning rate) are determined by trial and error based on model performance on the testing set, with the parameter ranges tested and the optimal values given in Table 4.6. It should be noted that each calibration run is repeated 10 times using a different random seeds.

To check the replicative validity of the ANN models, the residuals of the training data are examined, with the standardized residuals for the ANN 1 model shown in Figure 4.3. The fact that the residuals are approximately white noise and the auto-correlation coefficient is 0.3 suggests that the selected model is able to adequately capture the relationships contained in the data. In addition, almost all of the residuals are within the 95% confidence intervals. Similar results are obtained for the remaining ANN models.

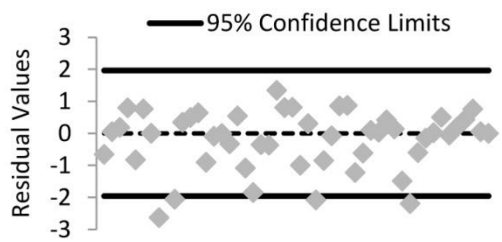

Figure 4.3: Graph of Training Data Standardized Residuals for the ANN 1 model.

Predictive validity is checked with the aid of the validation set and a number of performance metrics, including Root Mean Square Error (RMSE), Mean Average Error (MAE) and Mean Absolute Percentage Error (MAPE) (*Bennett et al.*, 2013; *Dawson et al.*, 2007), with the resulting values shown in Table 4.7. As can be seen, all models performed well, with MAPEs of the validation data varying between 7.3 and 9.6%.

Table 4.7: Error Measures for all Forecasting ANN Models

Model	Data set	MAE	RMSE	MAPE
ANN 1 (t+1)	Training Testing Validation	122.7 139.7 151.6	171.8 198.7 204.7	5.8% 6.7% 7.3%
ANN 2 (t+2)	Training Testing Validation	123.7 176.7 202.4	163.3 228.5 250.3	5.7% 8.5% 9.6%
ANN 3 (t+3)	Training Testing Validation	157.8 183.0 165.8	195.9 221.4 201.4	6.9% 8.8% 8.0%
ANN 4 (t+4)	Training Testing Validation	125.8 177.0 186.1	166.2 226.2 241.0	6.0% 7.9% 8.5%
ANN 5 (t+5)	Training Testing Validation	138.0 222.9 187.3	179.8 291.8 242.2	6.4% 10.6% 8.9%

4.3.5 Development of Environmental Flow Management Schedules

Once the problem is formulated and the environmental water allocations are forecast for each period for the EFMA schedule at *ut*, trial EFMA schedules can be developed. As the decision variables chosen at one time period, such as the duration of an environmental flow release, potentially have an impact on options available at subsequent time steps, trial schedules are developed with the aid of a decision tree graph consisting of the management alternatives and suboptions, which can be adjusted dynamically based on selected options (*Foong et al.*, 2008a; *Foong et al.*, 2008b; *Szemis et al.*, 2012; *Szemis et al.*, 2013).

An example decision tree graph that considers environmental flow release, as well as magnitude and duration suboptions, is given in Figure 4.4. The example considers four magnitude options (i.e. 0, 100, 200 and 300 gigalitres (GL)) and three duration suboptions, and is constructed over three time steps. If the maximum duration (i.e. 3 time intervals) is chosen at the first time step, the graph is adjusted dynamically so that no other decision paths are made available at subsequent time steps (decision points), as shown by the bottom path in Figure 4. On the other hand, if a duration option of one is chosen at the first time step (top path), then the number of available options decreases from three to two, as there are only two more time steps remaining. This results in a reduced search space, increasing the likelihood that optimal and near optimal schedules can be found (*Szemis et al.*, 2013). A detailed discussion of this approach for the development of EFMA schedules is given in *Szemis et al.* (2012; 2013).

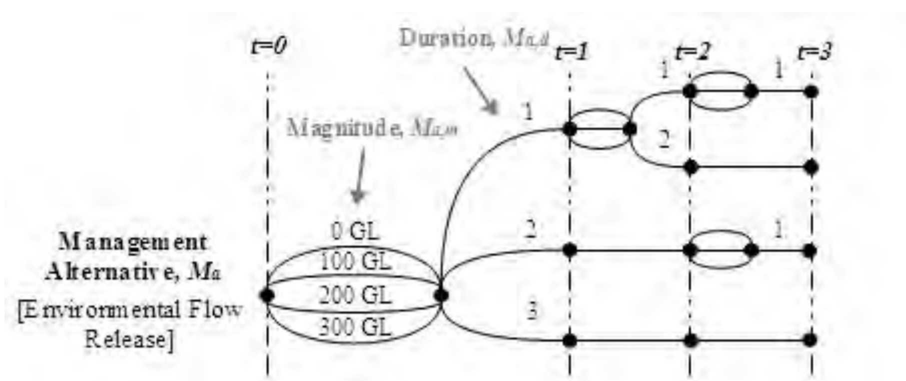

Figure 4.4: Example of an EFMA Schedule Graph for Environmental Flow Releases (In Gigalitres (GL)) incorporating Dynamic Constraints

4.3.6 Calculation of Objective Function and Assessment of Constraints

Once an EFMA schedule has been developed, its utility needs to be assessed, which is done via the objective function and constraints. In order to enable calculation of the objective function and constraint values, a hydrological model of the river system is developed so that the ecological response of the river system to changes in the flow regime can be determined with the aid of MFAT.

The hydrological model is based on backwater curves that relate flows at the South Australian border to the corresponding river height (T. Bjornsson, South Australian Department of Water, personal communication, December 8, 2010) and is used to develop relationships between the flow at the South Australian border and river height at the Brenda Park and Morgan Lagoon wetlands. Fill values, that is, the river height at which a particular wetland or floodplain is inundated, as well as area vs. average depth curves for each specified vegetation area, are determined using ArcGIS and a range of data sources that include a Digital Elevation Model (DEM) obtained from the Department of Environment, Water and Natural Resources baseline surveys *(SKM, 2004; Smith and Fleer, 2006; Waanders, 2007)* and wetland management plans *(Schultz, 2007; Turner, 2007)*. Once this is completed, the hydrological models for the wetlands and floodplains are developed using the water balance equations described in *Szemis et al.* (2013).

Average monthly evaporation data are obtained from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/). A value of 0.7 is chosen as the pan coefficient, as this is a commonly used value in the Murray Darling Basin *(Gippel, 2006)*. To account for rainfall, average monthly rainfall data for the case study area are used, which are also obtained from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/). It should be noted that both models are subject to a number of assumptions, including (i) water seepage is negligible since it is small compared with evaporation loss, and (ii) the rate of river level rise and fall occurs gradually over each month. The storage capacity of the wetlands is very small compared with the magnitude of streamflow, and thus has a negligible effect on downstream flow. Further details on the models are provided in *Szemis et al.* (2013).

4.3.7 Optimization

The Pareto Ant Colony Optimisation Algorithm (PACOA) (*Doerner et al.*, 2004) is used, as it has been used successfully for this problem and achieved better result than alternative multi-objective ACO variants in *Szemis et al.* (2013). To account for multiple objectives, this algorithm uses multiple pheromone matrices and updates the pheromone based on the first and second best solution. The steps in the optimization procedure are given in Figure 4.5. The first step is the initialization of the PACOA control parameters, after which the optimization process takes place. As part of this process, *b* ants generate *b* trial EFMA schedules by selecting a management alternative and associated sub-options (i.e. magnitude and/or duration) at each time step, as illustrated in the example in Figure 4.4. This is repeated for a large number of iterations (*its*).

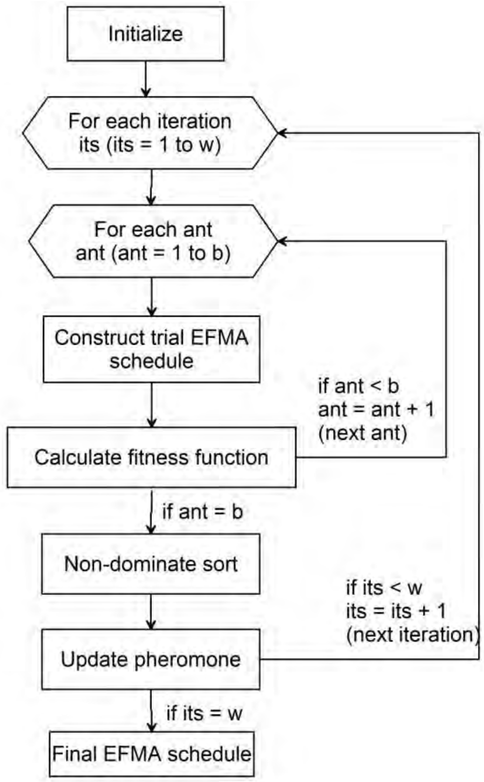

Figure 4.5: Pareto Ant Colony Optimization Algorithm Procedure

Once a complete trial EFMA schedule has been developed by an ant, the utility of this schedule is assessed using a fitness function, which utilizes objective function and constraint values. Fitness functions are used to drive the optimization process because ACO algorithms do not explicitly consider the constraints apart from upper and lower bounds on the decision variables, making it necessary to include penalties within the fitness function.

A number of different fitness function formulations are investigated for the case study, with the fitness function that performs best and is hence used in this study given below:

$$Y_{E,1} = \frac{1}{F_{E,1}} + Penalty_{a1} \tag{4.9}$$

where $F_{E,1}$ is the ecological response score calculated using MFAT (Equation 4.5) (which is inversed to ensure that the score is maximized), and $Penalty_{a1}$ is a penalty function that ensures the water allocation constraints for each period are adhered to, as given by:

$$Penalty_{a1} = \begin{cases} 0 & \text{if } \sum_{t=i_{ni(pd)}}^{f_{ni(pd)}} A_t \leq A_{\substack{\max \\ ni(pd)}} \\ \left\{ \sum_{t=i_{ni(pd)}}^{f_{ni(pd)}} (A_t) - A_{\substack{\max \\ ni(pd)}} \right\} \times 1000 & \text{if } \sum_{t=i_{ni(pd)}}^{f_{ni(pd)}} A_t > A_{\substack{\max \\ ni(pd)}} \\ 1{,}000 & \text{if } \quad F_{E,1} = 0.0 \end{cases} \tag{4.10}$$

where the variables in Equation 4.10 are defined in Equation 4.5. In this case, there is only one period (i.e. pd=1), where $i_{in(pd)}$=1 and $f_{in(pd)}$=60. It should be noted that the second objective, the minimization of differences between subsequent schedules, does not need to be transformed into a fitness function and as a result, Equation 4.1 is used within the optimization process. After each iteration, the b trial schedules generated by the b ants undergo a non-dominated sorting process in order to determine the schedules that are on the Pareto front for that particular iteration and are subsequently stored in an offline storage matrix.

As mentioned earlier, the first and second best solution for each *j* objective are used to update the *j*-pheromone matrices as part of the global update, using the following equation.

$$\tau_t^j = (1-\rho)\cdot\tau_t^j + \rho\cdot\Delta\tau_t^j \qquad (4.11)$$

$$\Delta\tau_t^j = \begin{cases} 15 & \text{if suboption is in best and second best solution,} \\ 10 & \text{if suboption is in best solution,} \\ 5 & \text{if suboption is in second best solution,} \\ 0 & \text{otherwise.} \end{cases}$$

where the pheromone value for each *tth* sub-option and *jth* objective (τ_t^j) is reduced by pheromone evaporation, ρ, and increased by a pheromone value ($\Delta\tau^j$), which is based on whether a given sub-option is within the best and/or second best solution. Pheromone evaporation is applied to sub-options of schedules that perform poorly, which deters the algorithm from selecting these sub-options again. In this manner, the environment is modified to guide the ants into regions of the search space that contain non-dominated schedules. The process of developing, assessing and updating the pheromone trails to guide the PACOA to near-optimal trade-offs continues until the specified stopping criterion has been satisfied, which corresponds to hypervolume convergence in this case.

Before the PACOA is applied, a sensitivity analysis is conducted such that optimal values of the parameters that control the searching behavior of the algorithm are identified. The ranges of parameter values tested and the final parameters selected are given in Table 4.8.

Table 4.8: Range of PACOA Parameters Investigated and Values Selected

PACOA Parameter	Range of Values Tested	Selected Value
Number of ants (*ant*)	20, 200, 300,500	500
Initial pheromone (τ_o)	0.5, 1.0, 10.0	0.5
Evaporation rate (ρ)	0.5, 0.1, 0.15, 0.2, 0.5	0.1
Evaluations	90,000	90,000

4.3.8 Updating of EFMA Schedule

An update interval, *xu*, of 1 year is used (see Table 4.1). Consequently, 20 updates of estimates of future environmental water allocations and optimal EFMA schedules are performed over the 5 year planning horizon over a 20 year period (1982-2002).

4.4 Analysis Conducted

In order to assess the utility of the proposed adaptive multi-objective optimization approach for the optimal scheduling of EFMA alternatives in an operational setting, its performance in terms of overall ecological response is compared with that of a number of alternative approaches over a 20 year period from 1982 to 2002, as detailed below. In all tests (Methods 1 to 4, Table 4.9), the number of magnitude options (n) is set to 37, while the maximum number of durations equals 12. The details of each asset subset (H_g), the number of species subsets in each asset ($R_{i,g}$), the number of years subset V (i.e. Y_K) and the allocation constraint period are given in Tables 4.1 and 4.3. It should be noted that minimum monthly flows within the river channel are set to South Australian entitlement flows (*MDBA*, 2012a), while weights for recruitment and maintenance within MFAT are set to 0.5 each, with the exception of the weight for the wetland flora species, which is set to 0.25 for recruitment and 0.75 for maintenance (*CRCFW*, 2003). An equal preference is given to all species and assets, and each optimization run is repeated 10 times with different starting positions in the solution space.

Table 4.9: Details of Methods Used

Method	Method for Obtaining Environmental Water Allocations	Annual Updating of Optimal Schedules	Minimization of Changes to Schedules
1	Fixed (570 GL/year)	No	No
2	ANN Models	Yes	Yes
3	ANN Models	Yes	No
4	Actual	Yes	No

4.4.1 Effectiveness of Using Optimal EFMA Scheduling

In order to test the effectiveness of using optimal EFMA scheduling as a means of maximizing ecological response for a given environmental water allocation, the performance of the proposed approach is compared with that of a benchmark approach that does not include any management of environmental water allocations (i.e. using the actual flows with no wetland regulators). It should be noted that as part of the proposed approach (Method 2, Table 4.9), the ANN models are used to obtain forecasts of environmental water availability over the next five years, optimal EFMA schedules are obtained over a five year period and these schedules are updated annually by re-optimizing using the multi-objective ACO approach that trades-off maximizing ecological response with minimizing changes to existing schedules. It should also be noted that optimal updated schedules selected from the Pareto fronts correspond to an inflection point on the trade-off curve (i.e. an EFMA schedule that determines a good balance between minimization of differences between subsequent schedules and maximizing the MFAT score).

4.4.2 Effectiveness of Adaptive Optimization Approach

In order to test the effectiveness of the proposed adaptive optimization approach (Method 2, Table 4.9) in improving ecological response, its performance is compared with that of the approach used in *Szemis et al*. [2013] (Method 1, Table 4.9), in which a known, constant environmental flow allocation of 570 GL/year is assumed each year and hence the updating of optimal schedules is not required.

4.4.3 Effectiveness of Minimization of Differences between Successive Schedules

In order to test the effectiveness of the proposed multi-objective formulation in being able minimize changes to existing schedules while maximizing ecological response, the performance of the proposed approach (Method 2, Table 4.9) is compared with that of an approach that only maximizes ecological response, without consideration of minimizing changes to subsequent schedules (Method 3, Table 4.9). It should be noted that the solutions for Method 3 are extracted from the same Pareto front as the solutions for Method 2, but correspond to the solutions that result in the highest MFAT score.

4.4.4 Effectiveness of ANN Forecasting Model

In order to test the effectiveness of the ANN models in producing forecasts of environmental water availability that maximize ecological response, the performance of Method 3 (Table 4.9), which utilizes the ANN forecasts but only maximizes ecological response, is compared with that of an approach that is identical, apart from using perfect knowledge of future environmental water allocations, instead of those produced by the ANN models (Method 4, Table 4.9).

4.5 Results and Discussion

4.5.1 Effectiveness of using Optimal EFMA Scheduling

As can be seen from Figure 4.6 by comparing the MFAT scores obtained using the benchmark (Actual) and the proposed (Method 2) approaches, there is significant benefit in optimal EFMA scheduling, as indicated by the substantial increases in ecological response. This indicates that it is worthwhile to operate regulators at the Morgan Lagoon and Brenda Park wetlands, particularly at times when there are lower flows, as is the case for the water years of 1994-1995, 1997-1998 and 2002-2003 (see Figure 4.7).

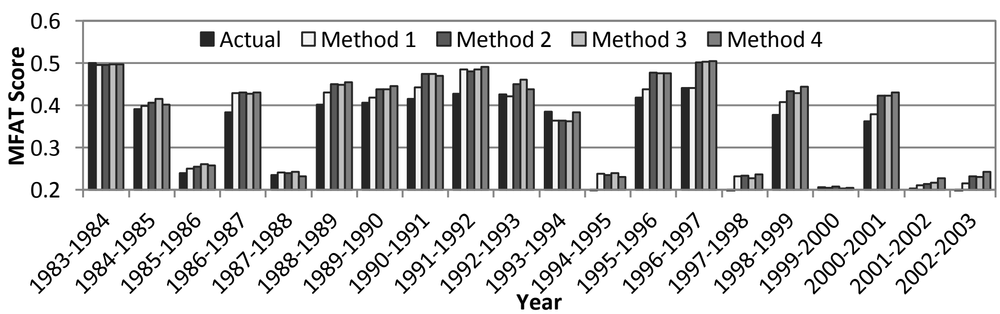

Figure 4.6: Average Annual MFAT Scores Achieved for each Method and Actual Data Between the Years 1983-2003

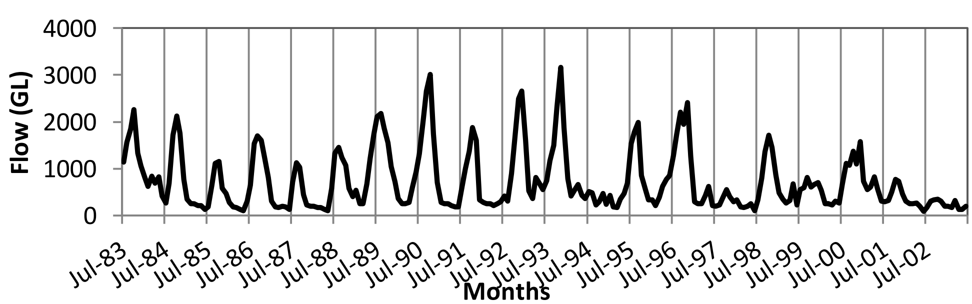

Figure 4.7: Actual Flows at the South Australian Border

4.5.2 Effectiveness of Adaptive Optimization Approach

When the proposed approach (i.e. Method 2) is used, annual MFAT scores are generally higher than those obtained using known, constant environmental water allocations (Method 1), as shown in Figure 4.6. This is particularly evident at higher flows (see years 1990-1991, 1992-1993, 1995-1996 and 1996-1997 in Figure 4.7), where the ANN models are able to forecast above average environmental water allocations, enabling releases and regulator operations to be altered. In contrast, when an average environmental allocation is assumed and higher flows are actually released, the EFMA schedule developed is sub-optimal, producing lower ecological response.

In order to better understand the reasons for the differences in MFAT scores, it is worthwhile to compare the MFAT scores for different wetlands, species and ecological processes (Figure 4.8), as these are aggregated to produce the annual scores presented in Figure 4.6. As can be seen in Figure 4.8a, there are generally only small differences in MFAT scores for Morgan Lagoon. However, the differences are more pronounced in water years 1990-1991 and 1996-1997, which is due primarily to the increased maintenance ecological response that could be achieved for river red gums by using the adaptive scheduling approach (Method 2 – Figure 4.8c). This is because when Method 1 is used, it is assumed that an average environmental allocation is available, which is not enough to overtop the regulator and inundate the higher lying vegetation, such as river red gums. Because of this, in 1990-1991, the regulator is opened for 8 months (i.e. July to January) to promote a response for lower lying vegetation.

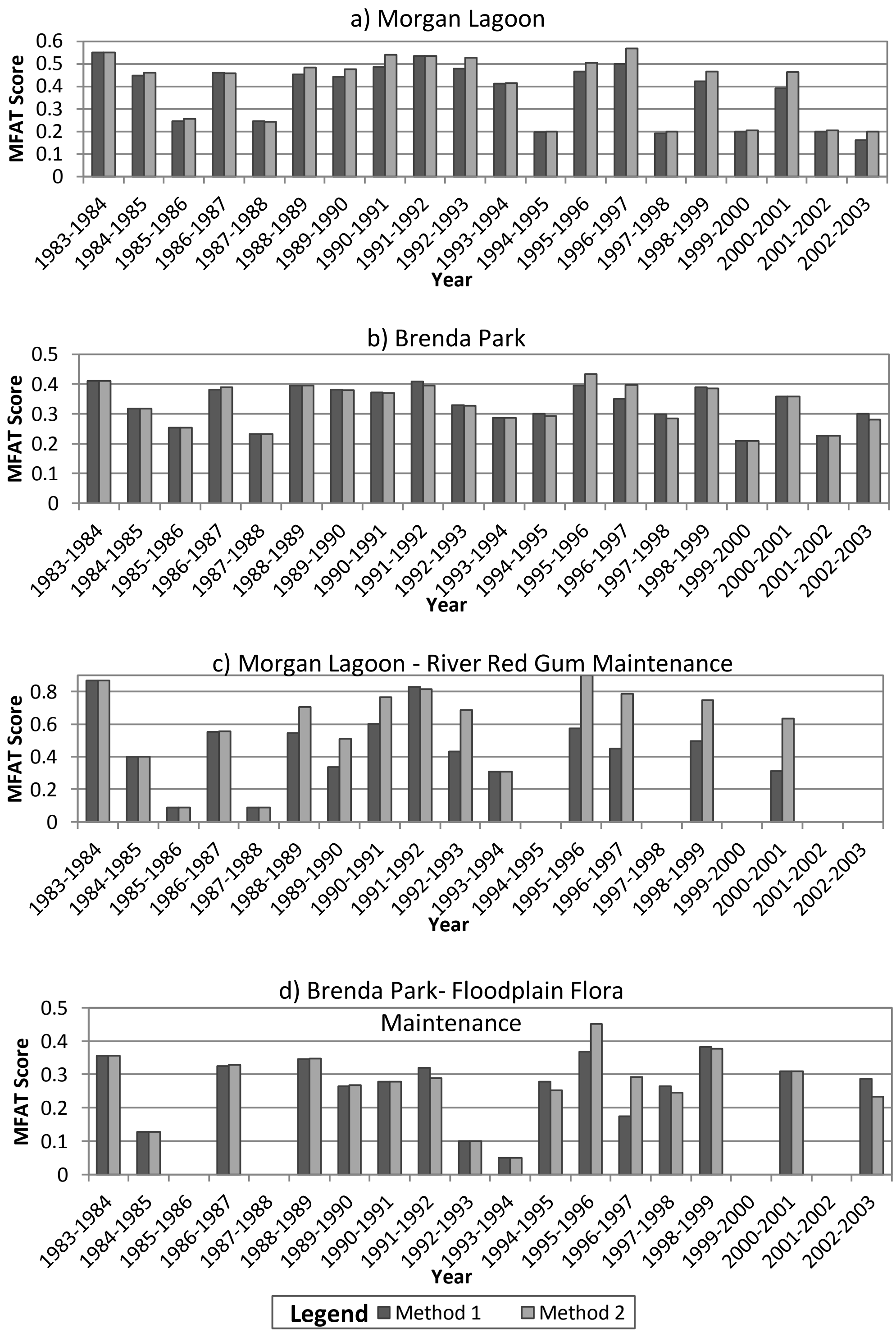

Figure 4.8: Average Annual MFAT Scores Achieved for Method1 and 2 for the Years 1983-2003

However, when higher environmental allocations are released, as is the case in 1990-1991, the Morgan Lagoon regulator is opened when it would normally be closed in order to obtain an ideal dry period. In comparison, Method 2, taking into consideration predicted higher environmental allocation, was able to adjust the schedule to open the gate in December, thereby achieving the required dry period.

While the MFAT scores obtained using Methods 1 and 2 are different for Morgan Lagoon (Figure 4.8a), this is not the case for Brenda Park (Figure 4.8b), suggesting that there is much more benefit in using the proposed adaptive scheduling approach for the former wetland. The only differences in the MFAT scores for Brenda Park (i.e. 1995-1996 and 1996-1997) when using the deterministic and adaptive approaches are primarily due to the maintenance MFAT scores achieved for the floodplain flora, as shown in Figure 4.8d. The largest difference occurs in 1996-1997, where a score of 0.17 is obtained when Method 1 is used, whereas a score of 0.39 is obtained when Method 2 is used. This increase in MFAT score for Brenda Park when Method 2 is used is due to the ability of this method to update the optimal EFMA schedule at the beginning of 1996-1997 using improved environmental water allocation estimates. In order to achieve a maintenance response for floodplain flora, the flora must undergo a dry phase. However, prior to 1996-1997, for the EFMA schedule developed using Method 1, the gate is closed and the wetland is allowed to dry. However, closing the gate for greater than 15 months has a negative impact on the floodplain flora. In contrast, in Method 2, the gate is closed from July to August, thereby providing sufficient time for the ideal dry period for the floodplain flora and achieve an overall maintenance score of 0.39.

The average MFAT score for the wetland and floodplain species within the case study area obtained using Methods 1 and 2 are shown in Figure 4.9. In the first four years, both methods achieve similar results, with wetland flora scores higher than those for floodplain flora. However, in the water year of 1987-1988, a higher wetland score is achieved for Method 1 than Method 2 because a higher environmental allocation is predicted using the latter method, and as such the EFMA schedule is adapted to suit higher lying vegetation. In reality, average flows were released and consequently, Method 1 achieves better results than Method 2. In 1991-1992, the floodplain flora scores for both Methods outperform the wetland flora scores, due to higher flow within the South Australian River Murray. This suggests that irrespective of the method used, when high flows are available, the floodplain flora will benefit more than the wetland flora, given that the latter will not experience ideal ecological conditions since it is flooded for a longer period. Finally, in 1995-1996 and 1998-1999, it can be seen that for Method 1, the wetland score achieved is higher than that achieved for Method 2. However, this is the reverse for the floodplain score. This is because in Method 1, lower allocations are assumed, and as such, the EFMA schedule developed favors wetland flora, whereas higher allocations forecast in Method 2 place more emphasis on the floodplain flora. As a result, when low flows are released, as is the case in 1995-1996 and 1998-1999, the predicted environmental allocations have an impact on which species should be favored. This suggests that at times of low flows, such as drought, managers should be aware of the impact the volume of environmental allocation has on these species, and as such should favor the species in need of improvement of ecological health.

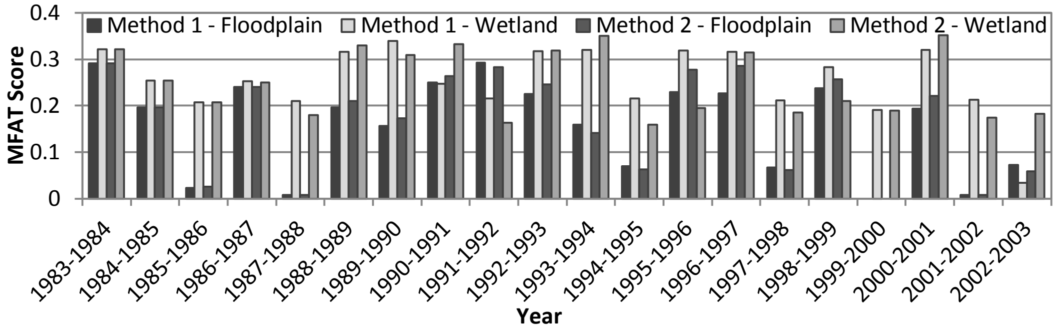

Figure 4.9: Average Annual MFAT Scores for Floodplain and Wetland Flora Achieved for Methods 1 and 2 Between the Years 1983-2003

4.5.3 Effectiveness of Minimization of Differences between Successive Schedules

In general, the performances of Methods 2 (trade-off between maximizing ecological response and minimizing disruptions to optimal schedules) and 3 (best possible ecological response) are very similar (Figure 4.6). In order to obtain a better understanding of the trade-offs between maximizing ecological response and minimizing changes to optimized EFMA schedules, the trade-off curves for the water years 1983-1984, 1992-1993 and 2002-2003 are shown in Figure 4.10. As can be seen, in all three years, substantial reductions in the number of changes to the optimal schedules can be achieved with very small reductions in MFAT score. These results indicate that the proposed multi-objective formulation is successful in reducing disruptions to existing schedules with minimal impact on ecological response, which is important from a practical management perspective. However, the exact nature of the changes from one schedule to the next would have to be examined by the appropriate authorities in order to determine the significance of the changes.

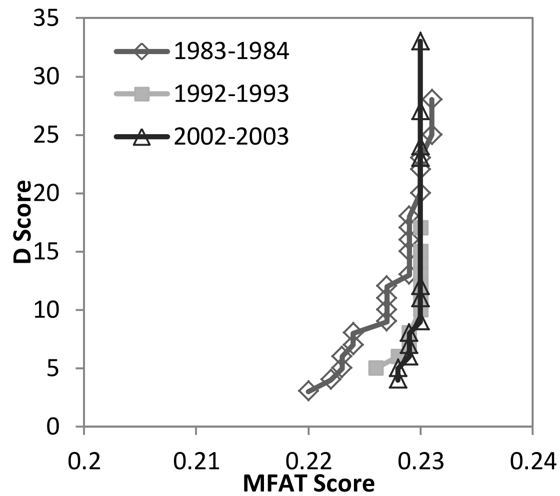

Figure 4.10: Trade-off Curves Developed using Method 2 for the 1st Year (1983-1984), 10th Year (1992-1993) and 20th Year (2002-2003)

4.5.4 Effectiveness of Minimization of Differences between Successive Schedules

As can be seen from Figure 4.6, the MFAT scores obtained using Methods 3 (using forecasts of future environmental water allocations using the ANN models) and 4 (using actual future environmental water allocations) are very similar. This suggests that the ANN models are performing well, as their use enables MFAT scores to be obtained that are close to the maximum scores that could be obtained with the aid of perfect knowledge of environmental water allocations over the next five years.

4.6 Conclusions and Recommendations

Overall, the results suggest that the use of optimal EFMA scheduling can result in substantial increases in ecological response and that the proposed adaptive scheduling approach is able to improve ecological response further in an operational setting, compared with approaches used previously. This is achieved by forecasting environmental water allocations over the next five years with the aid of artificial neural network models and updating schedules on an annual basis. From a practical perspective, the proposed multi-objective optimization formulation is able to reduce the number of changes to existing optimized schedules during the updating process at a very small reduction in ecological response.

Even though the results demonstrate the utility of the proposed adaptive optimization approach, improvements could be made by considering uncertainties, such as those associated with the estimation of ecological response and the forecasting of future environmental flow availability. For example, the Murray Flow Assessment Tool (MFAT) uses response curves that are based on imperfect knowledge (*Baihua and Merritt*, 2012), thus introducing uncertainties in the objective function. In order to address this issue, comprehensive sensitivity analysis could be used to assess the impact of the uncertainties of MFAT, as suggested by *Norton and Andrews* (2006) and *Baihua and Merritt* (2012). There is also uncertainty in the ANN forecasting models, which could be taken into account by considering more sophisticated ANN model development approaches (e.g. *Kingston et al.*, 2005; *Kingston et al.*, 2008; *Zhang et al.*, 2011) or by updating the ANN forecasting models as new data become available to extend their range of applicability (*Bowden et al.*, 2012).

Overall, the results demonstrate the utility and benefit of the proposed adaptive optimal EFMA scheduling approach in an operational setting. The approach has the potential to aid wetland managers in making informed decisions on how to best schedule EFMAs in an operational setting at times when environmental water allocations are likely to vary from year to year and when there is a limited amount of water available for the environment, which needs to be efficiently used to achieve the best possible ecological outcomes. In addition, the ability to assess the number of differences between schedules and understand the resulting impact on the ecological health of the system is likely to minimize any disruptions to the long term planning of EFMAs, as well reduce the resources required to make these changes.

Acknowledgements

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Chapter 5

5 Conclusions

The scheduling of environmental flow management alternatives is key to the preservation and restoration of rivers, wetlands and floodplains worldwide. However, the scheduling of EFMAs in river systems is a difficult and complex task for the following reasons: (i) there are multiple wetlands and floodplains all containing a variety of species that have different flow requirements that need to be considered; (ii) there is generally limited water allocated for environmental purposes since there multiple users (e.g. irrigation, domestic), all competing for the same water source; (iii) generally the schedules are developed over multiple years, introducing temporal dependencies; (iv) there are usually multiple competing objectives (e.g. water allocation and ecological response); and (v) flows in river systems are subject to constraints. Therefore, a generic adaptive multi-objective framework using ant colony optimization has been developed in this research to consider these key factors when scheduling EFMAs, which has been tested using hypothetical and real case studies. Information gathered from the application of the framework can aid wetland and water managers in making informed decision regarding the operation EFMAs at times when environmental water is limited and there exist restrictions associated with system constraints.

5.1 Research Contribution

The overall contribution of this research is the development of an adaptive multi-objective framework for the scheduling of EFMAs using ant colony optimization. This framework enables optimal EFMA schedules to be developed in order to maximise the ecological response of rivers, wetlands and floodplains at times when there is limited water for environmental purposes and there are constraints limiting flows in the system. The utility of the framework is demonstrated using a real case study in the South Australian River Murray, with information gained being able to assist with the decision making of EFMA operation under a range of different hydrological conditions. Details of specific contributions of this research are as follows:

1. An initial formulation of a single-objective framework using ant colony optimization is developed, which is able to account for the sequential nature of EFMA scheduling by representing the problem in the form of graphs. This representation allows for dynamically adjusting the tree as schedules are developed, thereby reducing the search space and increasing the likelihood that the global optimum will be found. This framework has been validated using a hypothetical case study based on the River Murray and its utility demonstrated using a range of investigations, including assessing the trade-off between recruitment and maintenance, assessing the trade-off between flora versus fauna and constraining allocations during certain time periods to assess the hydro inversion case. Results obtained provided further understanding in relation to: (i) when either recruitment, maintenance or a particularly species type is favoured and (ii) the allocation required to improve the ecological integrity of biota, in addition to the development of optimal EFMA schedules. Results also suggest the

framework presented is a valuable tool for determining the best possible ecological outcome at a given environmental water allocation.

2. The framework is extended to incorporate multiple objectives and applied to a real case study in the South Australian River Murray in order to develop trade-offs between ecological benefit and environmental water allocation under a variety of conditions, including: a) different system flow constraints; and b) different numbers of regulators. The performance of three multi-objective ant colony optimization algorithms (i.e. Pareto Ant Colony Optimization Algorithm (PACOA) (*Doerner et al.*, 2004), COMPETants (*Doerner et al.*, 2003) and m-ACO variant 3 (m-ACO_3) (*Alaya et al.*, 2007)) was compared, with the PACOA selected, as it performed the best. The results provide valuable insight into the management problem, particularly the ecological benefit gained in the case study area for an increased environmental allocation for a range of upstream flow constraints and different numbers of regulators. It was determined that as the system constraints became less restrictive, the ecological score increased, as a greater area was inundated. In addition, as the number of regulators increased, the maximum ecological score did not, but the required water allocation to achieve this score is reduced. The application of the framework and the outcomes of these investigations enable managers to make informed decision in relation to the management of environmental water releases, regulator operations and investment in additional infrastructure, particularly at times when limited water is available, as is often the case in the South Australian River Murray.

3. An adaptive approach, which extends the framework by (i) developing a forecasting model to predict environmental water allocation and using these predictions in EFMA schedule development; (ii) updating forecasts of future water allocation and optimal EFMA schedules at regular intervals over the planning horizon; and (iii) considering the trade-off between the minimization of the number of differences between optimal EFMA schedules at subsequent timesteps and ecological response. The approach is applied to a real case study in the South Australian River Murray. Four different optimal scheduling methods are compared to test the utility of the different features of the proposed approach. Results indicate that the proposed adaptive scheduling approach results in improved ecological response by using artificial neural networks to forecast future environmental water allocation and updating the schedules annually. In addition, the multi-objective optimization framework is able to decrease the number of disruption made to existing schedules with minimal affect on ecological response when the trade-off between ecological response and the number of differences between current and updated schedules is examined. In all, the approach has the potential to aid managers to make informed decision on how to best schedule EFMAs when environmental allocation varies annually and when there is limited water, while also being able to assses the ecological impact that minimising the number of changes to the EFMA schedules has on the area being investigated.

5.2 Limitations

The limitations of this research are discussed below.

1. A main limitation of this research is associated with the Murray Flow Assessment Tool (MFAT) developed by *Young et al.*, (2003) and results obtained using this as an ecological indicator. MFAT uses a number of preference curves to develop relationships between flow and ecological response for a range of species types. However, knowledge of these ecological relationships is imperfect, thereby introducing uncertainty into the model. In addition to this, the flow components for the species and processes using MFAT are aggregated, therefore, the actual response for individual species, for example, can be lost, resulting in potential difficulties in interpreting the results.

2. Another limitation is the uncertainties associated with the forecasting models developed to predict environmental water allocation. Limited data was usedto train, test and validate the models, thereby potentially not accounting for all the linear and non-linear relationships between the input and output data. As a result, forecasts may be incorrect, thereby potentially limiting the analysis and understanding gained about the area under investigation.

3. A simple water balance model is used to describe the river channel and its interactions between wetlands and floodplains, which is based on backwater curves for the real case study in the South Australian River Murray. However, in reality, groundwater interaction with the vegetation also has an impact on the ecological response. For example, river red gums (*Eucalyptus camaldulensis*) are opportunistic and will seek out other sources of water, including groundwater to survive in

periods of drought (*Mensforth et al.*, 1994). Therefore, the actual ecological response may be different to that modelled by the water balance model in conjunction with MFAT.

4. A final limitation is associated with the fact that there is no consideration of other water uses when the balance of environmental water and ecological response is investigated. In reality, there is a major conflict over water resources between not only the environment, but for human purposes, such as domestic, irrigation and industrial use. Thus, the overall trade-off between the ecological response and environmental water allocation could be different given that there are other water users.

5.3 Future Work

A number of limitations of the current research presented in the previous section also represent opportunities of future research, including:

1. Undertaking a sensitivity analysis on the response curves and aggregation approach used in MFAT, such as that used in *Norton and Andrews* (2006) and *Baihua and Merritt* (2012). This analysis would examine the robustness and variance of likely ecological response that could be obtained for a given EFMA schedule.

2. Future work on the forecasting environmental water allocation model in order to reduce the uncertainties associated with the predictions. Increasing the number of data points will ensure that all the underlying relationships between the input and output data can be taken into account, thereby improving predictive capability of the models. In addition to this, other more sophisticated ANN model development

approaches such as Bayseain ANNs (*Kingston et al.*, 2005; *Kingston et al.*, 2008) could be assessed as well as the re-calibratation of the ANNs as new data becomes available, thereby improving the applicability of the models (*Bowden et al.*, 2012). This would determine whether or not the ecological response within the area of interest obtained at regular intervals could be improved with a more sophisticated forecasting model.

3. The ecological response of vegetation species is not only based on surface water interaction between river and floodplains, but also groundwater. Future work could extend the water balance model to incorporate groundwater interaction and potential other water sources, such that a more likely ecological response could be determined, given the flow scenario. This may mean that a different ecological indicator may have to be selected, given that MFAT only considers surface water responses.

4. Finally, the conflict over water is real and generally environmental water allocation is the first to be reduced at times when water is limited (i.e. drought). Therefore, future work could incorporate additional water users (e.g. irrigation or domestic) by extending the framework to cater for more objectives (including economic and social objectives) and investigate the impact this has on the trade-off between water allocation and ecological response.

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Appendix A

Copy of Paper from Chapter 2

Szemis, J. M., H. R. Maier, and G. C. Dandy (2012), A framework for using ant colony optimization to schedule environmental flow management alternatives for rivers, wetlands and floodplains *Water Resources Research*, *48*, W08502, doi:08510.01029/02011WR011276. .

A framework for using ant colony optimization to schedule environmental flow management alternatives for rivers, wetlands, and floodplains

J. M. Szemis,[1] H. R. Maier,[1] and G. C. Dandy[1]

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[1] Rivers, wetlands, and floodplains are in need of management as they have been altered from natural conditions and are at risk of vanishing because of river development. One method to mitigate these impacts involves the scheduling of environmental flow management alternatives (EFMA); however, this is a complex task as there are generally a large number of ecological assets (e.g., wetlands) that need to be considered, each with species with competing flow requirements. Hence, this problem evolves into an optimization problem to maximize an ecological benefit within constraints imposed by human needs and the physical layout of the system. This paper presents a novel optimization framework which uses ant colony optimization to enable optimal scheduling of EFMAs, given constraints on the environmental water that is available. This optimization algorithm is selected because, unlike other currently popular algorithms, it is able to account for all aspects of the problem. The approach is validated by comparing it to a heuristic approach, and its utility is demonstrated using a case study based on the Murray River in South Australia to investigate (1) the trade-off between plant recruitment (i.e., promoting germination) and maintenance (i.e., maintaining habitat) flow requirements, (2) the trade-off between flora and fauna flow requirements, and (3) a hydrograph inversion case. The results demonstrate the usefulness and flexibility of the proposed framework as it is able to determine EFMA schedules that provide optimal or near-optimal trade-offs between the competing needs of species under a range of operating conditions and valuable insight for managers.

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1. Introduction

[2] Rivers and their associated wetlands and floodplains provide vital ecosystem services that people depend upon, such as water purification, habitat for wildlife and climate mitigation [*Millennium Ecosystem Assessment (MEA)*, 2005]. Many of these systems have been severely altered, or have even vanished, due to the development of infrastructure, such as channelization and dams, land conversion, and the over allocation of water for human needs [*Brookes*, 1988; *Kingsford*, 2000; *MEA*, 2005; *Nel et al.*, 2009]. This has altered the hydrological regime, reducing the level of connectivity and flooding between rivers and associated floodplains and wetlands, thereby changing their ecology and causing the death or poor health of their biota [*Kingsford*, 2000; *Kingsford and Auld*, 2005]. According to *National Research Council* [1992], the rate at which freshwater ecosystems are being altered or destroyed is much greater now than at any other time in human history. To mitigate the impacts of these alterations, there is an urgent need to improve the connectivity between rivers and their adjacent wetlands and floodplains, so that they can be maintained and protected for future generations.

[3] In order to address the problem outlined above, the provision of water for environmental flows has been suggested [*Arthington et al.*, 1998; *Kingsford*, 2000]. In the past, this consisted of releasing a minimum flow, which has now been deemed to be inadequate [*Arthington et al.*, 2006]. Instead, it has been suggested that managed flow regimes should follow the 'natural flow paradigm' developed by *Poff et al.* [1997] in order to reintroduce the flow variability that has been lost as a result of human induced flow alteration [*Poff*, 2009]. Five flow components were presented by *Poff et al.* [1997] as the key to ensuring the ecological integrity of river systems, including the timing, duration, magnitude, frequency and rate of rise/fall of flow. These components are also important when flooding adjacent wetlands and floodplains, as it is these factors that govern the structure and function, and in turn, the health of wetlands and floodplains [*Junk et al.*, 1989]. For example, the timing of inundation can affect the recruitment and regeneration of plants [e.g., *Cordes et al.*, 1997], flood duration can influence plant

[1]School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide, Australia.

Corresponding author: J. M. Szemis, School of Civil, Environmental and Mining Engineering, University of Adelaide, North Terrace, Adelaide, 5005, Australia. (jszemis@civeng.adelaide.edu.au)

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cover and diversity [e.g., *Busch and Smith*, 1995], while a combination of the timing, duration and rate of change of flooding can impact the life cycles of fish species [*Junk et al.*, 1989]. River, wetland and floodplain biota are dependent on these flow components and a significant amount of research has been undertaken to quantify these ecological responses [*Poff and Zimmerman*, 2010].

[4] The pursuit of environmental integrity criteria, such as those developed by *Poff et al.* [1997] constitute the primary objective of any management program. A number of management alternatives are available for achieving the corresponding environmental flow requirements for rivers, wetlands and floodplains, including environmental flow releases from upstream storages and the operation of flow control infrastructure, such as regulators and pumps. Decisions have to be made in relation to the timing, magnitude and duration of potential flow releases and infrastructure operation. In other words, at discrete points in time (e.g., day, week, month), decisions have to be made whether an environmental flow release should be made and/or whether a change should be made to the setting of flow control infrastructure. These decisions must be made in pursuit of an objective that seeks to maximize some measure of ecological health. If the decision is made to release environmental flows and/or make a change to the setting of flow control infrastructure, a choice has to be made in relation to what fraction of the available environmental flow allocation to release at this time and/or which of the available infrastructure change options should be implemented, and how long this management action should persist. Given that these decisions generally have to be made at discrete time steps over a given planning horizon (e.g., several years) and at numerous locations (e.g., locations of reservoirs, regulators and pumps), the search space of potential management alternatives in this scheduling problem is generally extremely large, particularly when dealing with extended spatial and temporal scales.

[5] The scheduling of environmental flow management alternatives (EFMAs) is further complicated by the fact that (i) there are often different processes that must be accounted for in managing a single species, such as (a) promoting the maintenance of adult species and the recruitment of juveniles (e.g., germination of plant species and breeding of wildlife), resulting in varying flow requirements [*Rogers*, 2011a], or (b) ensuring the succession and retrogression of floodplain vegetation, which introduces an additional shear stress factor [*Benjankar et al.*, 2011], (ii) flow requirements are generally different for each species of flora and fauna, and may be in competition with each other, which is a problem that is often exacerbated when considering extended spatial scales, as the number of species that need to be considered is generally larger, and (iii) schedules generally need to be developed over multiple years, since there are species, such as the Black Box woodland (*Eucalyptus largiflorens*), that require a maintenance flood frequency of 1 in 2–5 years [*Rogers*, 2011a], thereby introducing temporal dependencies into the scheduling process (i.e., decisions made at each time step are not independent of each other).

[6] Given the extremely large search space of management options, the large number of generally competing environmental flow requirements, and the temporal dependencies between management alternatives, the problem of scheduling EFMAs so as to maximize ecological outcomes is extremely difficult. However, such a goal is very important, particularly given that limited amounts of water are generally available for environmental purposes, as there is competition for water resources between various uses, such as irrigation, domestic and industrial water supply, power generation, recreation, and the restoration, rehabilitation and maintenance of ecological services. Given this complexity, there is potential benefit in using formal optimization approaches for addressing the environmental flow management problem. However, previous optimization studies in this field have primarily focused on the higher-level problem of the development of optimal reservoir/weir operating rule parameters or monthly reservoir releases, while trying to maintain an adequate balance between the needs of the environment and other water users (e.g., irrigation), rather than the specific problem of how to allocate a given environmental water allocation so as to maximize ecological outcomes. As a result, ecological objectives have been treated in a rather simplistic manner in past optimization studies. For example, in some studies, there was no consideration of the important flow components [*Chang et al.*, 2010; *Chaves et al.*, 2003], while in others, the importance of competing ecological objectives was neglected [*Cardwell et al.*, 1996; *Tilmant et al.*, 2010; *Yang*, 2011; *Yang and Cai*, 2011]. In almost all of the studies, there was no consideration of both river and downstream wetlands and floodplains, or the temporal dependencies between management options [*Homa et al.*, 2005; *Shiau and Wu*, 2004; 2007; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2010]. Only *Higgins et al.* [2011] considered the river, wetlands and floodplains on a landscape scale and used optimization to determine the best locations and operating regimes for wetland regulators and weirs by mimicking the natural flood timing, dry period and flood duration. However, there is no existing optimization framework that can be used to (i) develop schedules that maximize the ecological response of rivers and their wetlands and floodplains for a given environmental water allocation, (ii) incorporate not only flood timing, dry period, and duration but also depth (which affects seed germination [*Rogers*, 2011a]), and (iii) develop schedules that favor certain ecological process or species. Consequently, there is a need to develop and test a generic framework for determining the optimal schedule of EFMAs for rivers and their wetlands and floodplains for a given environmental water allocation that takes into account (i) rivers and adjacent wetlands and floodplains, (ii) a large number of potential management alternatives, (iii) multiple and potentially competing environmental objectives associated with important flow components, process and species, and (iv) temporal dependencies associated with the important flow components.

[7] In order to meet this need, the specific objectives of this paper are (i) to develop an optimization framework for maximizing the ecological response of rivers and their wetlands and floodplains (e.g., by using the Murray Flow Assessment Tool (MFAT) developed by *Young et al.* [2003], as is done in the case study presented in this paper) for a given environmental flow allocation, by determining the optimal scheduling of predetermined EFMAs, such as flow releases and regulator settings, which is able to take account of (a) a large number of possible management alternatives, (b) a range of environmental objectives (e.g., ecological responses of flora and fauna species and associated

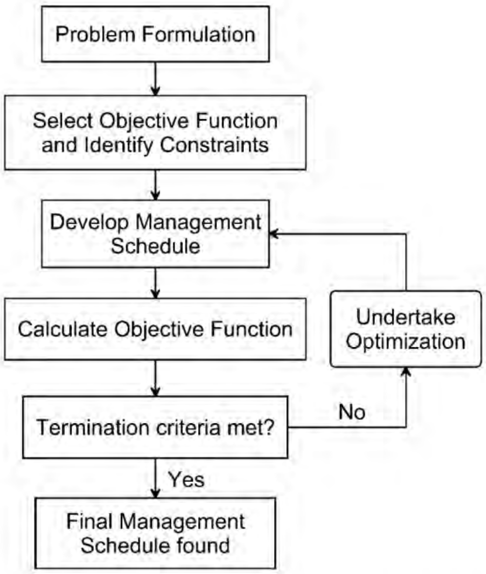

Figure 1. Representation of the optimal scheduling of environmental flow management alternatives.

processes), (c) constraints associated with environmental water allocations, and (d) the temporal dependencies associated with the management alternatives; (ii) to develop an approach that is capable of solving the optimization problem formulated in objective i, and (iii) to apply the optimization framework and solution methodology developed in objectives i and ii to a case study in order (a) to demonstrate how they are applied in practice, (b) to validate their performance, (c) to illustrate how they can be used to account for competing requirements of individual species, (d) to illustrate how they can be used to account for competing requirements of flora and fauna, and (e) to illustrate how they can be used to deal with environmental water allocations of different magnitude and timing (e.g., hydrograph inversion).

[8] The remainder of this paper is organized as follows. The novel optimization framework is introduced in section 2, followed by the optimization approach for solving it in section 3. The case study used to illustrate the utility and validate the proposed formulation and solution approach is introduced in section 4, while details of the numerical experiments conducted are provided in section 5. Results and discussion are presented in section 6, followed by a summary and conclusions in section 7.

2. Framework for the Optimal Scheduling of Environmental Flow Management Alternatives

[9] In this section, the framework for the optimal scheduling of EFMAs aimed at restoring, protecting and maintaining rivers and their wetlands and floodplains is introduced (objective i), which has been adapted from the systems approach proposed by *Biswas* [1976] and is shown in Figure 1.

[10] The first step in the optimization framework is problem formulation, which includes identification of the wetlands, floodplains and river reaches to be managed, identification and selection of appropriate ecological indicators (e.g., flora/fauna species, flow components or shear stress), the planning horizon over which the schedule for the EFMAs is to be developed (e.g., number of years), the time interval (e.g., monthly or yearly time steps) at which alternatives are to be scheduled, and finally, specification of the EFMAs that are available for achieving the desired ecological response (e.g., flow release options, regulator settings, pumping schedule), as well as the suboptions associated with each of these alternatives (e.g., magnitude, duration). Next, the objective function (e.g., maximization of ecological response) and any constraints (e.g., maximum available environmental water allocation) need to be defined, after which a schedule for the EFMAs can be developed. The objective function (e.g., overall ecological response of the system under consideration) is then calculated to assess the utility of the selected schedule. The process of selecting different schedules and evaluating their utility is generally repeated many times and guided by the selected optimization method in order to find optimal or near-optimal solutions (e.g., schedules of EFMAs). Each of these steps is discussed in more detail in sections 2.1–2.4.

2.1. Problem Formulation

[11] The first step in formulating the optimal scheduling problem, shown in Figure 2, involves the identification of the q wetlands, floodplains and river reaches that require protection, restoration or maintenance, where the wetlands, floodplains and river reaches are defined as H_i, and i ranges from 1 to q.

[12] Next, appropriate ecological indicators $E_{i,r}$, are specified for each wetland, floodplain and river reach, H_i, in

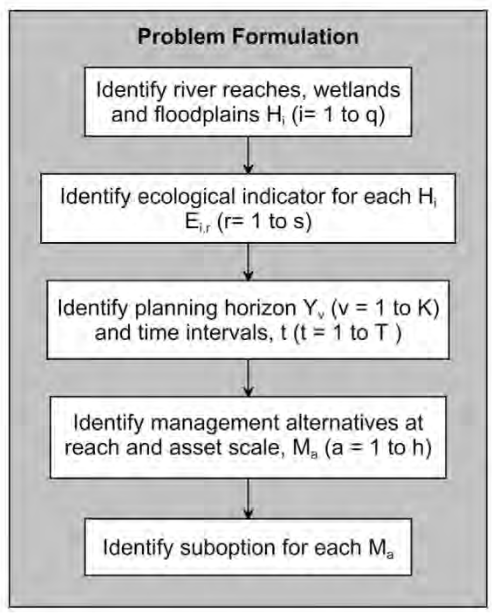

Figure 2. Steps in formulation of environmental flow management schedule optimization problem. The river reaches, wetlands, and floodplains are defined as H_i, and i ranges from 1 to q. The ecological indicators, $E_{i,r}$, where r ranges from 1 to s, are specified for each H_i. The planning horizon is defined as Y_v, where v ranges from 1 to v years, while the time interval, t, ranges from 1 to the final time interval, T. The number of management alternatives, M_a, ranges from 1 to h.

order to assess the performance of each potential management schedule in terms of ecological response. For example, the r ecological indicator/s (ranging from 1 to s) can be used to assess the ability to simulate the natural flow regime [*Richter et al.*, 1996], assess processes that govern the life cycle of different types of flora and fauna species [*Young et al.*, 2003], or measure the succession and retrogression of vegetation [*Benjankar et al.*, 2011]. The choice of the number and types of indicators is case study dependent. It should be noted that there are other ecological responses that can be taken into account, such as the fact that lower peak flows can increase ecological response through terrestrialization of riparian areas or the encroachment of the river channel by riparian communities [*Poff and Zimmerman*, 2010]. However, such ecological responses can only be incorporated if they can be represented in the form of an ecological indicator, which is a limitation of the proposed optimization framework.

[13] Once the wetlands, floodplains, river reaches and ecological indicators have been identified, the planning horizon over which the schedules need to be developed, Y_v, where v ranges from 1 to K years, and the time intervals between potential management actions during the period, t, which ranges from 1 to T time intervals, should be selected. Selection of appropriate values for these variables is also problem dependent.

[14] The next step in the problem formulation procedure is the specification of the management alternatives, which can be divided into two groups. The first category includes reach-scale management alternatives, which affect the hydrological regime of the entire river system. These include reservoir releases or weir operations that govern the flow within the entire river reach and affect wetland and floodplain inundation. The second type includes management alternatives that manipulate hydrological regimes for individual wetlands and floodplains. An example is the manipulation of water levels using individual gates and/or pumps at the entrances or exits of wetlands, which could prevent, allow, or force water from entering or leaving. The combination of reach, wetland, and floodplain scale management options constitutes the final set of management alternatives, M_a, where a ranges from 1 to h.

[15] The final stage of the problem formulation step involves the specification of the suboptions for each management alternative, that is, the magnitude, duration and timing of the proposed management interventions described in section 1. All of the available suboptions need to be specified for each of the management alternatives in order to define the decision space in its entirety.

2.2. Selection of Objective Function and Constraints

[16] The second stage of the proposed optimization framework involves definition of the objectives and constraints. It is important to select an appropriate objective function, as this characterizes how well different management schedules perform. The constraints, on the other hand, ensure that infeasible schedules are not considered.

[17] The objective function used to assess the performance of the proposed management schedules should consider all of the wetlands, floodplains and river reaches, as well as the selected ecological indicator(s). Since there are generally multiple, and at times competing, indicators, the values of individual indicators need to be summed over all ecological assets (e.g., river reaches, wetlands, floodplains) in order to obtain an estimate of the ecological response of the entire system under investigation for a given management schedule. In order to account for differences in the relative importance of various ecological assets, indicators, and time periods, user defined weights are included. Consequently, the proposed objective function takes the following form:

$$F = \sum_{i=1}^{q} w_{1i} \sum_{r=1}^{s} w_{2r} \sum_{v=1}^{K} \frac{w_{3v} E_{i,r,v}}{Y_K} \tag{1}$$

where $E_{i,r,v}$ is the indicator value for asset i, for indicator type r in the vth yearly time interval. In equation (1), the overall objective function value is obtained by summing (1) values of each ecological indicator over the q wetlands, floodplains and river reaches considered, (2) values of the s indicators used for each wetland, floodplain, and river reach, and (3) ecological indicator values over the number of years (Y_K) over which the schedule of EFMAs has been developed (i.e., the planning horizon). Weights, w_{1i}, w_{2r} and w_{3v} place emphasis on the qth wetlands, floodplains or river reaches, rth ecological indicator and Y_Kth year, respectively. Consequently, the proposed objective function is sufficiently flexible to cater to particular aspects of the problem (e.g., favoring an endangered species), while also ensuring that an overall ecological score is obtained for the river system.

[18] Once the objective function has been defined, the constraints need to be specified to ensure infeasible schedules of EFMAs are not developed. Since the aim of the research is to develop EFMA schedules that optimize the environmental benefit associated with a given amount of environmental water, constraints have to be placed on the total amount of water that is available for environmental purposes, which is likely to vary over the planning horizon (e.g., on a seasonal basis), as given by

$$\sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \leq A_{\max\_ni(pd)} \tag{2}$$

where pd is the number of periods of constrained environmental water allocations, ranging from 1 to np, while the number of increments in each period, $ni(p)$ ranges from 1 to Vp, and $i\_ni(pd)$ and $f\_ni(pd)$ are the corresponding initial and final time steps for pd, over which a particular water allocation is released. The duration of each increment is defined as $d_{ni(p)}$, and the summation of all duration increments for each period must equal the total duration interval, T_d. Being able to have different allocation constraints for different time periods during the planning horizon provides the ability to account for situations such as hydrograph inversion, or physical constraints on water release infrastructure.

[19] Constraints also have to be placed on the magnitude and duration of the suboptions for a particular management alternative, M_a, as given in

$$M_{a,m\_\min} \leq M_{a,m} < M_{a,m\_\max}, \quad m = 1 \text{ to } n \tag{3}$$

$$M_{a,d\_\min} \leq M_{a,d} < M_{a,d\_\max}, \quad d = 1 \text{ to } p \tag{4}$$

where the magnitude suboptions for wetlands, floodplains, and river reaches are $M_{a,m}$, which are constrained by minimum and maximum values of $M_{a,m\_\min}$ and $M_{a,m\_\max}$,

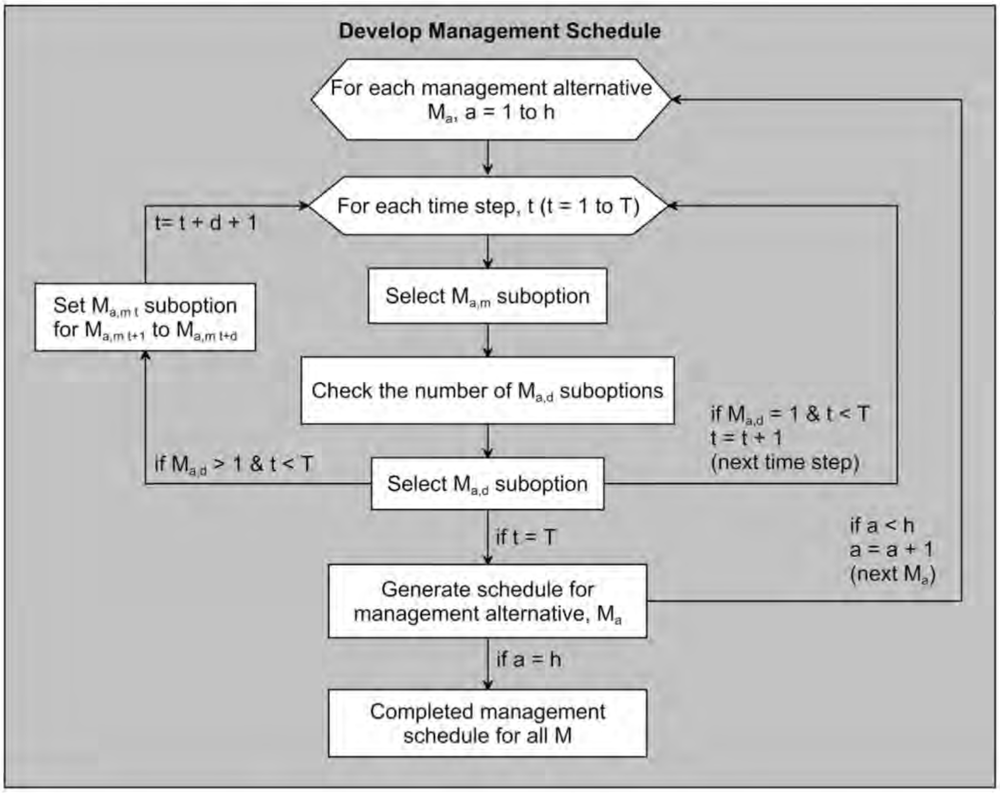

Figure 3. Environmental flow management schedule development, where the number of management alternative, M_a, ranges from 1 to h. The time step, t, ranges from 1 to T months, while $M_{a,m}$ and $M_{a,d}$ are the magnitude and duration suboptions for each M_a and d corresponds to the duration of $M_{a,d}$.

respectively, and the duration suboptions are $M_{a,d}$, which are constrained by minimum and maximum values of $M_{a,d\_\min}$ and $M_{a,d\_\max}$, respectively, for each management alternative. The m possible magnitude suboptions, $M_{a,m}$, range from 1 to n and $M_{a,d}$ is the number of duration suboptions available, where d is between 1 and p. Each management alternative must therefore be assessed individually in order to determine appropriate values for the above constraints. These ranges may depend on the characteristics of the wetlands and floodplains, or the chosen ecological indicator.

[20] If a yearly time step is chosen, then an additional timing constraint is required to determine during which month a particular management alternative should be implemented. However, such a constraint is not required if a monthly time step is adopted. Other constraints that must be taken into account are mass balance constraints, for instance the overall water entering the system must equal the water leaving system (through either water allocated to the wetlands and floodplains or evaporation).

2.3. Environmental Flow Management Schedules Development

[21] Once the problem has been formulated, management schedules can be constructed by first selecting a management alternative, as shown in Figure 3. Next, a schedule needs to be constructed for all T time intervals. In order to do this, the magnitude suboptions for M_a should be selected, followed by an assessment of the number of available duration suboptions, $M_{a,d}$. The second step is necessary, as the number of duration suboptions can change during the generation of a schedule. For example, if a monthly time step were used, there would be a maximum of twelve duration options at the beginning of a year, which would reduce to six halfway through the year. Consequently, the conditional dependencies associated with the selection of $M_{a,d}$ need to be taken into account during the schedule generation process, as shown by the loops in Figure 3. Once all suboptions have been selected at each time step for a particular management alternative, this process has to be repeated for all of the remaining management alternatives until a complete EFMA schedule has been developed.

[22] This procedure demonstrates the sequential nature and dependencies of the optimal scheduling problem, where decision made at certain time steps affect the choices that are available at subsequent time steps. It is vital that such information be taken into account, as it can affect the quality of the management schedule developed, as well as the efficiency with which it is generated.

2.4. Calculation of Objective Function and Optimization

[23] Once an EFMA schedule has been developed, its utility needs to be assessed, which is done via the objective function (equation (1)). In order to calculate the objective function, a simulation model, such as a hydrological model of the river system, is generally used in order to determine the flow regime within each river reach, floodplain and wetland, as well as the resulting ecological indicator score.

Once the objective function has been calculated, its value is used during the optimization procedure in order to develop better solutions (i.e., schedules of EFMAs), as shown in Figure 1. The cycle of development, simulation and assessment of EFMA schedules using optimization continues, until the selected termination criteria are met. A discussion of the proposed optimization method for solving the optimal scheduling problem is presented in the next section.

3. Proposed Ant Colony Optimization for the Scheduling of Environmental Flow Management Alternatives

[24] There are a number of candidate optimization algorithms for solving the optimal scheduling problem formulated in section 2, including traditional forms of optimization, such as linear and dynamic programming [*Taha*, 1997] and metaheuristics, for instance, genetic algorithms (GA) [*Goldberg*, 1989] and ant colony optimization (ACO) algorithms [*Dorigo et al.*, 1996]. Linear programming only works for linear objective functions and constraints [*Taha*, 1997], resulting in the inability to solve complex nonlinear problem, such as the optimal scheduling problem presented here. Dynamic programming, on the other hand, overcomes this problem by using the principle of optimality to determine optimal solutions [*Taha*, 1997], while genetic and ACO algorithms achieve this by using the principle of survival of the fittest [*Goldberg*, 1989] and the foraging behavior of ants [*Dorigo et al.*, 1996], respectively. However, dynamic programming suffers from the 'curse of dimensionality', which means that it has difficultly solving problems with large search spaces, as the computational requirements grow exponentially with increased complexity [*Madej et al.*, 2006]. Both GAs and ACO algorithms overcome this problem to a large extent by searching for near-optimum solutions using the search principles mentioned above, thereby only exploring a small fraction of the search space. Consequently, they sacrifice "the guarantee of finding the optimal solution for obtaining good solutions in a significantly reduced time" [*Blum and Roli*, 2003]. Despite this shortcoming, in tests of problems with known theoretically optimal solutions, GAs and ACO algorithms have been found to produce globally optimal or near-optimal solutions for a range of applications [*Back et al.*, 1997; *Blum*, 2005].

[25] GAs are probably the most widely used heuristic optimization method. However, as they represent solutions as strings of genes, which are modified from one generation to the next as the algorithm attempts to find the globally optimal solution, it is difficult to account for the sequential nature and conditional dependencies of the optimal scheduling problem outlined in section 2.3. In other words, as values of all decision variables are generated simultaneously in a particular population, there is no mechanism for adjusting the value of one decision variable based on the selected value of another. This increases the size of the search space unnecessarily and introduces a larger proportion of infeasible solutions, making it more difficult to find globally optimal or near-optimal solutions. In contrast, ACO algorithms are able to account for the sequential nature and conditional dependencies of the optimal scheduling problem explicitly, as the solution space is represented by a graph structure that can be adjusted dynamically based on the choices made at previous points in the decision graph during the constructions of solutions, thereby reducing the size of the decision space and increasing the proportion of feasible solutions [*Afshar*, 2010; *Foong et al.*, 2007, 2008; *Maier et al.*, 2003]. In other words, as solutions in ACO are constructed incrementally by stepping through a decision graph, rather than generating the entire solution simultaneously, as is the case with GAs, the options that are available at subsequent steps in the decision graph can be altered during the construction of a trial solution, based on the choices that were made at previous steps. This is because in ACO, solutions are generated based on changes in the decision space, rather than by modifying solutions themselves.

[26] ACO algorithms have been applied successfully to the traveling salesman problem [*Dorigo and Gambardella*, 1997b] and found to outperform other optimization algorithms, such as genetic algorithms, in terms of computational efficiency and solution quality [*Dorigo and Gambardella*, 1997a]. Other successful ACO applications include the quadratic assignment problem [*Mainiezzo and Colorni*, 1999], shop scheduling problems [*Blum and Sampels*, 2004], water distribution systems optimization problems [*Maier et al.*, 2003; *Zecchin et al.*, 2007], reservoir operation problems [*Jalali et al.*, 2007] and power plant maintenance scheduling problems [*Foong et al.*, 2007]. The sections 3.1–3.3 discuss the problem representation and steps in the ACO algorithm, as well as the implementation of dynamic constraints to account for the conditional dependencies of the EFMA scheduling problem discussed previously.

3.1. Problem Representation

[27] Before ACO can be used to develop an optimal or near-optimal schedule as per section 2.3, each management alternative must be first mapped onto a graph, which consists of a number of discrete time steps and a set of suboptions at each of these. An example EFMA schedule graph for flow releases is shown in Figure 4. As can be seen, there are two suboptions that are considered at each time step, magnitude and duration. The magnitude suboption for this case ranges from a minimum allocation of zero to a maximum allocation of 1000 gigaliters (GL), which is independent of time, and as such remains in a closed loop. However, the next suboption, duration, branches into 12 paths after each magnitude suboption, one for each month, thereby generating multiple possible solutions. The number of possible solutions begins to expand until the final time step, T, is reached. Other suboptions, such as timing, can be also be accounted for in the graph structure. Once the graph has been defined, it can be used to develop a trial schedule using the ACO algorithm, which will be discussed in the following section.

3.2. Ant Colony Optimization Algorithm

[28] The steps involved in the ACO algorithm are given in Figure 5. The process of generating a trial EFMA schedule begins with the initialization of the ACO control parameters. Next, the optimization process takes place, where b ants construct trial schedules during each iteration (*its*). An ant achieves this by traveling to each time step and selecting magnitude and duration suboptions (Figure 4), until it reaches the final time step, T. At each time step, the suboptions are selected probabilistically based on a pheromone intensity (τ) and heuristic information (η), as well as decision policy control parameters, α and β, that determine the

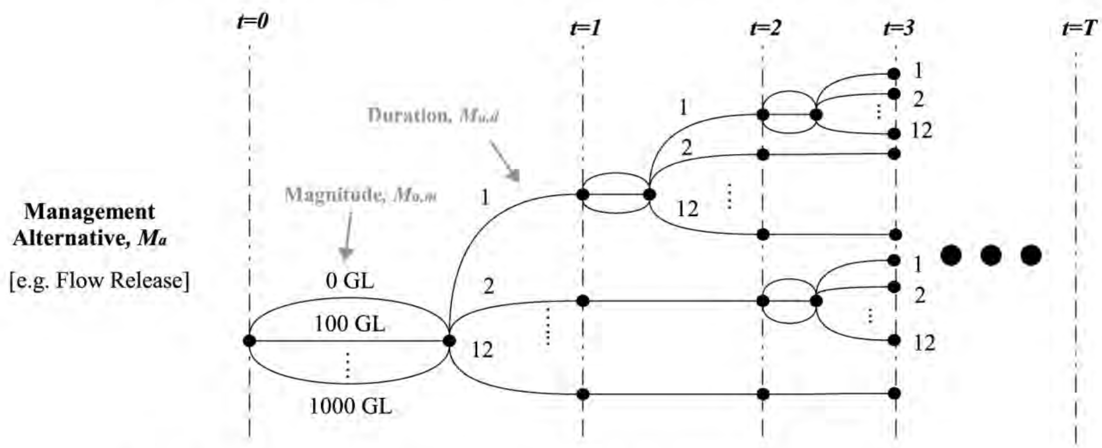

Figure 4. Example of an EFMA schedule graph for flow releases (in gigaliters (GL)).

relative importance of pheromone intensity and heuristic information, respectively [*Zecchin et al.*, 2005]. The pheromone intensity for a suboption is first initialized to a random value while for subsequent iterations, pheromone is added based on the initial pheromone (τ_o), a pheromone persistence factor (ρ) and a reward factor (Q) that is used to scale the pheromone addition [*Zecchin et al.*, 2005]. The heuristic value of a suboption, on the other hand, represents the quality of that suboption based on prior information.

[29] Once a complete trial schedule has been generated by an ant, the plan is evaluated using an objective function (see equation (1)). As discussed in section 2, a simulation model, such as a hydrological model for the river system under investigation, is used in the calculation of the objective function and any constraint violations (e.g., equation (2)). An iteration is completed once b ants have developed and evaluated a trial schedule.

[30] At the end of each iteration, the quality of the EFMA schedules generated by the ants is evaluated and pheromone values are modified accordingly (i.e., the better the solution, the higher the pheromone that is added to the "paths" that made up that solution). The pheromone intensity for a suboption thus reflects the quality of trial schedules developed in previous iterations that contained that particular suboption, which creates bias for ants in future iterations to develop solutions of high quality. Additionally, pheromone evaporation is applied to components of schedules that do not perform well, which in turn deters the ACO algorithm from choosing those paths again. In this manner, the environment is modified to guide the artificial ants to regions of the search space that contain attractive solutions. For an ACO algorithm to be effective in generating optimal or near-optimal solutions, it is important that the correct balance of exploration (i.e., exploring the search space widely) and exploitation (i.e., converging to an optimal solution as quickly as possible) is struck. A number of ACO variants that use different pheromone updating schemes have been developed to achieve this. Some of these include: Ant Systems [*Dorigo et al.*, 1996], Ranked-Based Ant System [*Bullnheimer et al.*, 1999] and MAX-MIN Ant Systems [*Stützle and Hoos*, 2000].

[31] The process of developing, assessing and updating the pheromone trails to guide the ACO algorithm to near-optimal schedules continues until the specified stopping criteria have been met. For a detailed description of the ACO algorithm and equations used, readers are referred to *Dorigo and Stützle* [2004].

3.3. Dynamic Constraint Adjustment

[32] As discussed above, ACO algorithms have the ability to cater to the sequential nature and conditional dependencies involved in the development of EFMA schedules (see section 2.3). This is achieved by dynamically adjusting the number of available suboptions as ants construct a trial schedule. An example decision tree graph that incorporates dynamic constraints for a flow release management alternative is shown in Figure 6. The example is for four time steps and considers magnitude and four duration suboptions.

[33] If the maximum duration, which is assumed to be greater than four time steps for the example in Figure 6, is

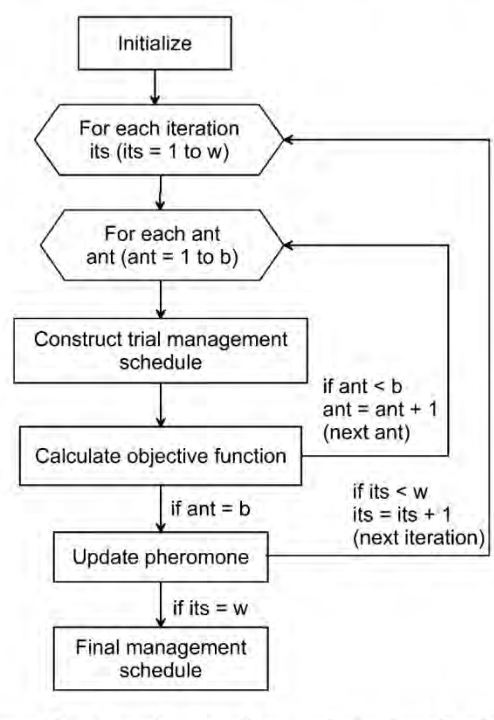

Figure 5. Steps in ant colony optimization algorithm.

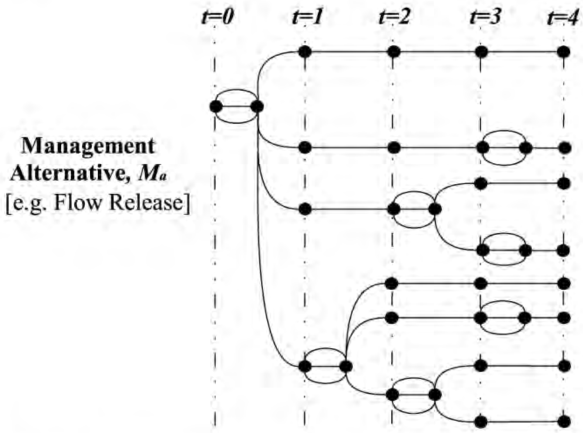

Figure 6. Example of an environmental flow management schedule decision tree graph using dynamic constraints.

selected by an ant at the first time step (decision point), then no other decision paths need to be made available at subsequent time steps (decision points), as shown by the top path in Figure 6. In this way, the decision tree is adjusted based on the choice made at the first decision point, thereby reducing the size of the search space and increasing the likelihood that globally or near globally optimal solutions will be found. On the other hand, if a duration option of one is chosen by an ant at the first time step (bottom path), then the potential duration suboptions are considered again at the following time step. However, the number of available options decreases from four to three, as there are only three more time steps remaining. If the number of available duration suboptions was not adjusted dynamically, four duration options would be considered after each magnitude suboption, which would result in a significantly larger search space. Therefore, this form of dynamically constraining the decision tree graph ensures that feasible EFMA schedules are developed, as well as ensuring that the ACO algorithm is able to find optimal solutions more efficiently.

4. Case Study

[34] In order to test and demonstrate the utility of the proposed optimization framework, it has been applied to a quasi-hypothetical case study based on the Murray-Darling river system in South Eastern Australia. The majority of this river system experiences arid or semiarid climate and incorporates a large array of connected wetlands and floodplains, which are mainly flooded during high streamflows [*Maheshwari et al.*, 1995]. However, due to the regulation of flow and over allocation of water to other users (e.g., irrigation), the flow regime has been changed, which has had significant negative impacts on the ecology of the river and adjacent wetlands and floodplains. In recent years, it has been recognized that the environment is a legitimate user of water and water allocations have been made available for environmental purposes. However, how this environmental flow allocation should be used in order to achieve the best ecological response remains a challenge.

[35] Figure 7 shows the layout of the case study used to meet the objectives outlined in the Introduction. It consists of a river reach, three wetlands and two floodplains that

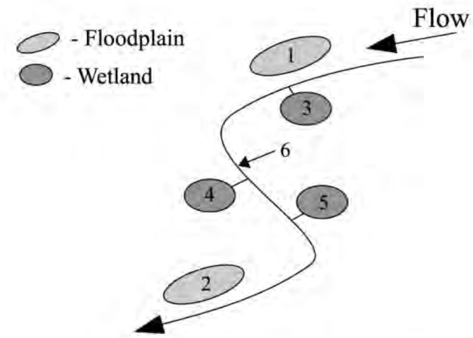

Figure 7. Layout of case study.

contain a variety of different flora and fauna species found in the River Murray. To quantify the ecological response of the species within the river reach, wetlands and floodplains, the Murray Flow Assessment Tool (MFAT) was used [*Young et al.*, 2003]. The minimum monthly river flows were based on entitlement flows used in the River Murray [*Murray-Darling Basin Authority*, 2010] and it was assumed that there were only gates (no pumps) to regulate flows into and out of the wetlands. Reservoir releases were taken as given and not considered part of the decision set. Details of how the proposed framework and solution approach, introduced in sections 2 and 3, respectively, have been applied to the case study are given in sections 4.1–4.4.

4.1. Problem Formulation

4.1.1. Identification of Ecological Assets and Indicators

[36] In this case study, there are two floodplains and three wetlands (Figure 7). The key flora and fauna species for each asset are given in Table 1, which were selected to represent the diversity and complexity that would occur in the River

Table 1. Wetland and Floodplain Specifications

Asset	Type	Dominant Species	Fill Value (GL/month)
1	Floodplain	Black box woodland (*Eucalyptus largiflorens*)	1200
2	Floodplain	River red gum forest (*Eucalyptus camaldulensis*)	800
		Lignum shrubland (*Muehlenbeckia florulenta*)	800
		Colonial nesting waterbird (e.g., ibis)	800
		Flood spawners (e.g., golden perch)	800
3	Wetland	Common reed (*Phragmites australis*)	300
		Cumbungi rushland (*Typha* sp.)	400
		Lignum shrubland (*Muehlenbeckia florulenta*)	500
		Waterfowl and grebes	500
4	Wetland	Ribbon weed herbland (*Vallisneria americana*)	400
		Giant rush rushland (*Juncus ingens*)	450
		Rats tail couch grassland (*Sporobolus mittchelli*)	500
5	Wetland	Spiny mudgrass grassland (*Pseudoraphis spinescens*)	300
		River red gum forest (*Eucalyptus camaldulensis*)	400
		River red gum woodland (*Eucalyptus camaldulensis*)	550
6	River	Main channel specialists (e.g., Murray cod)	450

Murray, Australia, as presented by *Rogers* [2011a]. The wetland and floodplain fill values, which relate to the minimum river flow required to inundate the assets, are also presented in Table 1. To delineate the flora and fauna species within each wetland and floodplain, a number of assumptions were made (R. Oliver, personal communication, 2009). First, it was assumed that the floodplain species lie on the same elevation plane, therefore once the river flow was above the fill value, all species were inundated at a specific depth, depending on the water level in the river. Second, wetland species were assumed to lie along a nonlinear gradient, resulting in a wetland depth range at which the species would be inundated, for instance, Cumbungi rushland would lie lower on the wetland gradient than Lignum shurbland. Therefore, if the wetland water depth (which is dependent on the river flow and regulator settings) was above the minimum species depth, then that species would be inundated.

[37] In order to obtain the required ecological flow requirements for the species of flora and fauna considered, the Murray Flow Assessment Tool (MFAT), developed by *Young et al.* [2003], was used. MFAT is a habitat simulation model that was developed specifically for the River Murray and can be used to assess the impact of different flow scenarios on vegetation and wildlife [*Young et al.*, 2003]. This is done using a set of response curves, which are based on important flow components, such as duration, timing and magnitude (which is represented in terms of depth), as well as the interdry period.

[38] The MFAT response curves for ten different species of vegetation used in this study are shown in Figure 8 for illustration purposes. As can be seen, a score between 0 and 1 is given for each flow component, where 0 corresponds to a poor and 1 to a good ecological response. It should be noted that the curves take into account different flow requirements for recruitment (i.e., promotion of seed growth) and maintenance (i.e., maintenance of adult habitat). As can be seen in Figure 8, there are curves for twelve different flow components, which can be divided into timing, frequency, duration and various inundation depth groups. It should be noted that there is an additional water depth response curve (in terms of maximum mean depth percent) for the wetland vegetation species ribbon weed herbland, which has not been presented here, as well as the flooding memory response curves for the various floodplain species. Other flow factors, such as the rate of rise and fall, have also not been presented in Figure 8. In total, there are approximately 48 curves for the vegetation species that, at times, have competing requirements, which highlights the complexity of the EFMA scheduling problem and the difficulties in developing optimal management schedules.

[39] The top four response curve graphs in Figure 8 are associated with wetlands, while the bottom six are for floodplains species. To determine the response from the wetland inundation and the floodplain flood timing and inundation depth curves, the median value of the 'best flood event' was used, where the 'best flood event' was the event that produces the highest overall ecological scores. For example, if the spiny mudgrass grassland was inundated from the beginning of March until the end of May, it would receive a wetland inundation score of 0.1, as this was the median value for that event. This region is depicted by the two bold lines in Figure 8a, where from March to May, the curve remains at a constant score of 0.1. On the other hand, inundation duration, recruitment and germination timing, and interperiod scores are based on a single value for the "best flood event." Therefore, the inundation duration for spiny mudgrass grassland is approximately 90 days, giving a score 0.5. This is represented by the bold line in Figure 8c. Additionally, it was assumed that a draw down and rewetting sequence must occur within a year, so that the interperiod could be calculated. Once all the scores have been obtained from Figure 8, they are used in equations to calculate an overall ecological response for each vegetation species in the MFAT [*Young et al.*, 2003]. It should be noted that there are weights x_1 and x_2 that emphasize, for example, the recruitment of vegetation seedlings and maintenance of adult plant species, respectively.

[40] There are an additional 12 response curves, not depicted in this paper, for assessing the health of the fauna species (i.e., fish and water birds). For waterbird responses, only the flood duration and dry period were taken into account, while for fish responses, the flood and spawning timing, inundation duration and dry period were considered. Other factors, such as thermal pollution (1.0), woody debris (1.0), the level of fish barrier (1.0), and channel straightening (0.78) were set to MFAT default values. For further details on the fauna and flora response curves and the equations used, readers are referred to *Young et al.* [2003] and the Inside MFAT Web site (http://www2.mdbc.gov.au/livingmurray/mfat/index.htm).

4.1.2. Planning Horizon and Time Interval

[41] A planning horizon of 5 years was chosen, as this (1) is the time period selected for the development of wetland management plans in the River Murray [*Schultz*, 2007; *Turner*, 2007], and (2) ensures that there is sufficient time to achieve the maximum ideal flooding frequency for the species of flora and fauna considered (see Figure 8g). A monthly time interval was selected, as this provides sufficient resolution for the hypothetical case study. This meant that the "rate of change" flow component in MFAT for flora and fauna species was not considered. Therefore, there are 60 time steps where an option has to be selected for each management alternative. This is discussed in section 5.

4.1.3. Management Alternatives and Suboptions

[42] There was one reach-scale management alternative (i.e., releases) for this case study and the associated suboptions include the magnitude and duration of the releases. An example of the resulting problem graph structure is shown in Figure 6. The number of magnitude options depends on the minimum and maximum fill values of the whole system. In this case, this could be anywhere between 100 GL/month, which was the minimum flow that needed to be added to the minimum river flows in order to inundate the wetland with the lowest fill value, and 1500 GL/month, which ensures that all of the wetlands and floodplains can be inundated simultaneously. An increment of 50 GL/month between these limits was chosen for the available suboptions to provide sufficient resolution to ensure that the ideal depth could be achieved for the different flora and fauna species considered. An additional zero allocation was defined to ensure that a "no release option" was available. Consequently, a maximum of 29 magnitude decision values are available (i.e., $n = 29$ for management alternative M_1). The number of duration options, p, available at each time step (i.e., month) varies throughout the year from 12 in January to 1 in December. The wetlands also have gates that can regulate

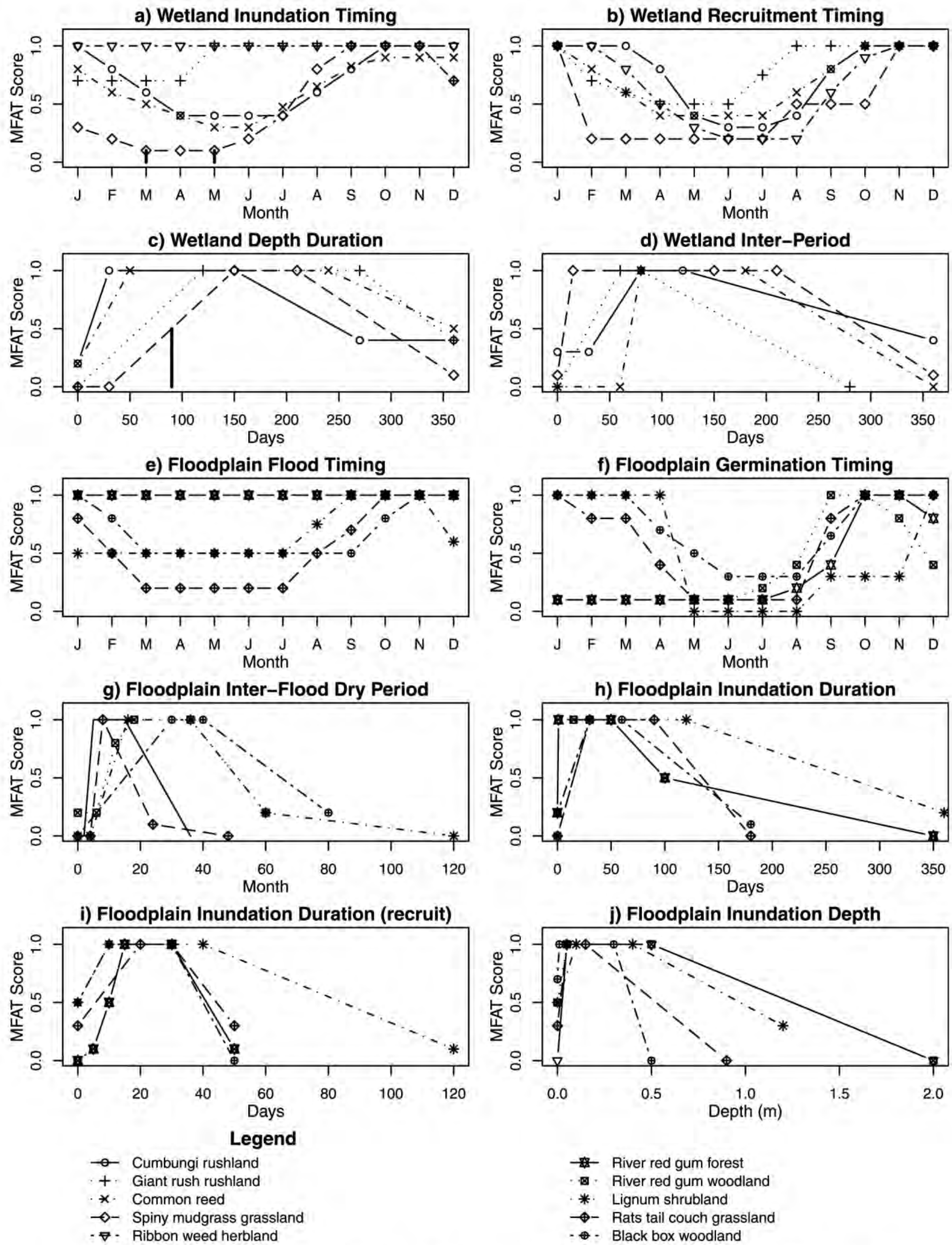

Figure 8. MFAT response curves adapted from *Young et al.* [2003] and the Inside MFAT website (http://www2.mdbc.gov.au/livingmurray/mfat/index.htm).

flow into the wetlands, while floodplains do not. This leads to three additional management alternatives, which control the flow into and out of the wetlands via gates (thus for M_2, M_3, and M_4, $n = 2$ and $p = 12$). Therefore, there are a total of four decision tree graphs similar to the one in Figure 6 that control the flow releases and flow via gates to the three wetlands. This produces a total search space size of 10^{141} discrete combinations of decision variable values, highlighting the potential benefit of using a formal optimization approach to solve this problem.

4.2. Objective Function and Constraints

[43] The ecological score for each species per asset was calculated using MFAT, which was described in section 4.1.1. The equation used to calculate an average MFAT score was based on the formulation presented in equation (1):

$$F = \sum_{i=1}^{6} \frac{w_{1i}}{6} \sum_{r=1}^{16} \frac{w_{2r}}{16} \sum_{v=1}^{5} \frac{w_{3v} E_{i,r,v}}{Y_5} \tag{5}$$

where the number of assets is 6, the number of ecological indicators is 16 for each flora and fauna species (see Table 1), and finally, the score, $E_{i,r,v}$ for each asset and indicator is calculated per year, with the total number of years equaling 5. To obtain an average score and an indication of the overall health of all the species and assets, $E_{i,r,v}$ was divided by the total number of assets and indicators. The weights (w_{1i}, w_{2r}, w_{3v}) were varied for the different investigations conducted in order to examine various trade-offs between competing objectives (see section 5 for details). In order to maximize F in equation (5), an objective function most appropriate for this case study needs to be selected, bearing in mind that the ACO algorithm minimizes the selected objective function and cannot accommodate constraints on environmental flow allocations explicitly. A number of different objective function formulations were assessed and the following form of the objective function (Y) was found to perform best and was hence used in this study:

$$Y = \frac{10}{10 + F} + Penalty \tag{6}$$

where F is the MFAT ecological score calculated using equation (5), and *Penalty* is a penalty function that was developed to ensure that the water allocation constraints for each period were adhered to and is given by

$$Penalty = \begin{cases} 0 & \text{if } \sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \le A_{\max\_ni(pd)} \\ \left\{ \sum_{t=i\_ni(pd)}^{f\_ni(pd)} (A_t) - A_{\max\_ni(pd)} \right\} \times 100,000 & \text{if } \sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t > A_{\max\_ni(pd)} \\ 100,000 & \text{if } F = 0.0 \end{cases} \tag{7}$$

where the variables in equation (7) have been defined in equations (1) and (2).

4.3. Calculation of Objective Function

[44] In order to calculate the objective function specified in section 4.2, the wetland and floodplain hydrology must be simulated for each management schedule. The following sections discuss the equations and assumptions used to achieve this.

4.3.1. Wetland Hydrology Model

[45] To ensure that the model adequately accounts for wetland hydrology, whereby wetlands fill quickly once the river level breaches the fill value and when gates are opened but then drain slowly either when the gates are closed or when the river level drops below the fill value, equations (8) and (9) have been utilized. A simple water balance relationship is

$$I_t - O_t = S_{t+1} - S_t \tag{8}$$

where I_t refers to the wetland inflows, O_t are the wetland outflows, while S are the wetland storages at time t. The outflows O_t are the summation of the flows out of the wetland (O_w) and evaporation (E_t). To calculate the evaporation loss from the wetlands, it was assumed that the wetland is rectangular with the longer sides parallel to the river, and that the bank slope remained constant. Consequently, the surface area versus depth relationship is linear. A simple relationship of $0.7 \times$ (pan evaporation) was used to determine the evaporation from the wetland, in meters/month. The value of 0.7 was chosen as it is a common value used to determine evaporation within the Murray Darling Basin [*Gippel*, 2006].

[46] To simulate the gate operations at the wetlands, logic (If-Then) statements were used to adjust the components of the water balance equations. If the gate was closed, the inflow at that time step was zero (i.e., $I_t = 0.0$) and if there was water in the wetland, wetland storage was only affected by evaporation:

$$S_{t+1} = S_t - E_t \tag{9}$$

If there was water remaining in the wetland and the gate was opened at the next time step, water would flow out until the fill value was reached, after which water would remain in the wetland and only be affected by evaporation (i.e., equation (9)). It should be noted that the mass balance constraints associated with the problem were also satisfied within this wetland hydrology model.

[47] Assumptions made include that water seepage, the effect of rainfall and the fill and drainage rate of the wetlands were negligible. This was considered reasonable, since a monthly time step was used. Additionally the storage capacity of the wetlands was set to be very small in comparison to the streamflows, thus having negligible effect on downstream flows as a result of upstream wetlands storage.

4.3.2. Floodplain Hydrology Model

[48] The floodplain hydrology model used the same equations and assumptions as the wetland model, with the

Table 2. MAX-MIN Ant Systems Parameters

ACO Parameter	Range Investigated	Final Value
Alpha (α)	0.5,1.0,1.5.2.0	1.0
Beta (β)	0.5,1.0,1.5.2.0	1.0
Initial pheromone (τ_o)	0.5, 1.0, 2.0, 5.0, 10.0	5.0
Pheromone persistence (ρ)	0.1,0.2,0.6,0.8,0.9,1.0	0.6
Pheromone reward factor (Q)	0.5, 1.0, 2.0, 5.0, 10.0	5.0
Number of ants (ant)	50–1500	500 and 1200

exceptions of (1) being only affected by the river level (i.e., if the river level is above the fill value then the floodplain would be inundated at a depth dependent on the river level or if the river level is below the fill value then the floodplain would not be inundated) and (2) not including gates to regulate the flow, and as such the gate operational equations were not used.

4.4. ACO Algorithm

[49] As discussed in section 3.2, there are various types of ACO algorithm, which generally differ in the pheromone updating methods used [*Dorigo and Blum*, 2005]. In this study, the MMAS algorithm was used, as it has been found to outperform other ACO variants in a variety of studies [*Foong et al.*, 2007; *Zecchin et al.*, 2007]. Details relating to the procedure and equations used by the MMAS are given by *Stützle and Hoos* [2000].

[50] An extensive sensitivity analysis was undertaken to determine the optimal values of the parameters that control the searching behavior of the MMAS algorithm. The range of parameter values tried and the final parameter values chosen are shown in Table 2. It should be noted that each sensitivity run was performed with 10 different random numbers (i.e., starting positions in the decision space) to minimize the impact of the random starting position in decision variable space on the results obtained.

5. Analyses Conducted

[51] In order to meet the objectives stated in the Introduction, a number of studies were conducted, which demonstrate how the proposed framework and optimization approach are applied in practice in different settings (objective iiia). In the first study (section 5.1), the proposed optimization approach was compared with and tested against a heuristic scheduling approach by analyzing whether it performed adequately on problems of varying complexity (objective iiib). In the second and third studies (sections 5.2 and 5.3, respectively), it is demonstrated that the proposed approach can account for the competing requirements of individual species (objective iiic) and the competing requirements of species of flora and fauna (objective iiid) (section 5.3), respectively. In the final study (section 5.4), it is illustrated that the proposed framework and solution approach can deal with environmental water allocations of varying magnitude and timing (objective iiie). Details of the various studies and the specific investigations conducted as part of each these are given in Tables 3 and 4, and described in detail below.

Table 3. Details of Each Study and Corresponding Objective

Study	Objective	Investigations	Species	Planning Horizon
Section 5.1	iiib	1–6	Flora	5 years
Section 5.2	iiic	7–9	Flora	5 years
Section 5.3	iiid	10–11	Flora and fauna	5 years
Section 5.4	iiie	12–13	Flora and fauna	5 years

Table 4. Details of the Investigations Used in Each Study

Investigation	Allocation Constraint Period/s	Allocation Constraint/s (GL)	Weight preferences
1	5 years	5000	Equal preference
2	5 years	1750	Equal preference
3	5 years	3500	Equal preference
4	5 years	4750	Equal preference
5	5 years	10,000	Equal preference
6	5 years	10,000	Equal preference
7	5 years	500–12,000	Recruitment favored
8	5 years		Processes equally favored
9	5 years		Maintenance favored
10	5 years	10,000	Flora favored
11	5 years		Fauna favored
12	5 years and 3 months	10,000 and Table 6	Equal preference
13	5 years	10,000	Equal preference

5.1. Validation of Optimization Framework

[52] In order to provide some degree of validation, and to assess the potential benefits, of the proposed optimization framework, it was compared with a heuristic EFMA scheduling approach for six investigations of varying complexity. It was recognized that the proposed ACO-based optimization approach should outperform a heuristic scheduling approach due its greater degree of sophistication. However, simply because an algorithm is highly advanced does not guarantee that it will perform well and it was therefore considered important to evaluate it against a benchmark approach that is representative of current practice in the River Murray before it was applied to more complex problems (sections 5.2 to 5.4). In addition, it highlights the complexity of the problem being addressed and the benefits of the approach introduced in this paper.

[53] The six investigations considered in this study only considered flora (Table 3), as this provided a sufficient level of complexity (i.e., 48 different MFAT response curves) to validate the optimization framework. The allocation constraint period was set to 5 years (Table 4), indicating that there were no constraints on the time periods during which the water available for environmental purposes was used over the planning horizon of 5 years (Table 3), as long as the total environmental water allocation was not exceeded. The total amount of water available for environmental flow purposes varied between investigations (Table 4) based on the outcomes of the heuristic scheduling procedure, as explained below, and equal preference was given to all components of the overall ecological score in equation (5) (i.e., species, assets and time period) (Table 4), such that w_{1i} = 0.2, w_{2r} = 0.08 and w_{3v} = 0.2 for i, r and v. Additionally, the recruitment and maintenance MFAT weights, x_1, and x_2, were both set to equal 0.5. The degree of complexity of the investigations was variable, both in terms of the number of species and the spatial extent considered (Table 5).

[54] Details of the heuristic approach are given in Figure 9. The first step is the identification of species groups with similar MFAT flow requirements for each management

Table 5. Details of the Six Investigations Used for Developing Heuristic and Optimization Based Management Schedules

Investigation	Total Number of Flora Species	Plant Species
1	1	River red gum forest in Asset 5
2	1	Rats tail couch grassland in Asset 4
3	1	Spiny mudgrass grassland in Asset 5
4	3	All flora species in Asset 3[a]
5	7	All flora species in Assets 1,3 and 5[a]
6	12	All flora species in Assets 1 to 5[a]

[a]Please see Table 1 for details.

alternative (M_a). These species groups are defined as $G_{a,c}$, where c ranges from 1 to nc number of species and a ranges from 1 to h (i.e., number of M_a). The groups are ordered so that the first group, $G_{1,1}$, has the largest number of species with similar MFAT requirements that is affected by M_1, $G_{1,2}$ the second largest number of species, and so on.

[55] For each management alternative, M_a, duration, timing and magnitude values are selected based on the MFAT flow requirements of the species in the largest group. $G_{a,c}$. The selection of these values may be repeated several times to ensure that the highest possible MFAT score is achieved for all species. Next, the selection process is repeated for the remaining $G_{a,c}$ species that are affected by the M_a under consideration, starting with the group with the second largest number of species. A check is then undertaken to ensure that the M_a values chosen (i.e., duration, timing and magnitude) for a particular $G_{a,c}$ do not negatively impact the MFAT scores of the species groups considered previously. This cycle continues until a complete schedule has been produced for management action M_a, after which the process is repeated for the next M_a until schedules have been developed for all M.

[56] It should be noted that this scheduling approach does not take into account any constraints on the amount of water that is available for environmental flow allocation purposes. Addressing the constrained scheduling problem would add another level of complexity, which was not considered warranted for the purposes of illustrating the complexity of this problem and validating the proposed optimization approach. Consequently, in order to provide a fair comparison between the heuristic and ACO-based approaches, the constraints in relation to the total water allocation used when developing the ACO-based schedules corresponded to the volumes found in the corresponding management schedules obtained using the heuristic approach. Additionally, for each investigation, all ACO optimization runs were repeated ten times with different random starting positions in decision variable space in order to minimize any effects of the probabilistic nature of the searching behavior of the ACO algorithm.

5.2. Determination of Optimal Trade-Offs Between Recruitment and Maintenance Scores for Different Flow Allocations

[57] As discussed in section 4.1.2, MFAT considers both recruitment (i.e., promoting and ensuring seedling growth) and maintenance (i.e., maintaining and ensuring the good

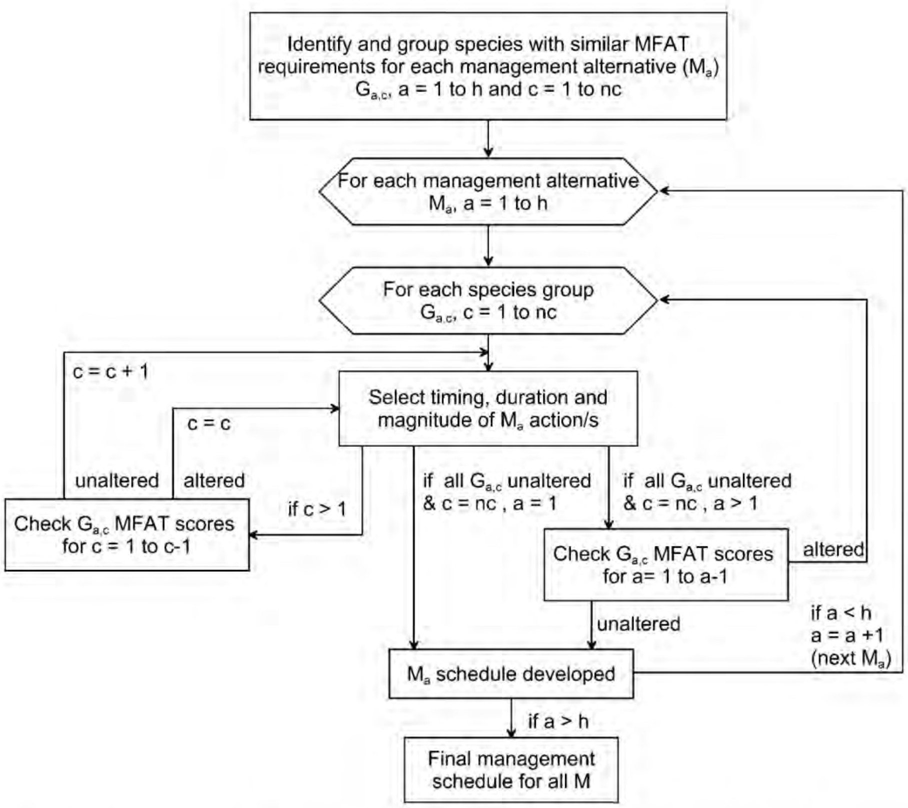

Figure 9. Environmental flow management schedule development using the heuristic approach.

Table 6. Seasonal Environmental Flow Allocation Used in Investigation 12

Season	Environmental Flow Allocation (GL)
Summer (Dec–Feb)	1500
Autumn (Mar–May)	1000
Winter (Aug–Jul)	500
Spring (Sep–Nov)	200

condition of current adult habitat) of flora species. These factors have differing and, at times, competing flow requirements and, as such, must be considered separately. In order to investigate the trade-offs between recruitment and maintenance, optimal management schedules for maintenance and recruitment of the flora species over a 5 year management period were generated (Investigations 7 to 9, Table 3). Further details of each investigation are presented in Table 4, with schedules that favor recruitment considered in Investigation 7, schedules that emphasize recruitment and maintenances equally in Investigation 8, and schedules that favor maintenance in Investigation 9. This was achieved by specifying additional weights as part of the calculation of MFAT scores that either emphasize recruitment (x_1, = 1.0 and x_2 = 0.0), maintenance (x_1, = 0.0 and x_2 = 1.0), or both (x_1, = 0.5 and x_2 = 0.5). The weights that control asset, flora type and release year (i.e., w_{1i}, w_{2r}, w_{3v}), were set to have equal preference, using the same values as in section 5.1. The planning horizon for this study was five years and seven different environmental water allocation constraints (i.e., different amounts of water available for environmental flow purposes), ranging from 500 to 12,000 GL (i.e., 500, 2000, 4000, 6000, 8000, 10,000 and 12,000 GL) were examined (Table 4), in order to investigate the impact of a number of different water policies (i.e., different amounts of water set aside for environmental flow purposes, as opposed to consumptive uses (e.g., irrigation, water supply)) on ecological response and the trade-off between maintenance and recruitment. Each optimization run for the 21 schedules developed was repeated ten times with different starting positions in the solution space in order to minimize the impact of the random starting position on the results obtained.

5.3. Determination of Optimal Trade-Off Between Flora and Fauna Ecological Response

[58] In order to investigate the trade-offs between the requirements of flora and fauna, the flow requirements of four fish and waterbird species (see section 4.1.1) were added to those of the flora species used in Investigation 6 of section 5.1 (Table 5), and optimal EFMA schedules generated using the proposed ACO-based approach. Details of this study are given in Tables 3 and 4, where a single environmental water allocation constraint of 10,000 GL was used over the adopted planning horizon of 5 years and different weightings were used to either favor fauna (Investigation 10) or flora (Investigation 11). The fauna species weights in Investigation 10 equaled 0.25 and the flora weights equaled 0.0, while in Investigation 11, the flora species weights equaled 0.08 and the fauna weights were set to 0.0. The other weights (i.e., w_{1i}, w_{3v}, x_1 and x_2) were set to provide equal preference. As was the case in section 5.1, each optimization run was repeated ten times from different starting positions in the solution space.

5.4. Determination of Optimal EFMA Schedules as a Result of Hydrograph Inversion

[59] Many regulated river systems, such as the Murray River, have reversed flow regimes with major flows now occurring in summer–autumn (i.e., December to May) to sustain human needs, instead of winter–spring (i.e., June to November). In order to assess the impact of the hydrograph inversion case, two investigations were developed, including Investigation 12, which considered an additional seasonal flow constraint, and Investigation 13, which had no such constraint. Details of these investigations are given in Tables 3 and 4. As can be seen, both flora and fauna species and a 5 year management period were considered, as well as a 10,000 GL total water allocation constraint. Additionally, equal weight values were used for all the weight groups, as was the case in the previous study (section 5.1). Table 6 presents the environmental flow allocations that were available in each season. As with the previous studies, each optimization run was repeated 10 times.

6. Results and Discussion

6.1. Validation of Optimization Framework

[60] The MFAT scores obtained using the ACO and heuristic approaches are given in Table 7. As can be seen, the ecological scores obtained using both approaches were the same for the first three investigations. This indicates that there do not appear to be any problems with the formulation and implementation of the proposed optimization framework. Additionally, the ACO-based approach was able to determine management schedules that use less water, with the exception of Investigation 2, which had identical allocations and scores. Once the number of species was increased to three in Investigation 4, the benefit of using the optimization framework was demonstrated clearly. The MFAT score of the management schedule obtained using the ACO approach was higher than that of the management schedule developed using the heuristic approach, with a significantly smaller amount of water (i.e., 600 GL less). This demonstrates the ability of the optimization approach to search effectively through the large number of potential management schedules using the ACO process described in section 3.2. This results in management schedules that use the available environmental water allocation in an efficient manner, as expected, which would be especially beneficial during times when water resources are limited and must be allocated effectively between competing stakeholders.

[61] The results for Investigations 5 and 6 (Table 7), which were significantly more complex since they considered a

Table 7. Heuristic and ACO Management Schedule Results for Investigation 1 to 6

	Heuristic		ACO	
Investigations	Allocation (GL)	MFAT Score	Allocation (GL)	MFAT Score
1	5000	1.00	4650	1.00
2	1750	0.91	1750	0.91
3	3500	1.00	3100	1.00
4	4750	0.86	4150	0.91
5	10,000	0.67	10,000	0.78
6	10,000	0.67	9850	0.83

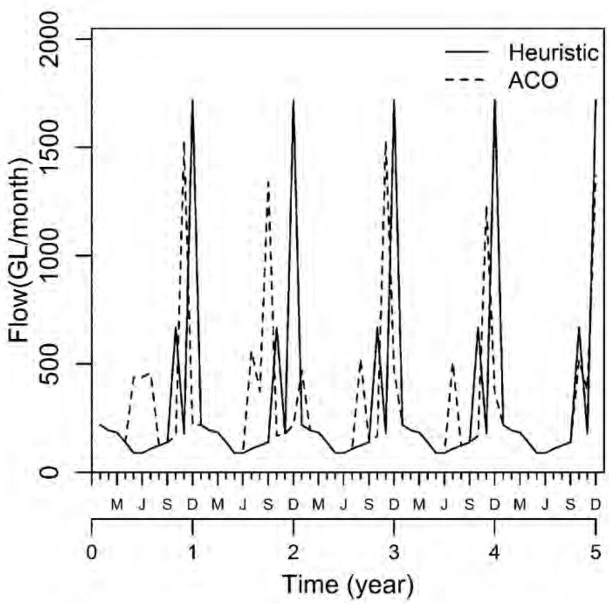

Figure 10. Monthly flow releases for heuristic and ACO management schedule for Investigation 6.

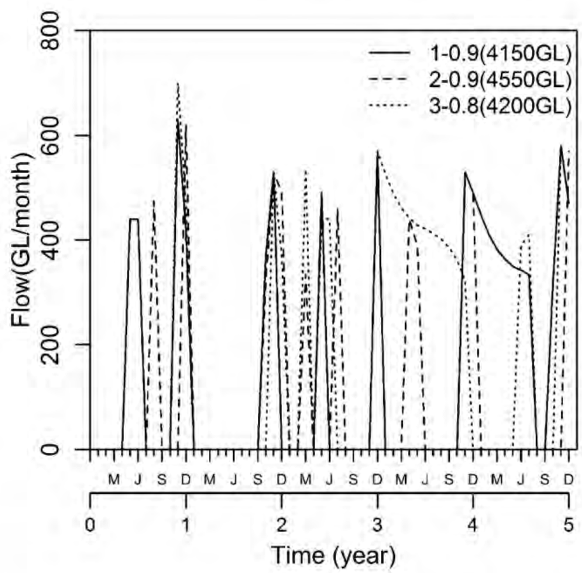

Figure 11. ACO management schedule for Investigation 3.

larger number of plant species (7 and 12, respectively), provided further evidence of the benefit of the proposed optimization approach. For instance, in Investigation 6, the management schedules developed using the ACO-based method resulted in an increase in MFAT scores of approximately 0.2 for all wetlands and floodplains, despite using less water. The corresponding flow releases obtained using the heuristic and ACO-based approaches are shown in Figure 10. It can be seen that there was more variability in the flows in the ACO-based management schedule, which ensured that all of the flow components in Figure 8 were accounted for. Generally, the larger flow releases obtained using both approaches occurred at similar times, except for year 2, where the flow releases obtained using the ACO-based approach occurred midyear instead of at the end of the year. These differences in flow releases contributed to a better MFAT score. In particular, there was significant improvement of approximately 0.4 in the MFAT score for assets 4 and 5, as shown in Table 8.

[62] It was found that this increase in MFAT score was because some species, such as giant rush rushland and spiny mudgrass grassland, were inundated for longer than one month. Ideally, giant rush rushland requires inundation for 120–270 days, while spiny mudgrass grassland requires 150–210 days of inundation. This was clearly not achieved by the management schedule developed using the heuristic approach, resulting in a much lower overall MFAT score, as the inundation requirement for maintenance was not satisfied. Another requirement that was difficult to meet in the development of the management schedule using the heuristic approach was the ideal depth for some of the floodplain species (e.g., river red gum forest, rats tail couch grassland), which corresponds to a certain depth that must be maintained to ensure the recruitment of these species. In contrast, this requirement was able to be satisfied by the management schedule developed using the ACO approach, thereby ensuring that a good recruitment score could be achieved. Overall, this study showed that once the number of wetlands and floodplains is moderately large, developing a management schedule heuristically over multiple years is extremely difficult. This is because there are too many wetlands and floodplains with different and competing water demands that must be considered. However, the optimization method can deal with these complexities with the aid of the searching process outlined in section 3.

Table 8. Difference in Annual MFAT Scores Between Management Schedules Obtained Using ACO and Heuristic Approaches for Investigation 6

	Difference				
Species	Year 1	Year 2	Year 3	Year 4	Year 5
	Asset 4				
Ribbon weed herbland	0.0	0.0	0.0	0.0	0.0
Giant rush rushland	0.5	0.6	0.5	0.5	0.5
Rats tail couch grassland	0.0	0.2	0.4	0.3	0.5
	Asset 5				
Spiny mudgrass grassland	0.3	0.5	0.4	0.4	0.5
River red gum forest	−0.1	0.5	0.6	0.4	0.5
River red gum woodland	0.0	0.3	0.3	0.2	0.1

[63] Another benefit of the ACO approach over the heuristic approach was that it provided a number of possible optimal management schedules for each investigation. For example, the releases and corresponding MFAT scores from three different management schedules for asset 3 in Investigation 4 generated using the ACO approach are shown in Figure 11. As can be seen, water was allocated to asset 3 twice in the first year in management schedules 1 and 2, while this was not the case in schedule 3. This resulted in a lower MFAT score of 0.74 in year 1 for schedule 3, while the corresponding score for schedules 1 and 2 is 0.8. This was because the interperiod for lignum shrubland (Figure 8d) was not achieved for schedule 3. The releases for the three management schedules then followed a similar

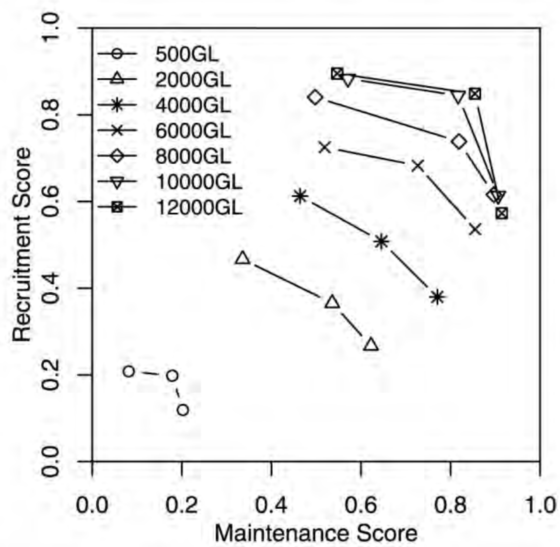

Figure 12. Optimal trade-offs between MFAT recruitment and maintenance scores for 500–12,000 GL allocations.

pattern in the second year, where, initially, there was a dry period until the end of the year, when asset 3 was inundated. In the third year, there was some variability between the management schedules, but generally flows were allocated at the end of the year in each of the schedules. Consequently, for years 2 and 3, the MFAT scores were similar for all management schedules. In the fourth year, a gate was used as part of management schedule 3, the effect of which was shown by the gradual change in flow (Figure 11). This contributed to a significantly lower maintenance score, as a longer duration of flooding negatively affected the wetland response. A gate was closed in the fourth year as part of management schedule 1; however, this did not negatively affect the final MFAT score. Finally, all three assets were inundated at the end of the fifth year, indicating that the species within this asset prefer to be flooded at the end of the year. This comparison can aid in the understanding of how sensitive the assets are to the flow regime. By knowing this sensitivity, managers have the ability to develop much more effective management schedules that efficiently use the water allocated for environmental flow management purposes, while achieving a high ecological response. Additionally, it provides wetland managers with a variety of different optimal management schedules that could be implemented, depending on prevailing social and economic factors, for example. This discussion further highlights the complexity of EFMA scheduling, as there are many different solutions that result in similar MFAT scores.

6.2. Determination of Optimal Trade-Offs Between Recruitment and Maintenance Scores for Different Flow Allocations

[64] The optimal trade-offs between recruitment and maintenance scores for total environmental water allocations ranging from 500 to 12,000 GL obtained using the ACO-based approach are shown in Figure 12. As can be seen, at an allocation of 500 GL, there was a small recruitment and maintenance response of approximately 0.2. However, this increased significantly to an average of 0.5 when the water allocation was increased to 2000 GL. The lower MFAT scores for the 500 GL allocation were due to insufficient water to inundate all of the wetlands and floodplains over the 5 year planning horizon. Only the wetlands with lower fill values were inundated. As the allocation increases from 2000 to 12,000 GL, more wetlands and floodplains were flooded and began to contribute to the overall score. Additional water was shown to have a decreasing marginal benefit and reached an asymptote of approximately 0.9, beyond which, further environmental flow allocations would not increase the overall MFAT scores.

[65] The maximum score obtained by either favoring maintenance or recruitment was approximately 0.9, which was shown by the outer two points for the 10,000 and 12,000 GL water allocations in Figure 12. The maximum value of 1.0 could not be achieved for a number of reasons. First, each wetland and floodplain had different flow requirements. Second, the maintenance and recruitment flow components for particular species were different, for instance favoring the maintenance and survival of a plant species such as, river red gum, could in turn limit its recruitment and regeneration capacity [*George et al.*, 2005; *Rogers*, 2011a], thus resulting in the inability to achieve the maximum response for all ecological processes, simultaneously. Finally, there were particular flood factors, such as the interdry flood period, which were difficult to satisfy. For example, the interflood dry period response curve was the only one that accounted for flooding over multiple years, while the remaining response curves were determined annually. Therefore, it had less impact on the objective function (and in turn the resulting management schedule), as only one graph governed the flooding over several years.

[66] Gate operations have the ability to increase significantly the efficiency of water use in the management schedule. Changes in gate settings were used extensively in the optimal schedules for the 500 and 2000 GL allocations. This was expected, since there is significant benefit in using gates to prolong inundation when a limited amount of water is available. Gate operations featured less prominently in the optimal schedules once allocations increased to 8000 GL, particularly if the aim was to favor recruitment or to balance recruitment and maintenance. As the flow allocations increased to 10,000 and 12,000 GL, gates were used to prevent inflows into wetlands, rather than prolonging inundation. It was evident from the optimal management schedules that the use of gates has the potential to improve MFAT scores, especially at times when water is limited and to prevent water flowing into the wetlands during flood events. This enables the ecological integrity of wetlands to be maintained over a wider range of flow conditions.

[67] In order to understand better the impact of the flow releases on recruitment and maintenance scores, the optimal releases obtained for the 10,000 GL allocation for Investigations 7, 8 and 9 were analyzed and are given in Figure 13. Generally, larger releases were scheduled at times that favored the timing of the processes that were emphasized by the weight preferences. For example, in Investigation 7, larger releases were scheduled between October and December (spring to summer), with the majority of the releases being allocated in November. This was a reasonable selection of releases for this investigation, as nine out of the ten MFAT plant species preferred recruitment inundation in November, with inundation in October and December being preferred

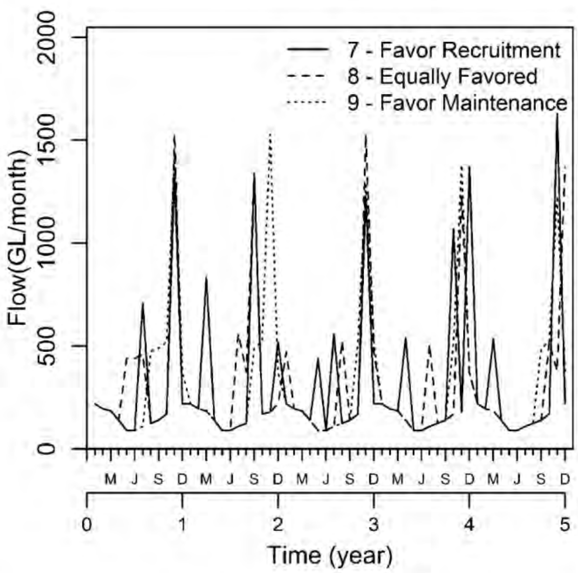

Figure 13. Monthly flow releases for the three points along the 10,000 GL allocation trade-off.

by seven and eight of the ten species, respectively. In all three investigations, most of the releases occurred in November, as the majority of the MFAT vegetation species preferred spring inundation for both recruitment and maintenance. However, the difficulty in the development of a management schedule arises in the determination of the magnitude and duration of releases, as these components vary from species to species (see Figure 8), which the optimization approach was able to account for. The maintenance and recruitment scores for each investigation and year are given in Table 9. It can be seen that, generally, when the preference is to ensure recruitment, the scores were approximately 0.95, with the exception of the first year. This was because recruitment timing for some species was based on the inundation from the previous year. When both recruitment and maintenance were favored, the scores were generally similar (see Table 9). On the whole, it seemed that the recruitment scores were higher than the maintenance scores. This was due to the difficulty associated with achieving the required interflood dry periods for maintenance, as discussed previously. The investigation favoring maintenance achieved an average score of approximately 0.9, while the recruitment score was not as high, at 0.6. This suggests that the optimization approach was able to ensure that the ideal maintenance flow components were met.

Table 9. Annual Recruitment and Maintenance Scores for the Three 10,000 Water Allocation Investigations

Investigation	Score	Year 1	2	3	4	5
7, Favor recruitment	Maintenance	0.47	0.48	0.70	0.59	0.62
	Recruitment	0.58	0.97	0.96	0.95	0.95
8, Equally favored	Maintenance	0.80	0.80	0.84	0.79	0.85
	Recruitment	0.55	0.89	0.93	0.93	0.93
9, Favor maintenance	Maintenance	0.91	0.91	0.88	0.91	0.92
	Recruitment	0.53	0.66	0.63	0.63	0.62

Table 10. Maintenance and Recruitment Scores for Investigations 10 and 11

Investigation	Maintenance Score	Recruitment Score
10	0.80	0.86
11	0.68	0.57

[68] Overall, the ACO-based approach was able to be guided by the preferences of either maintenance, recruitment, or even both, quite successfully. Even though the management schedules had similar major release timings, the magnitudes for the smaller allocations were different, thus introducing the required flow variability to incorporate the ideal recruitment and maintenance flow components shown in Figure 8 into the schedule. There was however a limitation with the use of MFAT as the ecological indicator, as it was unable to account for vegetation encroachment. According to *Dolores Bejarano and Sordo-Ward* [2011] altered flow regimes as a result of dams influence tree and shrub establishment patterns along the river and as such should be taken into account. Even with this limitation, the approach was able to be used to develop near-optimal management schedules based on preferences chosen by managers. This is not only restricted to maintenance and recruitment scores, but can also incorporate emphases on different types of species or river reaches, wetlands and floodplains, as shown in the following subsections.

6.3. Determination of the Optimal Trade-Off Between Flora and Fauna Ecological Response

[69] Table 10 shows the overall maintenance and recruitment scores for Investigations 10 and 11 (i.e., favoring flora and fauna, respectively). As can be seen, the overall maintenance and recruitment scores were significantly lower for Investigation 11, where fauna was favored, as only four species were considered within the objective function and therefore used to guide the ACO algorithm. Assets 1 and 5 were particularly affected, achieving a zero recruitment score, as there were no fauna species present in these assets, and there was therefore no contribution from these assets to the objective function. However, the fauna ecological scores in Investigation 10 were high, ranging from 0.8 to 1.0, which indicated that the optimization framework could be used to successfully find a management schedule that only focused on the fauna ecological response.

[70] On the other hand, higher recruitment and maintenance scores of 0.86 and 0.8, respectively, were obtained in Investigation 10. This was because, first, there were more species governing the development of the management schedule and second, the flora response curves were more difficult to satisfy and needed to be incorporated in the objective function, so that the resulting management schedules had higher overall MFAT scores. Although the flora species were preferred in Investigation 10, the fauna species also achieved high MFAT scores. This was because some of the fauna response curves were similar to the flora curves. For example, the ideal flood and spawning timing for main channel specialist fish, such as Murray Cod, is in late spring [*Ralph et al.*, 2011], which is within the range required for the ideal timing for the maintenance and recruitment of the majority of plant species (i.e., November). This suggests

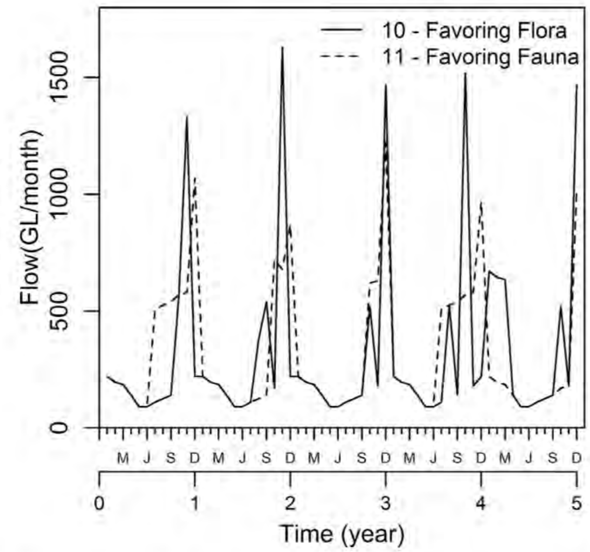

Figure 14. Flow releases for Investigations 10 and 11.

that ensuring major flows in late spring not only enhances the vegetation within the wetlands and floodplains, but also promotes the spawning and of recruitment of fish. Additionally, by flooding wetland/floodplain vegetation, habitat productivity is encouraged, resulting in an abundance of waterbird prey [*Rogers*, 2011b] and an ideal environment for waterbirds to forage and reproduce. Therefore, by ensuring flora species are of good health, the health of waterbird and fish species is also taken into account, indicating that in this particular case study, it is best to favor flora over fauna, as an overall better MFAT score can be achieved.

[71] The optimal flow releases for both investigations are presented in Figure 14, and it can be seen that the larger releases occurred between October and December in Investigation 10, which corresponded to the preferred timing (i.e., spring–early summer) for all the vegetation types in the case study. On the other hand, in Investigation 11, major releases of lower magnitude were scheduled in December, since the fish species preferred that timing and the fauna species did not require such high flow releases during that time. Additionally, longer inundation times of approximately 6 months in years 1 and 4 ensured that the waterbird species in asset 3 could achieve the ideal inundation duration. In doing so, there was not enough water to support the surrounding biota, resulting in a lower overall MFAT score, and in turn, a poorer ecological state.

[72] This study demonstrates the development of management schedules that favor specific species and the impact this might have on the remaining species. The results suggest that the proposed framework can be applied to cases when particular species (e.g., endangered species) need to be favored in the development of EFMA schedules, thereby providing wetland managers with valuable information about the trade-offs in ecological outcomes between different species for different management schedules. Finally, the study demonstrates the flexibility and versatility of the proposed optimization framework, as the additional fauna species could be incorporated into the study with ease.

6.4. Determination of Optimal EFMA Schedules as a Result of Hydrograph Inversion

[73] The average MFAT scores obtained for Investigations 12 and 13 are given in Table 11. The scores achieved when the seasonal constraints (i.e., Investigation 12) were included were lower compared with those produced when an overall constraint was applied over the entire 5 year planning horizon (i.e., 0.75 and 0.84, respectively). This was because the majority of environmental water allocation in the seasonal constraint case was available in summer and autumn (i.e., December–May), which was not ideal for the flora and fauna species in the case study. For instance, a total release of 200 GL was scheduled in spring (with the majority scheduled in summer) when a seasonal constraint was applied, while a release of 5450 GL of the 10,000 GL allocation was scheduled in the spring months (i.e., September–November) in Investigation 13, resulting in a higher MFAT score, as the majority of the biota prefer to be inundated at this time. On the other hand the hydrograph inversion case score was higher than expected, which may have been due to the assumptions made, such as setting the MFAT water temperature score to 1.0 (see section 4.1.1). In reality, river thermal regimes are altered by reservoir operations and can have a significant impact on fish species spawning [*Clarkson and Childs*, 2000] and the overall integrity of the ecosystem [*Olden and Naiman*, 2010]. Even though, the hydrograph inversion scores were relatively high, the seasonal restrictions had an impact on the overall ecological health of the river and associated wetlands and floodplains, since the required flow was not provided to the biota. However, by using the optimization approach introduced in this paper, the best possible ecological outcome, given the constraints on the water available for ecological purposes at different times of the year, can still be achieved.

[74] The individual MFAT scores for each asset are also given in Table 11. As can be seen, the scores were generally lower when the seasonal constraint was applied, with the exception of the fish species at asset 6, which had the same score. This was because, first, the ideal inundation duration of one month, as well as the ideal dry period of between 6 and 12 months, could be met, and, second, the preferred timing for spawning and flooding could both be achieved in spring and summer. This means that a high MFAT score for main channel specialists can be achieved in cases when the majority of environmental water is available in summer or spring.

[75] In comparison, there was a significant drop in MFAT scores for assets 2 and 5 of 0.14 and 0.19, respectively, when

Table 11. MFAT Scores for Each Asset and Overall MFAT Score for Investigations 12 and 13

	MFAT Scores	
Asset	Investigation 12	Investigation 13
1	0.72	0.79
2	0.76	0.90
3	0.82	0.86
4	0.71	0.78
5	0.58	0.77
6	0.95	0.95
Average score	0.75	0.84

the seasonal constraints were applied. This was mainly due to lower recruitment and maintenance scores for river red gums. Both assets contain this species of vegetation and both had lower MFAT scores. This was because the ideal flow requirements were not met, particularly the ideal timing for maintenance of current adult habitat and germination of seedlings, as both prefer inundation in spring. This indicates that for the hydrograph inversion case, there is significant impact on river red gums, which might threaten their survival. This impact would be worse if the available total environmental water allocation over the 5 year period was reduced. In the River Murray, the health and growth of river red gum areas have declined as a result of river regulation [*Bren*, 1988] and for this reason wetland management plans in this region focus on maintaining this particular species [*Tucker et al.*, 2002].

[76] Overall, the optimization framework was able to cater to the hydrograph inversion case and show that a particular plant species (i.e., river red gum) was particularly susceptible to seasonal constraints. It can therefore be used to identify species under threat and provide wetland and water resource managers with a better understanding of the management schedule that will ensure the ecological health of the entire river system, even if the river is regulated. Furthermore, the study demonstrated that the optimization framework can incorporate other constraints (e.g., seasonal, monthly or yearly), which managers may need to employ in other investigations.

7. Summary and Conclusions

[77] This paper provides a detailed formulation of the EFMA schedule optimization problem (section 2) and presents a novel and robust optimization framework for solving it (section 3). In order to be able to account for the sequential nature of the EFMA problem, it has been suggested to use ant colony optimization (ACO), as it uses a graph structure to represent the problem, which is able to be adjusted dynamically during the construction of trial solutions, thereby reducing the size of the search space and increasing the chances of finding globally optimal solutions. In order to demonstrate the utility of the proposed optimization framework, a case study based on the Murray River, Australia, was used, which consists of a river reach, three wetlands and two floodplains. In order to evaluate the effectiveness of the management schedules developed, the Murray Flow Assessment Tool, MFAT [*Young et al.*, 2003], was used.

[78] To validate the management schedules developed using the ACO-based optimization framework, the schedules obtained using the framework were initially compared with those developed using a heuristic approach. Although it is recognized that the use of a heuristic approach as a basis of comparison has its limitations, it provides some degree of validation of the proposed optimization approach, as well as illustrating its potential benefits. Six investigations of varying complexity were used as part of the validation process, with Investigations 1–3 having only one plant species, while the number of plant species ranged from 3 to 12 in the remaining three investigations. Identical MFAT scores were obtained for the first three investigations using both techniques, while for the more complex investigations, the management schedules constructed using the optimization approach were able to save water and achieve higher MFAT scores than the management schedules obtained using the heuristic approach. Based on these results, the optimization approach was considered successful in developing management schedules for both simple and complex circumstances.

[79] The optimization framework was then applied to a range of different studies that include (1) the development of optimal trade-offs between recruitment and maintenance for 12 species of flora for different 5 yearly flow allocations ranging from 500 to 12,000 GL, (2) the development of an optimal trade-off in ecological response between flora and fauna species, and (3) the development of EFMA schedules for a hydrograph inversion case. The results of the first study indicated that allocations greater than 10,000 GL did not change the final MFAT ecological scores for the wetlands and floodplains. Additionally, a maximum score of approximately 1.0 for both recruitment and maintenance could not be achieved, as there were competing flow components, where an increase in the score for a particular flow component decreased the score of another component, and vice versa. The second study indicated that favoring fauna species resulted in the surrounding biota having a lower score, while prioritizing flora achieved an overall higher score. Finally, the third study showed that the hydroinversion case could be easily incorporated within the optimization framework, as well as providing information on which species were particularly threatened. Overall, these studies were able to provide further understanding regarding when recruitment, maintenance, or a particular species are favored, the water allocation necessary to improve the ecological integrity of biota, as well as developing optimal flow management schedules in a regulated river system. This suggests that the proposed approach is a valuable tool in achieving the best possible ecological outcomes, given particular environmental flow allocations.

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Appendix B

Copy of Paper from Chapter 3

Szemis, J. M., G. C. Dandy, and H. R. Maier (2013), A multiobjective ant colony optimization approach for scheduling environmental flow management alternatives with application to the River Murray, Australia, *Water Resources Research*, *49*(10), 6393–6411.

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A multiobjective ant colony optimization approach for scheduling environmental flow management alternatives with application to the River Murray, Australia

J. M. Szemis,[1] G. C. Dandy,[1] and H. R. Maier[1]

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[1] In regulated river systems, such as the River Murray in Australia, the efficient use of water to preserve and restore biota in the river, wetlands, and floodplains is of concern for water managers. Available management options include the timing of river flow releases and operation of wetland flow control structures. However, the optimal scheduling of these environmental flow management alternatives is a difficult task, since there are generally multiple wetlands and floodplains with a range of species, as well as a large number of management options that need to be considered. Consequently, this problem is a multiobjective optimization problem aimed at maximizing ecological benefit while minimizing water allocations within the infrastructure constraints of the system under consideration. This paper presents a multiobjective optimization framework, which is based on a multiobjective ant colony optimization approach, for developing optimal trade-offs between water allocation and ecological benefit. The framework is applied to a reach of the River Murray in South Australia. Two studies are formulated to assess the impact of (i) upstream system flow constraints and (ii) additional regulators on this trade-off. The results indicate that unless the system flow constraints are relaxed, there is limited additional ecological benefit as allocation increases. Furthermore the use of regulators can increase ecological benefits while using less water. The results illustrate the utility of the framework since the impact of flow control infrastructure on the trade-offs between water allocation and ecological benefit can be investigated, thereby providing valuable insight to managers.

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1. Introduction

[2] River basin development, including land conversion, overallocation of water and the construction of barriers (e.g., dams) has altered many rivers and their adjacent wetlands and floodplains worldwide [*Kingsford*, 2000; *Millennium Ecosystem Assessment*, 2005]. To preserve and restore these systems, much focus has been given to environmental flow management [*Arthington and Pusey*, 2003; *Arthington et al.*, 2010; *Kingsford and Auld*, 2005; *Tharme*, 2003], which aims to follow the "natural flow paradigm" developed by *Poff et al.* [1997] and "mimic components of natural flow variability," in terms of flow frequency, duration, timing, rate of change, and magnitude [*Arthington et al.*, 2006]. These flow components are integral to maintaining and preserving biota within river-floodplain system [*Junk et al.*, 1989].

[3] The management and delivery of environmental flows (in terms of the five important flow components) is not an easy task, since (i) there are generally large numbers of wetlands and floodplains containing a variety of flora and fauna with different flow requirements that need to be taken into account, for instance, lignum shrubland (*Muehlenbeckia florulenta*) prefer an inundation duration of 1–6 months while great crested grebes prefer 2–5 months [*Rogers and Ralph*, 2011]; (ii) there is generally limited water available for environmental purposes, given that there are a number of users (e.g., irrigation, domestic, and industrial supply) all vying for the same water resource [*Wallace et al.*, 2003]; and (iii) there might be flow restrictions as a result of constraints in the system (e.g., upstream flows are limited to particular values in particular months) [*Murray-Darling Basin Authority* (*MDBA*), 2011b]. Therefore, in order to use environmental water effectively and efficiently so as to maximize the ecological integrity of rivers, wetlands, and floodplains, a number of environmental flow management alternatives (EFMAs) can be utilized, including upstream flow releases or the operation of gates and pumps to regulate water entering and leaving wetlands. Since decisions in relation to EFMAs (e.g., reservoir flow

[1]School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide, South Australia, Australia.

Corresponding author: J. M. Szemis, School of Civil, Environmental and Mining Engineering, University of Adelaide, North Terrace, Adelaide, SA 5005, Australia. (jszemis@civeng.adelaide.edu.au)

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releases or gate operations) are made at discrete time steps over a specific planning horizon (e.g., a number of years) and at numerous locations (e.g., different wetlands), the search space for this scheduling problem generally becomes very large, especially when extended spatial and temporal scales are considered [*Szemis et al.*, 2012]. Due to this complexity, there is potential benefit in employing optimization approaches to schedule EFMAs to maximize ecological integrity, given a particular environmental flow allocation.

[4] Optimization studies in this area have mainly focused on the development of optimal reservoir/weir operating rule parameters or monthly reservoir releases, while attempting to maintain an appropriate balance between the environment and other potential water users (e.g., irrigators), rather than how to schedule a given environmental water allocation in order to maximize ecological outcomes [e.g., *Chang et al.*, 2010; *Chaves et al.*, 2003; *Higgins et al.*, 2011; *Homa et al.*, 2005; *Shiau and Wu*, 2004, 2007; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2011, 2010]. Consequently, ecological objectives have been generally treated in a rather simplistic fashion. In order to overcome this shortcoming, *Szemis et al.*[2012] introduced an optimization framework for the development of environmental flow management schedules for maximizing the ecological response of rivers, wetlands, and floodplains that incorporates different EFMAs (i.e., wetland gate operations, reservoir releases), flow components (i.e., flood timing, flood duration, dry period, depth), and water allocation constraints. The framework is also able to cater for the relative importance of different ecological assets, species, and processes. However, the approach has only been tested on a hypothetical case study thus far. In addition, the optimization framework is single objective, whereas in practice, there is significant interest in the optimal trade-offs between the amount of water allocated to the environment and the corresponding optimal ecological responses of affected wetlands and floodplains or particular species.

[5] In order to address the shortcomings in existing literature identified above, the objectives of this paper are (i) to extend the single-objective optimization approach developed by *Szemis et al.*[2012] to include multiple objectives and compare the performance of three multiobjective algorithms in order to determine which is most suitable for the EFMA optimization problem, so that the optimal trade-offs between ecological response and environmental flow allocations can be obtained and (ii) to apply the approach to a real case study in the South Australian reaches of the River Murray. This case study is well suited to testing the multiobjective EFMA approach, as flow in the River Murray is overallocated and a number of options are being considered for increasing the ecological health of the many wetlands and floodplains in the region. These include different environmental flow allocations and infrastructure options for maximizing the benefit of these allocations. One of these infrastructure options is the utilization of wetland regulators to enable direct control over the flow regime in the wetlands (e.g., introducing a drying phase to wetlands that are permanently inundated) and to reduce evaporation losses [*Higgins et al.*, 2011]. However, where these regulators should be located and how they should be operated, as well as their effect on the optimal trade-offs between the amount of water allocated to the environment and the corresponding optimal ecological response, is unknown. The second infrastructure option considered is the potential increase in the maximum rate of upstream environmental flow releases, thereby enabling the magnitude of flow events, and hence levels of inundation, to be increased. However, the impact of these system constraints on the optimal trade-offs between environmental flow allocations and ecological response is currently unknown.

[6] The remainder of this paper is organized as follows. The case study area, problem formulation, and multiobjective optimization approach used to develop the environmental flow management schedules, including the comparative study of three multiobjective algorithms, are described in sections 2 and 3. The analyses conducted are described in section 4, while the results, discussion, and limitations are discussed in section 5. Finally, the conclusions of the study are given in section 6.

2. Case Study: River Murray in South Australia

[7] The South Australian reaches of the River Murray are part of the Murray-Darling river system, which is located in south eastern Australia and spans a number of Australian States, including Victoria, New South Wales, Queensland, and South Australia (see Figure 1) [*Reid and Brooks*, 2000]. Since the 1920s, the South Australian reaches of the River Murray have become significantly regulated with the construction of six locks along the river channel and a number of upstream structures in New South Wales and Victoria [*George et al.*, 2005]. An annual water entitlement of 1850 GL has been allocated to South Australia by the Murray-Darling Basin Authority (MBDA). This is predominantly for main channel flows, irrigation, and water supply for Adelaide, the capital of South Australia, which has a population of 1.21 million [*Australian Bureau of Statistics*, 2012], with only 38.7 GL of this entitlement being used for wetlands, and recreational and environmental use [*South Australian Murray-Darling Basin Natural Resources Management Board*, 2009].

[8] The increase in river regulation and overallocation of water (due to an expansion of irrigation), and the effect of drought over a long period of time, have reduced the flow variability within the river system and highly stressed and altered the biota in the river and adjacent wetlands and floodplains [*Overton et al.*, 2010]. In response, the Commonwealth Government of Australia approved a basin wide plan developed by the MDBA that determined the water allocation for each user and intends to increase the annual environmental water for the entire basin by 3200 GL/yr, taking it to a total volume of 4023 GL/yr [*MDBA*, 2012d]. In addition, the MBDA modeled and recommended the relaxation of system constraints, such as increasing the maximum flow releases from Hume Dam (an upstream dam) from 25,000 to 40,000 ML/day in order to allow higher flows to reach the South Australian River Murray and inundate mid-elevation to high-elevation floodplains [*MDBA*, 2012b]. However, many scientists recommend that further investigations should be conducted to assess the impact of an increase in the environmental water allocation to 4000 GL/yr, ensuring that high-elevation

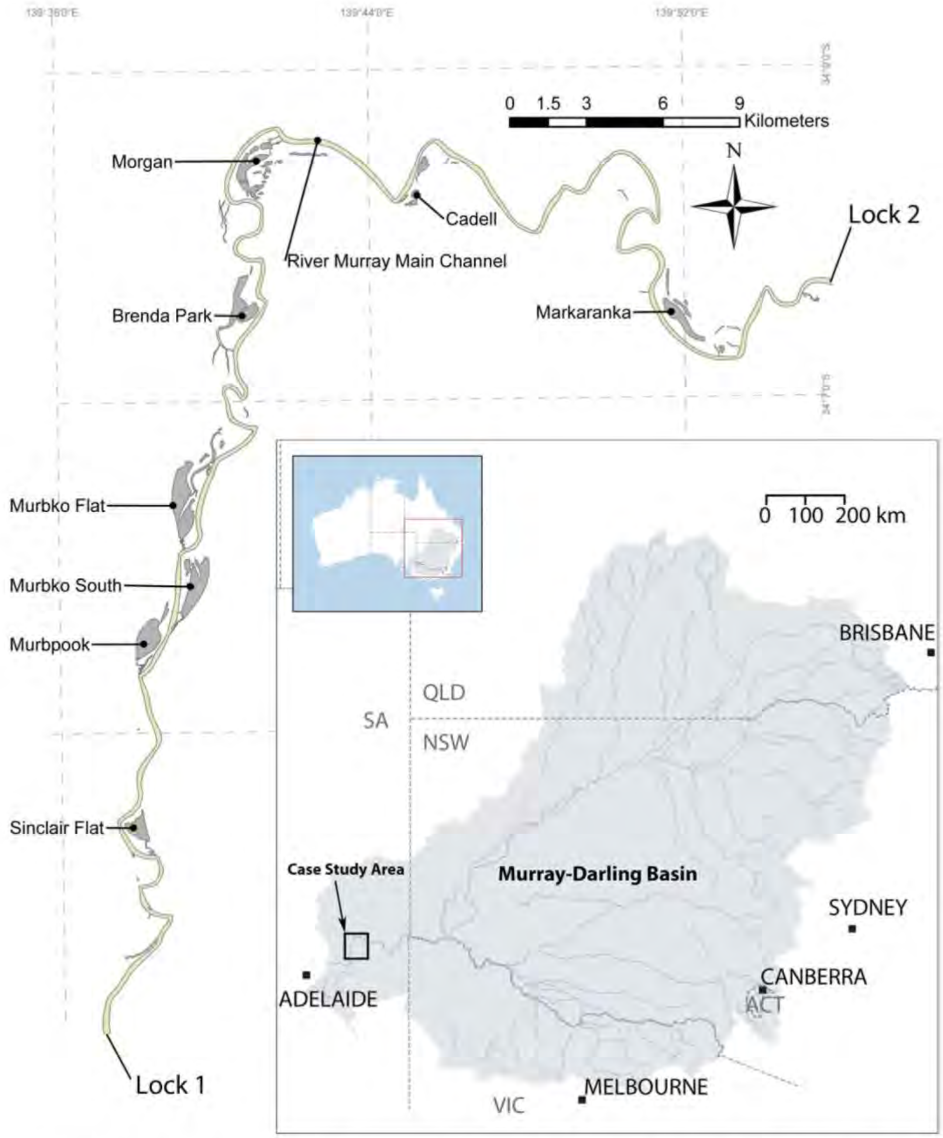

Figure 1. Map of case study area adapted from Murray-Darling Basin Authority website (http://www.mdba.gov.au/river-data/spatial-data-services/spatial-information).

floodplains are inundated periodically [*Government of South Australia* (*GSA*), 2012].

[9] The case study area under investigation is a reach of the River Murray between Locks 1 and 2 shown in Figure 1. This reach spans 89.0 km [*Overton et al*., 2006] and accommodates eight wetlands and a large number of high lying floodplains along the river channel. Due to the construction of the locks, the wetlands closer to Lock 1 have become permanently inundated (i.e., continual connection to the river) and experience no drying, which has reduced the ecological health of the biota, such as Lignum (*Muehlenbeckia florulenta*), which dies when inundated for a prolonged period of time [*Kingsford*, 2000; *Smith and Smith*, 1990; *Walker and Thoms*, 1993]. In contrast, wetlands closer to Lock 2 are temporary and rarely inundated due to upstream system constraints. Each wetland and surrounding floodplain houses a variety of flora and fauna, ranging from high-lying river red gums (*Eucalyptus camaldulensis*) to water birds and fish (e.g., ibis and carp gudgeon) [*Turner*, 2007].

[10] As discussed in section 1, the use of wetland regulators has been suggested in the case study area. Currently, there are two wetlands with gates [*Schultz*, 2007; *Turner*, 2007], with a proposal to add flow regulation systems to a further three [*Ecological Associates* (*EA*), 2007; *Overton et al*., 2010]. In addition to the manipulation of regulators, ecological response can also be influenced by upstream flow releases from the South Australian border. As stated in section 1, the objectives of this paper are to investigate the effect system constraints and regulator locations and

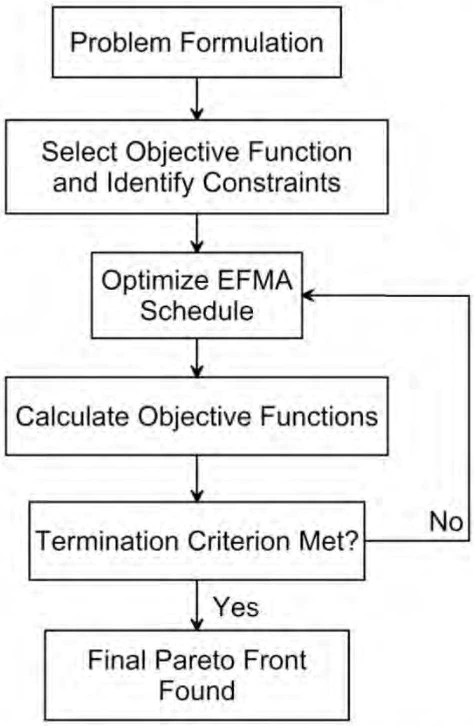

Figure 2. Steps in optimization framework.

settings have on the optimal trade-off between environmental flow allocations and different aspects of ecological integrity within the case study area. The methodology for achieving this is given in section 3.

3. Methodology

[11] In order to investigate the optimal trade-offs between environmental flow allocations and ecological response(s) for the case study area under a range of scenarios, optimal EFMA schedules (i.e., flow releases and regulator settings) have to be identified over the selected planning horizon. This is achieved by modifying the optimization framework presented by *Szemis et al.* [2012] to incorporate a multiobjective optimization approach. The steps in the framework are shown in Figure 2 and include problem formulation, which includes the identification of the river reaches, wetlands, and floodplains to be managed, as well as the indicator(s) for measuring ecological response, and potential management alternatives and associated suboptions (section 3.1). The objective function and constraints are then identified (section 3.2), after which a trial schedule of flow releases and regulator settings can be developed over the adopted planning horizon, and assessed by calculating the objective functions using a hydrological model (section 3.3).

[12] This process of developing and evaluating management schedules is repeated multiple times and guided by a multiobjective optimization algorithm in order to develop the final Pareto front, which contains EFMAs that represent the optimal trade-offs between the total environmental flow allocation and the corresponding ecological response(s). Based on the rationale presented in *Szemis et al.* [2012], Ant Colony Optimization (ACO) is used as the optimization algorithm, since (i) it can solve complex nonlinear problems, in contrast to traditional optimization methods, such as linear programming, which can only solve linear problems [*Taha*, 1997], and dynamic programming, which suffers from the "curse of dimensionality" [*Madej et al.*, 2006], and (ii) unlike other metaheuristics, such as Genetic Algorithms [*Goldberg*, 1989], it can accommodate the sequential nature and the conditional dependencies of the EFMA scheduling problem by using a decision tree graph to represent the problem [*Szemis et al.*, 2012] and is capable of adjusting constraints dynamically during the optimization process in order to reduce the size of the search space [*Afshar*, 2010; *Foong et al.*, 2007, 2008; *Szemis et al.*, 2012]. In order to ensure that the most appropriate multiobjective ACO algorithm is selected, a comparison between three multiobjective ACO algorithms is conducted, as discussed in section 3.5.

3.1. Problem Formulation

3.1.1. Identification of Assets and Ecological Indicators

[13] The first step of the Problem Formulation stage involves the identification of the ecological assets to be managed, H_i, where i ranges from 1 to q. In this case study, the management of eight wetland areas is considered (i.e., $q = 8$) (Step 1, Table 1), which include the wetlands themselves, the high-lying floodplain areas surrounding the wetlands, and the adjacent main river channel. Baseline surveys and wetland management plans have been used to delineate areas of vegetation within the wetland and floodplain areas, as well as to identify the location of certain fish and waterbirds [*EA*, 2007; *Marsland and Nicol*, 2008; *Schultz*, 2007; *Sinclair Knight Merz* (*SKM*), 2004; *Smith and Fleer*, 2006; *Turner*, 2007; *Waanders*, 2007; *Watkins et al.*, 2007].

[14] The Murray Flow Assessment Tool (MFAT) developed by *Young et al.* [2003] is used as the ecological indicator ($E_{i,r}$, where r is the number of species per wetland or

Table 1. Details of Problem Formulation for Case Study

	Problem Formulation Steps	Specification
1	Managed Ecological Assets H_i, $i = 1$ to q	$q = 8$
2	Ecological Indicator $E_{i,r}$ $r = 1$ to $s(i)$	Murray Flow Assessment Tool (MFAT) [*Young et al.*, 2003] Total number of species = 211
3	Planning Horizon Yv, $v = 1$ to K Time Interval t, $t = 1$ to T	$Y_K = 5$ years Monthly, $T = 60$ months
4	Management Alternatives M_a, $a = 1$ to h	$h = 6$ (1 reach and 5 asset scale)
5	Management Alternative Suboption $M_{a,m}$ and/or $M_{a,d}$	Reach—magnitude and duration, Asset—duration

Table 2. Species Composition in Case Study Area

		Species Composition (% per asset)				
Asset	Wetland Name	Floodplain Flora	Wetland Flora	Waterbird	Fish	Regulator
1	Markaranka	50.0	0.0	42.0	8.0	
2	Cadell	73.0	0.0	18.0	18.0	
3	Morgan	50.0	11.0	25.0	14.0	Current
4	Brenda Park	53.0	0.0	29.0	18.0	Current
5	Murbko Flat	64.0	13.0	17.0	6.0	Proposed
6	Murbko South	85.0	4.0	0.0	11.0	
7	Murbpook	52.0	7.0	30.0	11.0	Proposed
8	Sinclair	61.0	22.0	0.0	17.0	Proposed

floodplain) in order to quantify the ecological response of each species (i.e., vegetation, waterbird, and fish) within the river, and adjacent wetlands and floodplains (Step 2, Table 1). MFAT is a habitat simulation model that was developed specifically for the River Murray and can be used to determine the impact of different flow scenarios on the ecological response of biota in terms of two ecological processes, that is, recruitment (e.g., promoting seed germination) and maintenance (e.g., preserving adult habitat) [*Young et al.*, 2003]. This is achieved by using a number of response curves that are based on the five flow components discussed previously (i.e., frequency, duration, timing, rate of change, and magnitude) and include factors such as depth, dry period, flood timing, rate of depth change, inundation area, and flow magnitude. The response curves used for the case study area are those given in *Cooperative Research Centre for Freshwater Ecology* (*CRCFW*) [2003] and *Overton et al* [2010], and include species such as river red gum (*Eucalyptus camaldulensis*), black box woodland (*Eucalyptus largiflorens*), ribbon weed herbland (*Vallisneria americana*), main channel specialists (e.g., Murray cod), and colonial nesting waterbirds. It should be noted that as part of the MFAT score calculation, weights need to be placed on the recruitment and maintenance processes, which are chosen based on literature or expert opinion. A total of 211 species have been defined for the case study area and the proportions of each species type per wetland are given in Table 2. As can be seen, approximately 60% of the species are floodplain flora, followed by waterbirds, fish, and a small proportion of wetland flora.

3.1.2. Selection of Planning Horizon and Time Interval

[15] The third step of the problem formulation includes the selection of the planning horizon, Yv ($v = 1$, K years) and time interval, t, where t ranges from 1 to the final interval, T (Table 1). A planning horizon of five years has been selected, as environmental water management plans in the study area are generally developed over five years [*EA*, 2007; *Schultz*, 2007], while a monthly time step has been chosen, since wetland gate operations are set on a month-by-month basis [*Schultz*, 2007; *Turner*, 2007]. This means that the final interval, T, equals 60.

3.1.3. Determination of Management Alternatives and Suboptions

[16] The identification of the management alternatives M_a, (where a ranges from 1 to h) and suboptions constitute the final two steps of the problem formulation process. The environmental flow release at the South Australian border has been selected as the sole reach scale management alternative, while the asset scale management alternatives include the operations of gates at selected wetlands. Currently, flow at two wetlands (i.e., Morgan and Brenda Park, see Figure 1) can be regulated, with another three being proposed, as shown in Table 2. Consequently, there are six management alternatives (i.e., $h = 6$) that can be considered in the development of environmental flow management schedules (Table 1). Next, the suboptions for each of the management alternatives, M_a, are defined. Duration, $M_{a,d}$, and magnitude, $M_{a,m}$, suboptions have been selected as the only reach-scale management suboptions, while duration suboptions have been selected for all asset-scale management alternatives (see Table 1). The number of possible duration suboptions ($M_{a,d}$) available at each monthly time step ranges from 1 to p, with p varying from 12 for July to 1 for June the following year. On the other hand, the number of magnitude suboptions ranges from 1 to n, with the selection of the maximum number of magnitude suboptions (n) dependent on the case study area and system constraints. This is discussed detail in the next section.

3.2. Identification of Objective Functions and Constraints

[17] Once the problem has been formulated, the objective functions and constraints need to be defined (Figure 1). As discussed previously, the two broad objectives that need to be considered in the problem being addressed are the maximization of ecological response and the minimization of environmental water allocation. However, as ecological response is comprised of a number of different components (e.g., different types of ecological assets such as wetlands, and floodplains, different species, different ecological processes), the objective of optimizing ecological response can be represented by one or more objective functions, corresponding to different levels of aggregation of these components. In order to account for this, the single ecological response objective introduced by *Szemis et al.* [2012] has been modified to enable consideration of multiple ecological objectives. To develop the multiecological response objective, the number of assets, species, and years considered in the case study area need to be defined as sets. Consequently, the number of assets ranging from 1 to q is defined in set H, while the number of species per ith asset (e.g., wetland) is identified as the R_i set, with each ith asset housing $s(i)$ species. Finally, the total year set, V, ranging from 1 to a maximum year of Y_K is also defined, with the sets shown below.

$$i \in H = \{1, 2, \ldots, q\}$$

$$R_i = \{1, 2, \ldots, s(i)\}$$

$$V = \{1, 2, \ldots, Y_K\}$$

[18] Once the asset, species and year sets have been defined, the ecological components that are of interest (e.g., specific area of wetlands or vegetation species) as part of the gth ecological response objective, where g ranges from 1 to fg are defined in the form of g subsets, which also

range from 1 to fg. When $fg = 1$, a single-objective function is used, in which the ecological responses of all components are aggregated, when $fg = 2$, two ecological objective functions are used in which different subsets of ecological components are considered and so on. The subsets are given below.

$$i \in H_g \subseteq H$$

$$R_{i,g} \subseteq R_i, \quad g = 1 \text{ to } fg$$

$$V_g \subseteq V$$

where H_g is the gth subset of H and contains ecological components related to the assets and enables examination of the ecological response of wetlands and floodplains at different locations, while $R_{i,g}$ is the gth subset of R_i and contains information about which species (e.g., fish) are included in the gth ecological response objective. Last, V_g is the gth subset of V, which defines the years considered and allows for the investigation of ecological responses at a specific year or over a number of years.

[19] Once the fg subsets are defined, each of the g ecological response objectives can be determined using equation 1. It should be noted that each objective function includes weights in order to account for the relative importance of various aspects of the problem, such as favoring certain species or wetlands.

$$\begin{aligned} F_{E,1} &= \sum_{i \in I_1} w_{1i} \sum_{r \in R_{i,1}} w_{2r} \sum_{v \in V_1} \frac{w_{3v} E_{i,r,v}}{Y_{K,1}}, \quad g = 1 \\ F_{E,2} &= \sum_{i \in I_2} w_{1i} \sum_{r \in R_{i,2}} w_{2r} \sum_{v \in V_2} \frac{w_{3v} E_{i,r,v}}{Y_{K,2}}, \quad g = 2 \\ &\vdots \\ F_{E,fg} &= \sum_{i \in I_{fg}} w_{1i} \sum_{r \in R_{i,fg}} w_{2r} \sum_{v \in V_{fg}} \frac{w_{3v} E_{i,r,v}}{Y_{K,fg}}, \quad g = fg \end{aligned} \qquad (1)$$

where $E_{i,v,r}$ is the MFAT value for asset i, for indicator type r in the vth yearly time interval for each of the g objective functions corresponding to g separate ecological components. In equation 1, each of the g objective function values is obtained by summing (i) values of each ecological indicator used in the particular objective function over the wetland areas (including the floodplain areas surrounding the wetlands and the adjacent river reach) defined in subset I_g, (ii) values of the species indicators identified in $R_{i,g}$ to be aggregated in the gth objective function, and (iii) ecological indicator values used in the particular objective function over the years defined in subset V_g, over which the schedule of EFMAs has been developed (i.e., the planning horizon, which is five years in this instance), with the total number of years considered in the gth ecological response function defined as $Y_{K,g}$. Weights, w_{1i}, w_{2r}, and w_{3v} place emphasis on the ith wetlands, floodplains, or river reaches, rth ecological indicator and Y_Kth year, respectively, and are defined by the user before commencement of the optimization process. Consequently, each objective function is sufficiently flexible to cater for particular aspects of the problem (e.g., favoring sensitive or endangered species).

[20] Another component of the extension from the single to the multiobjective optimization framework presented in this paper is the addition of an environmental water allocation objective, F_W, which accounts for the total amount of environmental water that is allocated over the five year planning horizon and is given below:

$$F_W = \sum_{t=1}^{T} A_t \qquad (2)$$

where A_t is the environmental water allocation in month t, which is calculated using the reach-scale management alternative magnitude suboptions selected at each tth time step.

[21] In addition, constraints are defined on the magnitude and duration of the suboptions for a particular management alternative, M_a, as given in equations 3 and 4:

$$M_{a,m_{\min}} \leq M_{a,m} < M_{a,m_{\max}}, \quad m = 1 \text{ to } n \qquad (3)$$

$$M_{a,d_{\min}} \leq M_{a,d} < M_{a,d_{\max}}, \quad d = 1 \text{ to } p \qquad (4)$$

where the magnitude suboptions ($M_{a,m}$) are constrained by minimum and maximum values of M_{a,m_min} and M_{a,m_max}, respectively, and the duration suboptions ($M_{a,d}$) are constrained by minimum and maximum values of M_{a,d_min} and M_{a,d_max}, respectively, for each management alternative. Each management alternative must therefore be assessed individually in order to determine appropriate values for the above constraints. The specification of M_{a,m_min}, M_{a,m_max}, M_{a,d_min}, and M_{a,d_max} is user-defined, based on the requirements of the case study area under consideration (e.g., M_{a,m_max} could be selected based on a maximum achievable flow in the case study area).

[22] A further constraint relates to the maximum allowable monthly flow at the South Australian border, which permits the assessment of the impact of system flow constraints, and is given as follows:

$$Q_t \leq Q_{t\max}, \quad t = 1 \text{ to } T \qquad (5)$$

[23] The monthly flow has been defined as Q_t, while Q_{tmax} is the maximum flow at the South Australian border each tth month. The selection of Q_{tmax} is user-defined and is generally based on system constraints within the case study area.

3.3. Development of Management Schedules

[24] After the objectives and constraints have been defined, management schedules are developed (as shown in Figure 2), which is done by selecting values for each of the suboptions. Based on the framework developed by *Szemis et al.* [2012], the management alternatives and suboptions are represented in the form of a decision tree graph, which is able take into account the sequential nature and temporal dependencies associated with the EFMA scheduling problem (e.g., the fact that the values of decision variables selected at one time period, such as the duration of a particular flow release, have an effect on the options that are available at subsequent time periods). Using this graph, a management schedule is developed by selecting one of the available alternatives at each of the nodes. Determination of the management schedules that provide the best possible

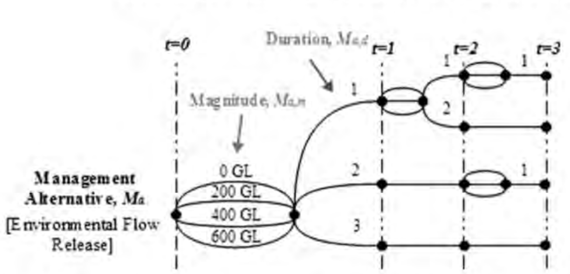

Figure 3. Example of an EFMA schedule graph for environmental flow releases (in Gigalitres (GL)) incorporating dynamic constraints.

trade-offs between the competing objectives of minimizing the environmental water allocation and maximizing the ecological response(s) is achieved over a number of iterations with the aid of the multiobjective ant colony optimization algorithm, details of which are given in section 3.5.

[25] An example decision tree graph that incorporates magnitude and duration suboptions, as well as the conditional dependencies associated with the duration suboptions via dynamic constraints, is given in Figure 3. The example considers four magnitude options (i.e., 0, 200, 400, and 800 gigalitres (GL)) and three duration suboptions and is constructed over three time steps.

[26] If the maximum duration has been selected at the first time step, then no other decision paths need to be made available at subsequent time steps (decision points), as shown by the bottom path in Figure 3. In this way, the decision tree is adjusted based on the selection made at the first decision point, thereby reducing the size of the search space and increasing the likelihood that global or near globally optimal solutions are identified. On the other hand, if a duration option of one is chosen at the first time step (top path), then the potential duration suboptions are considered again at the following time step. However, the number of available options decreases from three to two, as there are only two more time steps remaining. If the number of available duration suboptions is not adjusted dynamically then three duration options would be considered after each magnitude suboption, which results in a significantly larger search space. Therefore, this form of dynamically constraining the decision tree graph ensures that feasible EFMA schedules are developed, as well as ensuring that the optimization algorithm is able to find optimal solutions more efficiently and cater for the conditional dependencies associated with the EFMA problem [*Szemis et al.*, 2012].

3.4. Calculation of Objective Function

[27] In order to evaluate the objective functions defined in section 3.2 for the selected management schedules, a hydrological simulation model is developed for the river reach under investigation. This is achieved with the aid of backwater curves (T. Bjornsson, personal communication, 2010) that relate river height to river flows at the South Australia border (e.g., 5000 ML/day, 10,000ML/day). This allows a relationship between flow and river height along the length of the main channel to be developed, such that for a certain flow release at the South Australian border, the corresponding river height at the eight wetland locations can be determined. In addition to this, fill values (i.e., the river level at which the wetland or floodplain is flooded) at the eight wetland locations, as well as area versus average depth curves for each of the specified areas of floodplain and wetland flora and fauna, have been determined using ArcGIS and a range of data sources, including a Digital Elevation Model (DEM) obtained from the Department of Environmental, Water and Natural Resources baseline surveys [*Marsland and Nicol*, 2008; *SKM*, 2004; *Smith and Fleer*, 2006; *Waanders*, 2007] and wetland management plans [*EA*, 2007; *Schultz*, 2007; *Turner*, 2007]. Once the flow versus river height relationships have been developed and the fill values obtained, the hydrological models can be developed using the equations employed in *Szemis et al.* [2012], as detailed below.

[28] To ensure that the model adequately simulates the hydrology, whereby wetlands fill quickly once the river level breaches the fill value and when gates are opened, equation 6 is used, while equation 7 is utilized to simulate the slow draining of a wetland when the gates are closed, or when the river level drops below the fill value. Equation 6 represents the water balance for a wetland as follows:

$$I_t - O_t = S_{t+1} - S_t \tag{6}$$

where I_t are the inflows, O_t are the outflows, and S_t are the storages at time t. The outflows O_t are the sum of the flows out of the wetland (O_w) and evaporation (E_t), while the inflows are the sum of rainfall (R_t) and flows into the wetland. A simple relationship of 0.7× (pan evaporation) is used to determine the evaporation from wetlands, in meters/month, with average monthly evaporation sourced from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/). The value of 0.7 is chosen as it is a common value used to determine evaporation within the Murray-Darling Basin [*Gippel*, 2006].

[29] To simulate gate operation, logical (If-Then) statements are used to adjust the appropriate components of the water balance equations. If a gate is closed, the inflow at that time step is set to zero (i.e., $I_t = 0.0$) and if there is water in the wetland at that time, wetland storage at subsequent time steps is only affected by rainfall and evaporation for the duration of the gate closure, as follows:

$$S_{t+1} = S_t - E_t + R_t \tag{7}$$

[30] If there is water remaining in the wetland at the time step the gate is opened, water is allowed to flow out of the wetland until the fill value is reached, after which water remains in the wetland and only is affected by evaporation and rainfall (i.e., equation 7). It should be noted that average monthly rainfall data in the case study area have been used. These were obtained from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/).

[31] Once the river level is above the fill value or maximum gate height (i.e., the maximum river level at which the gate can operate), the floodplain hydrological model is used. This model utilizes equation 6, whereby floodplain hydrology is only dependent on the river level (i.e., if the river level is above the fill value, the floodplain is inundated and the area of flooding is dependent on the height of the river. For example, as the river level increases, so does

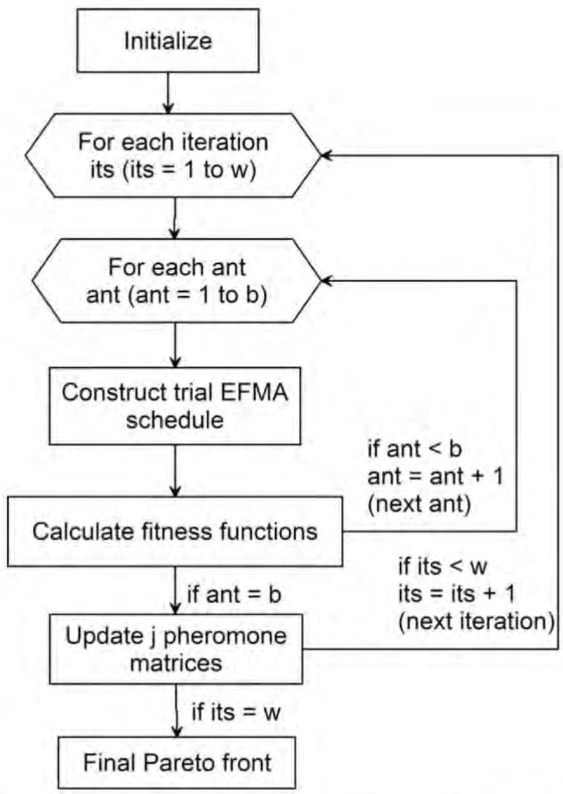

Figure 4. Traditional Ant Colony Optimization procedure.

the area and depth of inundation). It should be noted that the mass balance constraints associated with the problem are also satisfied within each hydrological model.

[32] A number of assumptions have also been made for both models, including (i) water seepage is negligible since it is small compared to the evaporation loss and (ii) the rate of river level rise and fall occurs over each month. Additionally, the storage capacity of the wetlands has been examined and it has been determined that this is very small compared with the magnitude of the streamflows, and thus has a negligible effect on downstream flows.

3.5. Multiobjective Optimization

[33] As mentioned in section 3, a multiobjective ACO algorithm is used to iteratively determine management schedules that improve all objective functions with the aim of finding schedules that represent globally optimal or near globally optimal trade-offs between all objectives (i.e., schedules that are on the Pareto front—see Figure 2). The traditional multiobjective ACO procedure for determining optimal or near optimal trade-offs is shown in Figure 4, where a trial EFMA schedule is initialized, after which the optimization process takes place. This firstly involves the construction of a trial schedule for each b ants during each iteration. Ants achieve this by traveling to each time step and selecting magnitude and duration suboptions until they reach the final time step, T. The selection of these suboptions is done probabilistically based on the j pheromone matrices (τ^j) associated with each suboption, with the number of pheromone matrices used dependent on the multiobjective ACO algorithm used, as discussed below. As part of the optimization process, the j pheromone matrices are manipulated to increase pheromone levels for suboptions that have contributed to good overall solutions, so that they are more likely to be selected in subsequent iterations. Additionally, pheromone evaporation is applied to suboptions of schedules that do not perform well, which in turn deters the algorithm from choosing these paths again.

[34] Once an iteration has been completed by an ant, the resulting schedule is evaluated using fitness functions, which are the objective functions (i.e., equations 1 and 2) transformed in order to efficiently guide the search of the algorithms. Further details regarding the fitness functions are given in section 3.5.4. The calculation of the fitness functions is achieved with the aid of the hydrological model of the case study area (see section 3.4). This model is also used to assess whether there are any constraint violations (see section 3.5.4). The process of selecting an EFMA schedule and evaluating it against the fitness functions is repeated for each ant. The pheromone levels are then updated and this process continues until the maximum iteration, w, is reached. It should be noted, that once the final iteration is complete, the convergence of the Pareto front is checked using the hypervolume, which measures the volume of area dominated by the approximated Pareto front set [*Zitzler and Thiele*, 1999]. This has been selected to indicate the point at which there is no further reduction in the volume of the Pareto front, thereby suggesting convergence has been reached.

[35] As part of this study, the performance of three multiobjective ACO algorithms that utilize the traditional ACO procedure (shown in Figure 4) has been compared to determine the most suitable algorithm for the case study area. The algorithms considered include the Pareto Ant Colony Optimization Algorithm (PACOA) [*Doerner et al.*, 2004], COMPETants [*Doerner et al.*, 2003], and m-ACO variant 3 (m-ACO_3) [*Alaya et al.*, 2007]. These algorithms have been selected because they use different pheromone updating approaches in determining the optimal or near optimal trade-off. PACOA uses multiple pheromone matrices, as well as the best and second best solution during the pheromone update process, COMPETants uses multiple colonies and pheromone matrices, while m-ACO_3 employs a single pheromone matrix and updates the pheromone level using the nondominated solutions determined after each iteration. It should be noted that other ACO algorithms, such as the population-based ACO [*Guntsch and Middendorf*, 2003], have not been considered in this comparison, as they do not follow the traditional ACO process shown in Figure 2. A description of the three algorithms used, and the pheromone update process utilized in each, is presented in the following sections.

3.5.1. Pareto Ant Colony Optimization (PACOA)

[36] The PACOA developed by *Doerner et al.* [2004] utilizes Ant Colony Systems [*Dorigo and Gambardella*, 1997] as the underlying ACO algorithm, however, unlike Ant Colony Systems, it uses both the first and second best solutions during the global pheromone update [*García-Martínez et al.*, 2007]. In addition, the algorithm employs multiple pheromone matrices, one for each objective

considered. The pheromone update process is given by the following equation:

$$\tau_t^j = (1-\rho)\cdot\tau_t^j + \rho\cdot\Delta\tau_t^j$$
$$\Delta\tau_t^j = \begin{cases} 15 & \text{if suboption is in best and second best solution,} \\ 10 & \text{if suboption is in best solution,} \\ 5 & \text{if suboption is in second best solution,} \\ 0 & \text{otherwise}. \end{cases} \tag{8}$$

where the pheromone level on all suboptions is reduced at a rate that is controlled by the pheromone evaporation factor (ρ), while an increase in pheromone levels for each jth fitness function ($\Delta\tau^j$) is based on whether that particular suboption is part of the best or second best solution. The b trial schedules generated by the b ants then undergo a nondominated sorting process in order to determine the schedules that are on the Pareto front for that particular iteration and are subsequently stored in an offline storage matrix. Readers are referred to *Doerner et al.* [2004] for a detailed description and the equations used in the PACOA.

3.5.2. COMPETants

[37] The COMPETants algorithm proposed by *Doerner et al.* [2003] utilizes multiple colonies and pheromone matrices to determine the optimal or near-optimal Pareto front. Each colony focuses on one objective and constructs solutions independently from each other, with the exception of a group of ants, called spies, that use a weighted sum approach that aggregates the pheromone matrices for each objective.

[38] As was done by *López-Ibáñez and Stützle* [2012], the COMPETants algorithm is formulated using a single-colony algorithm in which the ants are divided into subgroups that either focus on a given objective or act as spies. The pheromone levels for each subgroup are then updated using equation 8, with the level of pheromone increase for each jth objective, $\Delta\tau_t^j$, given in equation 9 as follows:

$$\Delta\tau_t^j = \begin{cases} 10 & \text{if suboption is in best solution for the jth objective,} \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

[39] The update process is independent for each subgroup, such that ants from each subgroup update their own pheromone matrix using the best solution.

[40] As was done by *López-Ibáñez and Stützle* [2012], the COMPETants algorithm employed in this study equally portioned the number of ants used between the j objectives and spy subgroups. For further information regarding the COMPETants algorithm, readers are referred to *Doerner et al.* [2003] and *López-Ibáñez and Stützle* [2012].

3.5.3. m-ACO variant 3 (m-ACO$_3$)

[41] The ACO variant suggested by *Alaya et al.* [2007] proposes the use of a single pheromone matrix, which is updated using the nondominated solution determined in the current iteration set. The pheromone values, τ_t^j, are updated using equation 8 (with $j = 1.0$) and the increase in pheromone level $(\Delta\tau_t^j)$ during the pheromone update process is based on whether a suboption is in the nondominated solution set for the current iterations, P, which is shown in equation 10.

$$\Delta\tau_t^j = \begin{cases} 10 & \text{if suboption is in P,} \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

[42] This is different to the two previous algorithms, which use the best solutions to update pheromone levels after each iteration.

3.5.4. Fitness Functions

[43] Before the performance of the multiobjective ACO algorithms can be compared, the objectives defined in equations 1 and 2 need to be transformed to fitness functions (i.e., equations 11 and 12) in order to effectively guide the search of the algorithms, as the algorithms (i) attempt to minimize all objectives, whereas the aim of this study involves the minimization of the environmental water allocation objective and the maximization of the fg ecological response objectives (i.e., MFAT score) and (ii) like other evolutionary algorithms, are unable to explicitly take into account the constraints that are not directly related to the decision variables, necessitating the inclusion of penalties in the fitness functions. Therefore, the following fitness function/s ($Y_{E,fg}$) have been developed, such that $F_{E,fg}$ would be maximized:

$$Y_{E,g} = \begin{cases} 1/F_{E,g} + Penalty_{E,g} & \text{if } F_{E,g} > 0 \\ Penalty_{E,g} & \text{if } F_{E,g} = 0 \end{cases}, \; g = 1 \text{ to } fg$$
$$Penalty_{E,g} = \begin{cases} 0 & \text{if no constraint violation} \\ 1,000 & \text{if system constraint violation} \end{cases}, \; g = 1 \text{ to } fg \tag{11}$$

[44] As can be seen, a penalty of 1000 is used if the system flow constraints at the South Australia border are violated for the fg ecological response objectives considered. This value was found to produce good results as part of preliminary trials.

[45] The fitness function corresponding to the objective of minimizing the total environmental water allocation (F_W, equation 2), Y_W, is shown below.

$$Y_W = F_W + Penalty_W$$
$$Penalty_W = \begin{cases} 0 & \text{if no constraint violation} \\ \sum_{t=1}^{T}(Q_t - Q_{\max})\cdot 1,000 & \text{if system constraint violation} \end{cases} \tag{12}$$

[46] In order to take into account the system flow constraints, the fitness function above also includes a penalty to deter the algorithms from selecting infeasible solutions and instead encourage the determination of optimal schedules within the given constraints. The optimal form of the penalty was determined as part of preliminary trials and has been selected since it is able to severely penalize solutions that include flows that significantly exceed system constraints, while marginally penalizing solutions that include only slight violations of system constraints. This deters the algorithm from developing infeasible solutions, while simultaneously encouraging the search for good solutions and quicker convergence.

3.5.5. Comparison of Performance of Multiobjective Optimization Algorithms

[47] Before the performance of the multiobjective ACO algorithms can be compared, a comprehensive sensitivity

Table 3. Range of ACO Parameters Investigated for Each Algorithm

ACO Parameter	Range of Values Tested
Number of ants (*ant*)	30, 300, 510, 1200
Initial pheromone (τ_o^j)	1.0, 10.0
Evaporation rate (ρ)	0.02, 0.1, 0.5, 0.9, 0.98
Evaluations	102,000, 240,000

analysis is required to determine the optimal values of the parameters that control the searching behavior of each algorithm. The range of values tested, as well as the final values selected, are given in Tables 3 and 4. As can be seen in Table 4, two different sets of optimal parameter sets are selected, depending on the size of the search space, as dictated by the number of management alternatives (h) considered within the EFMA schedule development. It should be noted that each sensitivity run was repeated ten times (i.e., with 10 random starting positions in decision space) so as to minimize the impact of the starting position on the results obtained.

[48] Finally, to ensure that the Pareto fronts generated by each algorithm have converged when the optimal ACO parameters in Table 4 are used, the hypervolume of the Pareto front, as described in section 3.5, has been assessed. The hypervolume convergence for each algorithm when the number of management alternatives is less than 4 is given in Figure 5. As can be seen, all algorithms have converged, with the PACOA converging to a hypervolume of approximately 3.0×10^5 at 160 iterations, COMPETants converging to a hypervolume of approximately 2.9×10^5 at 140 iterations, and m-ACO_3 converging to a hypervolume of 2.7×10^5 at 700 iterations. This indicates that the number of evaluations selected is sufficiently large for each of the algorithms to converge to a given Pareto front. It should be noted that hypervolume convergence has also been assessed for the case of six management alternatives, with the results obtained similar to those shown in Figure 5.

[49] In order to assess the quality of the Pareto fronts obtained, the empirical attainment function (EAF) developed by *da Fonseca et al.* [2001] is used. This is because it enables Pareto fronts obtained by two algorithms to be compared, which is not the case for other measures, such as the chi-square-like deviation developed by *Srinivas and Deb* [1994] [*López-Ibáñez and Stützle*, 2012]. Use of the EAF involves determining the probability that each point in the objective space is attained by an algorithm in a single run [*López-Ibáñez and Stützle*, 2012]. To assess two Pareto fronts, the difference in EAFs of each point in the objective space is determined. In this study, a graphical technique

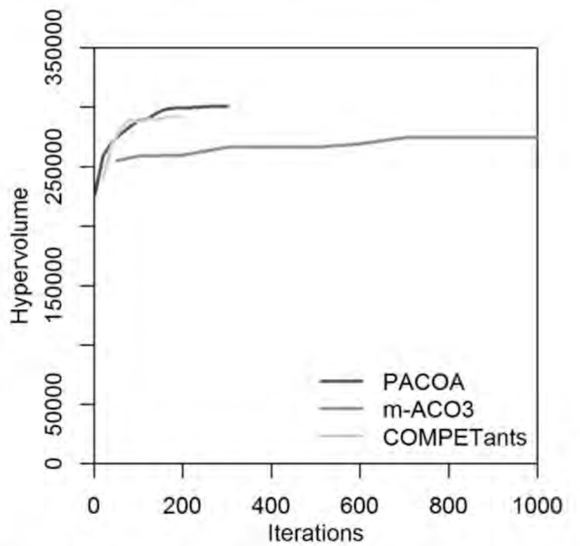

Figure 5. Hypervolume convergence for each multiobjective ACO algorithm when $h < 4$.

[*López-Ibánez et al.*, 2006, 2010; *López-Ibáñez and Stützle*, 2012] is utilized in order to achieve this, with plots generated using the eaf R package, which is available at http://cran.r-project.org/package=eaf.

[50] In order to compare the performance of the three multiobjective algorithms, one of the studies (i.e., Investigation 3) described in section 4 is used, which considers two objectives (i.e., total ecological response and environmental water allocation), three management alternatives (h) (i.e., flow releases and the operation of two wetland regulators) and an upstream flow constraint of 1800 GL/month. The number of flow magnitude suboptions (n) equals 28, while the number of duration suboptions equals 12 at the beginning of the year, but changes depending on selections made during the investigation. Further details, such as the asset (H), species (R_i), and year (V) sets for this investigation are given in section 4.1 and Tables 5 and 6. The graphs comparing the Pareto fronts developed by PACOA, COMPETants, and m-ACO_3 for Investigation 3 in terms of EAF difference are given in Figure 6. As can be seen, PACOA performs better than both COMPETants and m-ACO_3 (top and middle plots). This is shown by the black region in the PACOA graphs (i.e., left graphs), indicating that the PACOA algorithm attained the points in the objective space at least 80% more frequently than COMPETants and m-ACO_3, whereas the regions of white in the m-ACO_3 and

Table 4. Adopted ACO Parameters for Each Algorithm

	Adopted Value(s)					
	$h < 4$			$h = 6$		
PACOA Parameter	*PACOA*	*COMPETants*	*m-ACO_3*	*PACOA*	*COMPETants*	*m-ACO_3*
Number of ants (*ant*)	300	510	30	510	1200	300
Initial pheromone (τ_o^j)	1.0	1.0	1.0	1.0	1.0	1.0
Evaporation rate (ρ)	0.1	0.1	0.1	0.1	0.1	0.5
Evaluations		102,000			240,000	

Table 5. Details of Investigations for Trade-Offs Between Environmental Allocation and Total Ecological Response

Investigation	Upstream System Flow Constraint, Q_{tmax} (GL/month)	Magnitude Suboptions (n)	Ecological Response Objectives (fg)	Management Alternatives (h)	Regulators
1	1200	20	1	3	2
2	1650	26	1	3	2
3	1800	28	1	3	2
4	2400	37	1	3	2
5	3000	45	1	3	2

COMPETants plots (i.e., right graphs) suggest that the same probability of attaining these points is achieved by all algorithms. On the other hand, the graph that compares the performance of COMPETants and m-ACO$_3$ (bottom plot) indicates that COMPETants performs better for solutions that minimize environmental water allocation, as indicated by the black region in the top left corner (see left graph), while m-ACO$_3$ finds solutions that maximize the MFAT score and, in turn, the ecological response of the wetlands and floodplains in the case study area.

[51] The results of the comparison study indicate that the PACOA performs best, given that it is able to develop Pareto fronts with solutions that favor the objectives investigated (i.e., water allocation and ecological response), as indicated by the spread of the black region in the upper EAF difference plots in Figure 6. It should be noted that additional analyses have been conducted for the case where the number of management alternatives, h, equaled 6, with results obtained following a similar trend as those shown in Figure 6. Based on these findings, the PACOA is used for the analysis for the case study area, with details of the analysis conducted and results given in sections 4 and 5, respectively.

4. Analyses Conducted

[52] In order to meet the objectives stated in section 1, two studies have been formulated. The first of these (section 4.1) focuses on the impact of upstream flow constraints on the optimal trade-offs between environmental flow and ecological response. Two analyses have been conducted as part of this study. The first examines the trade-offs between environmental flow and the total ecological response of the case study area for a range of upstream system constraints, while the second investigates the trade-offs between environmental flow, the wetland ecological response, and the floodplain ecological response. The second study (section 4.2) examines the impact of the number of regulators on the optimal trade-offs between environmental water allocation and resulting ecological score in the case study area. Details of the two studies and corresponding investigations

Table 6. Details of Number of Species Per Asset and Number of Years Considered in Total Ecological Response Objective ($g = 1$) for Investigations 1–5 and 7–10

Asset Set $i \in H$	Number of Species ($s(i)$) in $R_{i,1}$ ($g = 1$)	Number of Years ($Y_{K,1}$)
1	26	5
2	15	5
3	28	5
4	17	5
5	53	5
6	27	5
7	27	5
8	18	5

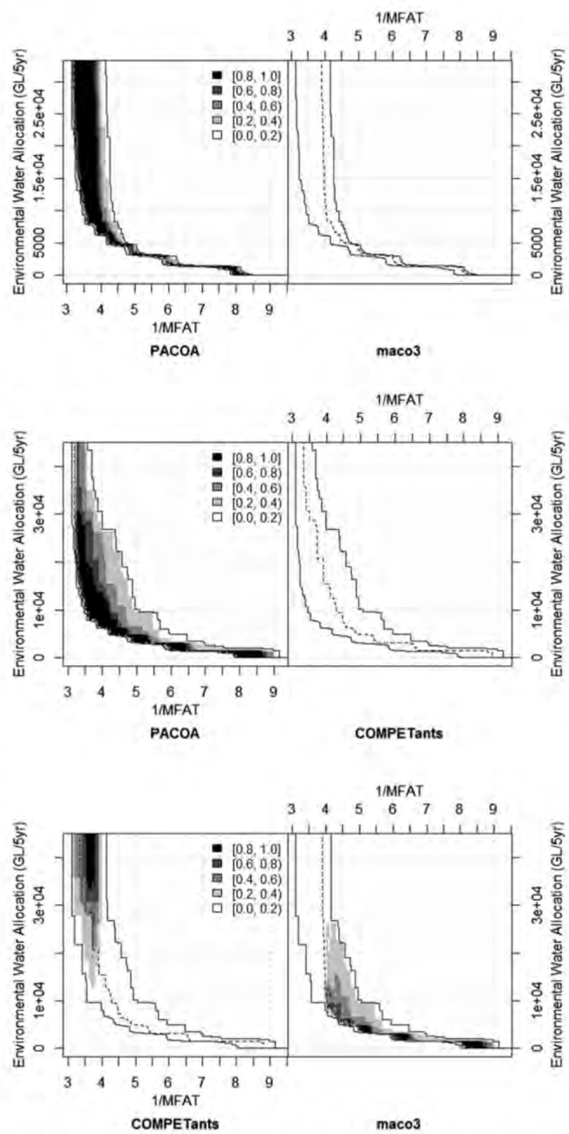

Figure 6. Comparison of performance of PACOA, COMPETants, and m-ACO3 using EAF differences plots.

Table 7. Details of Investigations Conducted as Part of Examining the Trade-offs Between Environmental Flow, Wetland Ecological Response, and Floodplain Ecological Response

Investigation	Upstream System Flow Constraint, Q_{tmax} (GL/month)	Magnitude Suboptions (n)	Ecological Response Objectives (fg)	Management Alternatives (h)	Regulators
6	1800	28	2	3	2

are given in Tables 5–7 and are discussed in detail in the following subsections. It should be noted that minimum monthly flows within the river channel have been set to South Australian entitlement flows [*MDBA*, 2012a], while weights for recruitment and maintenance within MFAT have been set to 0.5 each, with the exception of the weight for the wetland flora species, which has been set to 0.25 for recruitment, and 0.75 for maintenance [*CRCFW*, 2003]. An equal preference has been given to all species and assets, and each optimization run has been repeated 10 times with different starting positions in the solution space.

4.1. Impact of Upstream Flow Constraints

4.1.1. Trade-Offs Between Environmental Flow Allocation and Total Ecological Response

[53] As discussed in section 2, the Murray-Darling Basin (MDB) is a highly regulated system with many users, resulting in a number of system constraints. Five investigations (i.e., Investigations 1–5 in Table 5) have been conducted in order to assess the effect different upstream flow constraints, including maximum upstream releases of 1200, 1650, 1800, 2400, and 3000 GL/month, have on the optimal trade-off between total environmental flow allocation and total ecological response. These constraints have been selected based on the current situation in the MDB, where flows less than or equal to 1200 GL/month (or 40,000 ML/day) at the South Australian border can be achieved relatively easily, whereas flows of 1200–2400 GL/month (or 40,000 and 80,000 ML/day) are much more difficult to achieve due to upstream system constraints [*Heneker and Higham*, 2012], while flows equal to or greater than 3000 GL/month (or 100,000 ML/day) are not deliverable unless these constraints are relaxed by altering existing upstream flood mitigation constraints at times when there are large inflow events at a number of upstream tributaries [*MDBA*, 2011a, 2012c].

[54] It should be noted that for each investigation, the number of flow magnitude suboptions (n) differs, as shown in Table 5, while the duration suboptions for each investigation begin with 12 months at the beginning of each year, but are then dynamically changed depending on prior selections made during a particular iteration. As part of these investigations, only one ecological response objective is considered (i.e., $g = 1$), that is, the total ecological response of the case study area, with the number of assets (i.e., i) in the H set equal to 8, while the number of species considered in each R_i set ($s(i)$) and the number of years (Y_K) are shown in Table 6. In addition, only the two existing regulators at Morgan and Brenda Park wetlands are taken into account resulting in three EFMAs (i.e., $h = 3$), including upstream flow releases and the operation of these two regulators. Consequently, the total search space consists of 10^{135} discrete combinations of decision variable values.

4.1.2. Trade-Off Between Environmental Flow Allocation, Wetland Ecological Response, and Floodplain Ecological Response

[55] The final investigation (i.e., Investigation 6) as part of this study examines the trade-off between three objectives, that is, the environmental water allocation, the ecological response of the wetlands, and the ecological response of the floodplains for a given upstream flow constraint. This investigation has been conducted because wetlands and floodplains lie on different regions of the flood gradient, each with different flow requirements [*Rogers*, 2011], and the trade-off between these three aspects is currently unknown. Details of the investigation are given in Table 7, with the upstream system flow constraint set to 1800 GL/month and the number of magnitude options (n) set to 28. The number of ecological objectives, fg, equals two, with one ecological response objective focusing on the wetlands (i.e., $g = 1$), and the other on the floodplains (i.e., $g = 2$). In order to account for the two ecological response objectives, fg subsets needed to be defined, with details of each asset subset (H_g), number of species subset in each asset ($R_{i,g}$) and the number of years subset V (i.e., Y_K) given in Table 8. As in Investigations 1–5, two regulators at Brenda and Morgan are in operation resulting in a total of three EFMAs (i.e., flow releases and two regulators), with a total search space of 10^{122} discrete combinations of decision variables.

4.2. Impact of Additional Regulators

[56] In recent years, it has been suggested that the flow regime within a wetland should be controlled in order to maximize ecological health, while maintaining the same level of water use and reducing evaporation loss [*Overton et al.*, 2010]. As mentioned previously, two of the wetlands

Table 8. Details of Number of Species Per Asset and Number of Years Considered in Wetland Ecological Response ($g = 1$) and Floodplain Ecological Response ($g = 2$) Objectives for Investigation 6

Asset Set $i \in H$	Number of Species ($s(i)$) in $R_{i,1}$ ($g = 1$)	Number of Species ($s(i)$) in $R_{i,2}$ ($g = 2$)	Number of Years for $g = 1$ and $g = 2$ ($Y_{K,g}$)
1	13	13	5
2	1	10	5
3	14	14	5
4	8	9	5
5	19	34	5
6	4	23	5
7	13	14	5
8	7	11	5

Table 9. Details of Investigations Conducted as Part of the Assessment of the Impact of Additional Regulators

Investigation	Upstream System Flow Constraint, Q_{tmax} (GL/month)	Magnitude Suboptions (n)	Ecological Response Objectives (*fg*)	Management Alternatives (*h*)	Regulators
7	1200	20		1	0
8				6	5
9	1800	28	1	1	0
10				6	5

in the case study area currently have regulators, with an additional three wetlands proposed to have such control structures (see Table 2). However, the impact of these control structures on the optimal trade-off between environmental flow allocation and ecological response has not been assessed in previous studies. Consequently, an additional four studies have been formulated, the results of which can be compared with results obtained in Investigations 1 and 3. Thus, the effect of zero and five regulators is examined under the current system constraint of 1200 GL/month in Investigations 7 and 8, respectively, and under an increased system constraint of 1800 GL/month in Investigations 9 and 10, respectively. The number of management alternatives for each Investigation ranges from 1 to 6, depending on the number of regulators considered (Tables 5 and 9), resulting in a search space ranging from 10^{87} to 10^{177}discrete combinations of decision variable values. It should be noted that the total ecological response objective (i.e., $g = 1$) of the case study area is considered in Investigations 7–10 and thus uses the same asset (H), species (R_i), and year (V) sets as defined in Investigations 1–5, which are given in Table 6.

5. Results and Discussion

[57] The results obtained are in the form of optimal trade-offs between the total amount of water available for environmental purposes and ecological response. In order to assess the impact of different upstream flow constraints, and numbers of regulators on the optimal trade-off between environmental flows and ecological response, as per the stated objectives of the paper, the discussion of the results focuses on the following issues:

[58] 1. The impact of different upstream flow constraints and numbers of regulators on various aspects of the optimal trade-off curve between environmental flow and ecological response, such as changes in the rate of increase in ecological response relative to the rate of increase in environmental flow, changes in the presence and location of "break points," at which a change in the relative rate of change in one objective occurs to that of the other, and changes in the best possible ecological response (sections 5.1.1 and 5.2.1).

[59] 2. The impact of different upstream flow constraints and numbers of regulators on the effectiveness of a number of proposed environmental flow allocations (sections 5.1.2 and 5.2.2). These include the current (2012) allocation of 2105 GL/yr (i.e., 10,525 GL over 5 years) (Allocation 1), the allocation of 4023 GL/yr (i.e., 20,115 GL over 5 years) that the MDBA is trying to achieve by 2019 [*MDBA*, 2012d] (Allocation 2), and the allocation of 4823 GL/yr (or 24,115 GL over 5 years) [*GSA*, 2012] (Allocation 3), which has been suggested by independent scientists, such that required salt export from the Lower Murray Region and adequate water for significant floodplains along the South Australian River Murray can be met [*Bloss et al.*, 2012; *Higham*, 2012].

5.1. Impact of Upstream Flow Constraints

5.1.1. Impact on Optimal Trade-Off Curve

5.1.1.1. Trade-Offs Between Environmental Flow Allocation and Total Ecological Response

[60] The optimal trade-offs between environmental water allocation and corresponding MFAT score obtained as part of each investigation described in section 4.1 are shown in Figure 7. It can be seen that there is little improvement in MFAT score with increased environmental water allocation at the current upstream flow constraint of 1200 GL/month. In contrast, as the upstream flow constraint is relaxed to between 1650 GL/month and 3000 GL/month (Investigations 2–5), there is an almost linear increase in MFAT score with an increase in environmental flow allocation up to a certain point, at which there is a very small increase in MFAT score with increased flow allocation. This point is termed a breakpoint and identifies a solution at which there is a significant change in the ecological benefit obtained per unit allocation of environmental water, as mentioned previously. The locations of the breakpoints are shown in Figure 7, with BP1 through to BP5 referring to the breakpoints for Investigations 1–5, respectively.

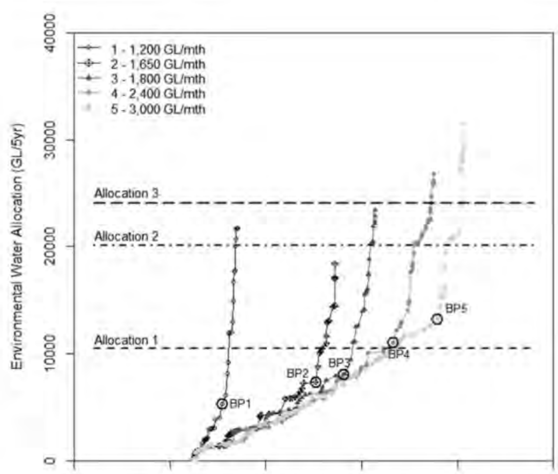

Figure 7. Optimal trade-offs between environmental water allocation (GL/5 yr) and MFAT score for Investigations 1–5.

Table 10. MFAT Score and Allocation at the Breakpoint for Each Investigation, as Well as the Rate at Which the MFAT Score Increases Per 1000 GL Environmental Allocation Before and After the Breakpoints

Investigation	MFAT Score	Allocation (GL/5 yr)	Change in MFAT Score/1000 GL in Region Before Breakpoint	Change in MFAT Score/1000 GL in Region After Breakpoint
1	0.15	5324	0.022	0.002
2	0.25	7350	0.034	0.003
3	0.28	8055	0.035	0.002
4	0.33	11,055	0.030	0.002
5	0.38	13,200	0.028	0.002

[61] The breakpoint values for each of the five investigations are given in Table 10. As can be seen, for Investigation 1, the breakpoint occurs at an MFAT score of 0.15 and an allocation of 5324 GL/5 yr. After this point, there is very little additional benefit in allocating more water, since the rate of MFAT score increase per 1000 GL is only 0.003, whereas the same value is 0.022 before the breakpoint. The breakpoints for the remaining four investigations are much more distinct (Figure 7 and Table 10). For Investigations 2–5, the increase in MFAT score/1000 GL of additional upstream release before the break point is approximately the same at around 0.03 (ranging from 0.028 for Investigation 5 to 0.035 for Investigation 3) and reduces significantly to less than 0.004 after the break point (ranging from 0.002 for Investigation 3 to 0.003 for Investigation 4). However, the flow allocation, and hence MFAT score, at which the breakpoints occur increases significantly from Investigation 2 to Investigation 5, indicating the increased benefits of additional environmental flow allocations as the upstream system constraints related to the maximum flow release are relaxed.

[62] The increased benefit of additional environmental flow allocations as upstream system constraints are relaxed can also be seen from the maximum MFAT scores that can be achieved, and the corresponding flow allocations (Table 11). The maximum MFAT score that can be achieved with the current system constraint (Investigation 1) is 0.17, which is much lower than those obtained as part of the other Investigations, which ranged from 0.27 for Investigation 2 (i.e., 1650 GL/month upstream flow release constraint) to 0.41 for Investigation 5 (i.e., 3000 GL/month upstream flow release constraint).

[63] The reason for the increase in MFAT scores with increasing system constraints is a corresponding increase in the maximum water level that can be achieved. For example, with the current system constraint (Investigation 1),

Table 11. Maximum MFAT Scores and Corresponding Allocations (GL/5 yr) for Each Investigation

Investigation	MFAT Score	Allocation (GL/5 yr)
1	0.17	12,000
2	0.27	14,400
3	0.31	22,125
4	0.36	26,000
5	0.41	29,500

some of the temporary wetlands, such as Cadell, and the higher elevated floodplains containing river red gums (*Eucalyptus camaldulensis*) and black box woodland (*Eucalyptus largiflorens*), which account for the majority of the species in the case study area (see Table 2), cannot be inundated. This, and the effect of drought, have resulted in the deterioration of many of the high lying floodplain species in the South Australian River Murray [*GSA*, 2012; *Overton et al.*, 2010]. In addition, current system constraints prevent the inundation of 50% or more of the floodplain area, which is a requirement for achieving higher MFAT scores for the floodplain species [*Young et al.*, 2003]. As discussed above and illustrated in Figure 7, at the current system constraint, MFAT scores are virtually independent of any additional environmental flow allocation, as the occurrence of the larger flow events needed to inundate key ecological assets is prevented.

[64] As the upstream flow constraints are relaxed to 1650 and 1800 GL/month, there are significant benefits associated with increased environmental flow allocations (Figure 7), as greater areas of the wetlands and floodplains can be inundated and two of the temporary wetlands (Cadell and Markaranka) can be filled, almost doubling the corresponding MFAT scores to 0.27 and 0.31, respectively (Table 11). This enables some of the important flora species to be restored or maintained. This trend continues as the constraints are relaxed further to 2400 and 3000 GL/month, with increased environmental flow allocations resulting in maximum MFAT scores of 0.36 and 0.41, respectively (Table 11).

[65] As can be seen in Figure 7, there are a number of step changes in the trade-off curves for Investigations 2–5, with points along the step changes for Investigations 2 (i.e., Points A–F) and 5 (i.e., Points 1–6) labeled and shown in Figure 8. For Investigations 2 and 5, each step change is the result of an additional major flow release (where a major flow release is defined as the largest flow release

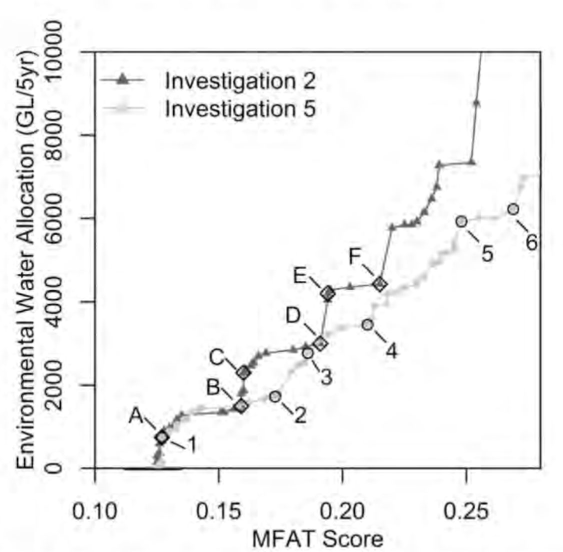

Figure 8. Optimal trade-offs between environmental water allocation (GL/5 yr) and MFAT score for Investigations 2 (i.e., 1650 GL/month) and 5 (i.e., 3000 GL/month).

relative to other monthly flow releases) over the five year planning horizon. For example, for Investigation 2, the region between points A and B included one major flow release, while the regions between points C and D and points E and F, included two and three major flow releases, respectively. Similarly, for Investigation 5, the regions between points 1 and 2 and points 5 and 6 included one and three major flow releases, respectively. For regions of the trade-off curves that included a particular number of major releases (e.g., regions A–B, E–F, 1–2, and 3–4, Figure 8), MFAT scores increased with little additional environmental water allocation as a result of the inundation of the temporary wetlands, Cadell and Markaranka. For example, flows greater than 1500 GL/month are required to inundate Cadell, which can only be achieved when the environmental allocation is greater than 1375 GL. Once this allocation is obtained for the planning horizon, Cadell's MFAT score can increase from 0.04 to 0.14, resulting in a significant increase in MFAT score with minimum additional environmental water (i.e., regions A–B).

[66] Overall, the results highlight the need to assess the impact of a range of upstream system flow constraints on the ecological integrity of the case study area. The limited ecological benefit of increasing environmental flow allocations at the current system constraints and the step changes in the trade-off curves, provide valuable insight to water managers and ensures that optimal EFMA schedules can be developed that use the available water in the most efficient manner, while also maintaining the integrity of the biota.

5.1.1.2. Trade-Off Between Environmental Flow Allocation, Wetland Ecological Response, and Floodplain Ecological Response

[67] The optimal tradeoffs between environmental water allocation, the ecological response of the wetlands and the ecological response of the floodplains in terms of the MFAT score that have been developed as part of Investigation 6 can be seen in Figure 9, where two slices of the three objective trade-off are shown. It can be seen in the top graph that the wetland MFAT score ranges from 0.20 to 0.45 as the environmental water allocation increases from 0 to 50,000 GL/5 yr. Additionally, there is an increase of 0.10 in the MFAT score as the allocation increases from 0 to 10,000 GL/5 yr mark. However, after this point, an additional allocation of 30,000 GL/5 yr is required to achieve the same increase of 0.10 in the wetland MFAT score. This suggests that after the 10,000 GL/5 yr environmental water allocation point, the ecological benefit for the wetlands as more water is added into the case study area is minor.

[68] It can also be seen in the top graph that there is very little spread in the points along the wetland MFAT score axis, indicating that the same wetland MFAT score can be achieved at a given environmental allocation, irrespective of the timing, magnitude, and duration of the management alternatives selected as part of the development of an EFMA schedule. In contrast, when comparing the trade-off between floodplain MFAT score and environmental water allocation in the bottom graph in Figure 9, it can be seen that the spread of points along the floodplain MFAT axis becomes greater at higher allocations. This suggests that at higher allocations, the scheduling of management alternatives (e.g., magnitude, duration) can have a major impact on the overall floodplain MFAT score, with differences in floodplain MFAT scores of 0.1 being obtained for a given allocation and wetland MFAT score. In addition, it can be seen that once the environmental water allocation of 40,000 GL/5 yr has been exceeded, the floodplain MFAT score begins to decrease to 0.10, suggesting that too much environmental water has been released, thereby prolonging inundation of these areas and reducing the overall ecological integrity of the floodplains. Finally, it can be seen that the overall floodplain MFAT score achieved is much less than that achieved for the wetlands. This is because of the system constraint (i.e., 1800 GL/month) considered in this investigation, which is not high enough to result in inundation of larger portions of the floodplains at higher elevations.

[69] Overall, this study highlights the valuable insights that can be obtained when assessing the trade-offs between different components of ecological response (in this case the wetlands and floodplains) and environmental water allocation. In particular, the sensitivity of the floodplain MFAT scores at higher allocations can provide further information to water managers, specifically in the selection

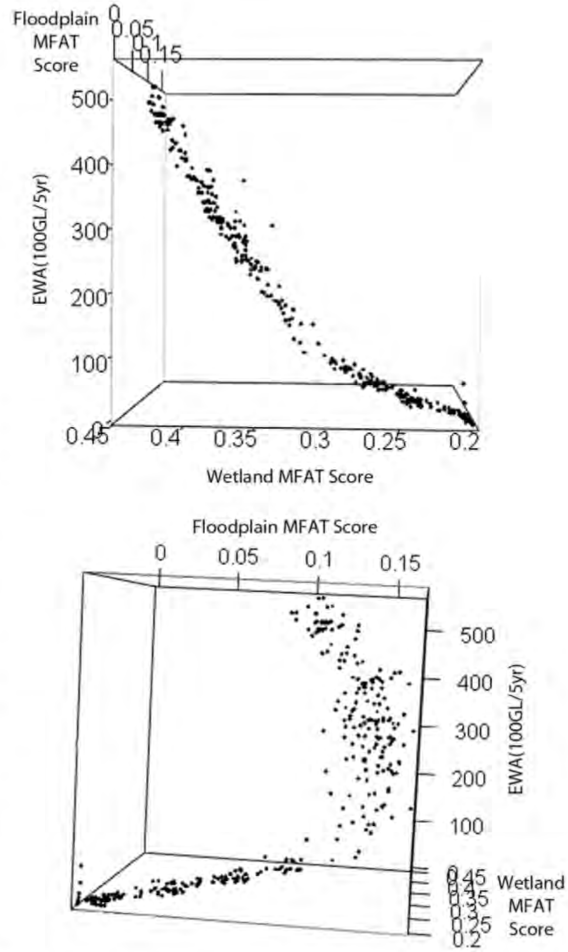

Figure 9. Optimal trade-off between environmental water allocation (EWA (100 GL/5 yr)) and wetland and floodplain MFAT score for Investigation 6.

Table 12. Maximum MFAT Scores for Each Allocation and Investigation

Investigation	Allocation 1	Allocation 2	Allocation 3
1	0.16	0.17	0.17
2	0.26	0.27	0.27
3	0.29	0.31	0.31
4	0.33	0.36	0.37
5	0.34	0.40	0.40

of the best EFMA schedule at higher allocations, which will ensure not only the best wetland ecological outcome, but also that for the floodplains.

5.1.2. Impact on Effectiveness of Various Environmental Flow Allocations

[70] The MFAT scores at the three suggested environmental flow allocations considered for each investigation are shown in Figure 7 and Table 12. It can be seen that for Investigation 1, an MFAT score of approximately 0.17 is achieved at each allocation, indicating that at the current system constraint of maximum upstream releases of 1200 GL/month, the allocation of environmental water above the current allocation in the MDB does not increase the overall ecological benefit within the case study area. As discussed in section 5.1.1, this is because the maximum possible flows are not sufficient to inundate the temporary wetlands and achieve the 50% floodplain area inundation needed in the MFAT calculation [*Young et al.*, 2003]. Similarly, there is very little change in MFAT scores for the different flow allocations for Investigations 2 and 3, with increases ranging from 0.01 to 0.02 when moving from Allocation 1 to Allocation 2, and no further increase in the scores when moving to Allocation 3. On the other hand, there is a slight increase in MFAT scores when moving from flow Allocations 1 to 3 for Investigations 4 and 5, with a maximum increase in MFAT score of 0.04 for Investigation 4 and a maximum increase of 0.06 for Investigation 5, suggesting that there is only a slight ecological benefit associated with increased environmental water allocations if the upstream flow release constraint is increased to 2400 GL/month or greater.

[71] Overall, the results suggest that there is limited ecological benefit beyond Allocation 1 (i.e., the current environmental allocation), while the upstream flow constraint has a significant impact. As discussed above, this is because the major factor affecting the ecological health of the case study area is whether the high lying wetlands and floodplains can be inundated or not. This requires the occurrence of high-magnitude flows, which simply cannot be achieved unless the upstream flow constraints are relaxed. However, this results in flooding of upstream agricultural and recreational (e.g., holiday houses) areas located adjacent to the Murray River, which can result in other problems, such as the loss of crops and profits. On the other hand, unless the system constraints are relaxed, the required ecological benefits within the case study area can only be achieved if natural major flooding occurs.

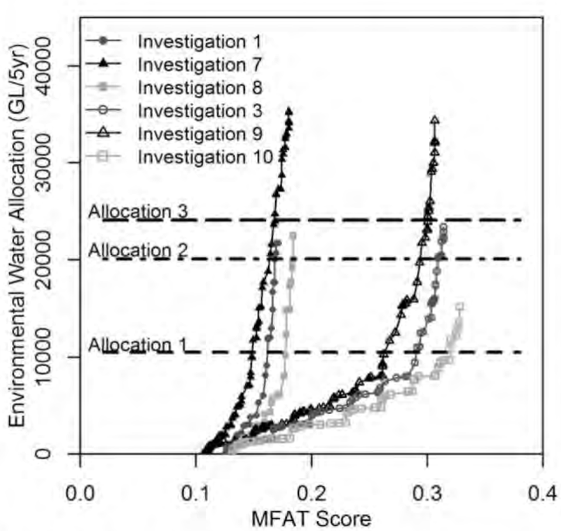

Figure 10. Optimal trade-offs between environmental flow allocation and MFAT score for Investigations 1, 3, and 7–10.

5.2. Impact of Additional Regulators

5.2.1. Impact on Optimal Trade-Off Curve

[72] The optimal trade-offs between environmental water allocation and MFAT score developed as part of the investigations discussed in section 4.2 are shown in Figure 10. As can be seen, the general shape of the trade-off curves is not affected by the number of regulators (i.e., zero, two, or five) for both upstream system flow constraints considered (i.e., 1200 and 1800 GL/month). However, there was a distinct advantage in the addition of more regulators, as indicated by a shift in the trade-off curves to the right with an increase in the number of regulators for both of the upstream system constraints.

[73] The maximum MFAT scores and associated environmental flow allocations for each investigation are given in Table 13. For Investigations 7 and 9, where no regulators are present, an environmental allocation greater than 29,000 GL/5 yr is required to achieve MFAT scores of 0.18 and 0.30, respectively. Once two regulators are in operation within the case study area (i.e., Investigations 1 and 3), a water saving of 20,000 GL/5 yr is achieved in order to obtain MFAT scores that are similar to those obtained in the corresponding investigations that considered no regulators. As the number of regulators in operation increases to five in Investigations 7 and 9, there is little difference in the scores and allocations obtained compared with those

Table 13. Maximum MFAT Scores and Associated Allocations Achieved for Each Regulator in Operation

Regulators	System Constraint (GL/month)	Investigation	MFAT Score	Allocation (GL/5 yr)
0	1200	7	0.18	32,478
	1800	9	0.30	29,100
2	1200	1	0.17	12,000
	1800	3	0.31	22,125
5	1200	8	0.18	17,750
	1800	10	0.34	15,225

obtained in the investigations where two regulators are used (i.e., Investigations 1 and 3).

[74] Overall, the use of two regulators for both system constraints considered does not alter the maximum MFAT score, but results in a substantial reduction in the environmental water allocation required to achieve this score. This suggests that the regulators are best used as water saving measures and would benefit areas where limited water is available as a result of drought or when multiple users are present, as is the case in the South Australian reaches of the River Murray.

5.2.2. Impact on Effectiveness of Various Environmental Flow Allocations

[75] The MFAT scores at the three suggested environmental flow allocations for each investigation are shown in Figure 10, Tables 14 and 15. It can be seen in Table 14 that at the current environmental allocation (i.e., Allocation 1), for the upstream system flow constraint of 1200 GL/month, the MFAT score increases marginally by 0.01 as the number of regulators increases from two to five. Once the allocation increases to the volume proposed by the MDBA (i.e. Allocation 2), the MFAT score gradually increases from 0.16 to 0.18 as more regulators are considered, while at Allocation 3 (i.e., the allocations proposed by environmental scientists), a 0.01 improvement in MFAT score is obtained when five regulators are taken into account. This indicates that at lower allocations, a marginal ecological benefit is achieved with the operation of two regulators, however, once the allocation increases to Allocation 3, a small improvement in MFAT score is only obtained when five regulators are in operation.

[76] The MFAT scores achieved for a system constraint of 1800 GL/month are given in Table 15 for each of the three environmental water allocations considered. It can be seen that at Allocation 1, there is a marginal increase in MFAT score of 0.03 when two regulators are considered, while the addition of three regulators increases the MFAT score by 0.01. On the other hand, for Allocations 2 and 3, a score of approximately 0.29 is achieved when no regulators are in operation, which increases to 0.31 and 0.34 as the number of regulators increases from two to five, respectively. This suggests that a positive impact can only be achieved at larger allocations when 5 regulators are considered, compared with the use of two regulators, which improved the score for all allocations.

[77] In summary, this study showed the improvement in MFAT scores achieved as additional regulators are introduced in the case study area for different environmental flow allocations. It showed that if five regulators are in operation, an improvement in MFAT score can only be achieved at higher allocations, while the use of two regulators can marginally improve the ecological health at lower allocations.

Table 14. MFAT Scores Achieved for Each Allocation and Investigation for the 1200 GL/Month System Constraint

		Allocations		
Regulators	Investigation	1	2	3
0	7	0.15	0.16	0.17
2	1	0.16	0.17	0.18
5	8	0.17	0.18	0.18

Table 15. MFAT Scores Achieved for Each Allocation and Investigation for the 1800 GL/Month System Constraint

		Allocations		
Regulators	Investigation	1	2	3
0	9	0.26	0.29	0.31
2	3	0.29	0.31	0.33
5	10	0.30	0.34	0.34

5.3. Limitations

[78] While the results obtained provide valuable insight into the management of environmental water in order to maximize ecological response, there are some limitations with the findings as a result of the uncertainties associated with the ecological scores calculated using the Murray Flow Assessment Tool (MFAT). The MFAT model uses preference curves to develop a relationship between flow and ecological response for species types, however, knowledge of these ecological relationships is imperfect, thereby introducing uncertainty into the model and the final results [*Fu and Merritt*, 2012]. To overcome this shortcoming, a sensitivity analysis, as conducted by *Norton and Andrews* [2006] and *Fu and Merritt* [2012] on the preference curves and/or aggregation approach, could be performed. Such an analysis would examine the robustness and variance of the likely ecological response that could be obtained for a given EFMA schedule. This would provide detailed information to water managers and further understanding of the likely ecological benefit that could be achieved for a particular EFMA schedule. However, such an analysis is beyond the scope of this study. Finally, it should be noted that the results and conclusions obtained from this analysis are only applicable to the case study area.

6. Summary and Conclusion

[79] In this paper, the optimization framework developed by *Szemis et al.* [2012] is extended to incorporate multiple objectives and applied to a real case study in the South Australian River Murray. The aim is to assess the trade-offs between environmental flow allocations and ecological benefits based on the impact of (a) upstream system flow constraints and (b) the number of regulators used to control the flow at wetlands. In order to achieve this, the performances of three multiobjective ACO algorithms (i.e., COMPETants [*Doerner et al.*, 2003], m-ACO_3 [*Alaya et al.*, 2007], and PACOA [*Doerner et al.*, 2004]) are compared, with the PACO algorithm found to perform best (see section 3.5.5). The PACOA is coupled with a hydrological model consisting of eight wetlands, five of which can be regulated. Each wetland is composed of a variety of flora and fauna species, obtained using DEM and baseline survey data of the case study area. The management options considered as part of the development of EFMA schedules include the scheduling of environmental flow allocations and regulator operations. The ecological benefit of each EFMA schedule developed is assessed using the Murray Flow Assessment Tool developed by *Young et al.* [2003],

while a hydrological model is used to determine the total environmental water allocation.

[80] Two studies are undertaken to achieve the objectives of the paper. In the first study, the impact of upstream system flow constraints on the optimal trade-off between environmental water allocation and ecological benefit is assessed, while in the second study, the effect of additional regulators on these trade-offs is investigated. The shape of the trade-off curve, the effectiveness of three different environmental water allocations and the impact of flow releases and gate operations on EFMA schedule development are analyzed for each study.

[81] The results of the first study indicate that increased environmental water allocations only have a positive ecological impact if the current upstream flow constraints are relaxed, which enables large areas of floodplain flora to be inundated. In addition, results from assessing the trade-offs between environmental flow allocation, floodplain ecological response, and wetland ecological response indicate that floodplain scores are more sensitive at higher allocations compared with the wetland ecological response. The results of the second study indicate that the addition of regulators only marginally improves the ecological response in the case study area, but that this can be achieved with significantly smaller volumes of water. In addition, the results obtained indicate that at lower system constraints (e.g., 1200–1800 GL/month), the allocations recommended by the MDBA and environmental scientists may be too large for the case study area, as only a marginal ecological benefit is achieved for Allocations 1–3. However, once the system constraints are relaxed, there is a significant improvement in the MFAT scores as environmental allocations increase from those recommend by the MDBA to those proposed by the environmental scientists.

[82] Overall, the studies provide valuable insight into the EFMA scheduling problem, particularly the ecological benefit gained from an increase in environmental allocation for a range of upstream system flow constraints and numbers of regulators. The approach presented in this study enables water managers to make informed decisions regarding the management of environmental releases, regulator operation, and investment in additional infrastructure, particularly when there is limited water available, as is the case for the South Australian River Murray.

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