

Compartmental Flow Modelling of Acute Care Hospital Bed Occupancy for Strategic Decision-Making

A thesis presented towards the degree of Doctorate of Philosophy

By

Mark Mackay BSc(Hons) BEc BComm

School of Psychology

University of Adelaide

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Abstract

The research presented in this thesis focuses on the investigation of whether the compartmental flow models of bed occupancy originally described by Harrison and Millard (1991) for decision-making around geriatric service care in the English National Health Service can be used to describe data from acute care hospitals in Australia and New Zealand.

Australia's total health expenditure for 2004-05 was \$87.3 billion. The use of health care services and expenditure pattern is well established and Australia follows the pattern found in most developed countries, with the greatest expenditure occurring on services for the elderly. Australia is experiencing a shift in population structure, with the proportion of older people forecast to increase. It is expected there will be a need for a greater level of expenditure on health care as the number of elderly people increase.

There is an emerging gap between the ability to supply health services and the demand for them. Furthermore, acute care hospital treatment is generally considered expensive and governments have been keen to control this expenditure.

It is imperative that governments are able to make decisions based upon robust policy advice. There are serious consequences in both economic resource allocation and patient (and population) health outcomes if decisions about future health service structures are incorrect. In particular, there is a need for better decision-making around bed management *at the strategic level*. Strategic decision-making relates to decisions that will occur in a longer time frame.

Decision-making can benefit from the use of modelling. Models represent a simplified version of reality that preserve the essential features of the situation being examined and can be used as a tool to investigate decision-making options, particularly in complex environments such as the health sector.

Historically decision-making relating to hospital beds has used either simple “back of the envelope” calculations or adherence to “rule of thumb” approaches. Most of the approaches have relied upon using the average length of stay metric. While the modelling of hospital bed numbers is not new, much of this work has relied upon the average length of stay, which is known to be a poor measure.

Harrison and Millard (1991) introduced the application of the compartmental flow model for modelling hospital bed occupancy and noted its potential to be used to influence policy decision-making. The flow model results are plausible and easily interpreted. However, relatively little work has focussed on the ability of these models to be generalized and be used for predictive purposes.

The research undertaken for this thesis consisted of a series of modelling experiments that can be grouped into two key stages: whether the models could be successfully applied to the acute care data; and whether the models could be used for novel purposes, such as forecasting, evaluation of service change, and benchmarking. This entailed the further development of the model, and a consideration of basic modelling issues such as the balance between data-fit and model complexity, in order to capture

better variation in the data and also to facilitate linkage to changes in population and seasonality.

Declaration Statement

This work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

I give my consent to this copy of my thesis, when deposited in the University Library, being made available in all forms of media, now or hereafter known.

Signed.....
(Mark Mackay)

Date.....

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Glossary and Abbreviations

A	The first parameter of the first compartment in the flow model that relates to the total number of occupied beds or patients in the first or short-stay compartment.
ABS	Australian Bureau of Statistics
Acute care hospital	A hospital that provides short-term medical care especially for serious acute disease or trauma
ALOS	Average length of stay
ARDRG	Australian refined diagnostic related group
ARIMA	Auto-Regressive Inductive Moving Average
B or b	The second parameter of the first compartment in the flow model that relates to the flow of patients through the first or short-stay compartment.
BIC	Bayesian information criterion
BOMPS	Bed Occupancy Management and Planning System

C	The first parameter of the second compartment in the flow model that relates to the total number of occupied beds or patients in the second or long-stay compartment.
D or d	The second parameter of the second compartment in the flow model that relates to the flow of patients through the second or long-stay compartment.
DRG	Diagnostic related Groups (see also ARDRG)
Elective admission	A planned admission of a patient into a hospital bed, as opposed to emergency admission.
Emergency admission	An unplanned admission of a patient into a hospital bed.
Long-stay patients	Patients who stay for a longer period of time than short-stay patients. Arises from the fitting of a double compartmental flow model to acute care hospital data. Long-stay is a relative term and differs when applied to alternative types of care paradigms, for example, geriatric care services (see also short-stay patients).
LOS	Length of stay

Short-stay patients	Patients who stay for a short period of time in an acute care hospital. Arises from the fitting of a double compartmental flow model to acute care hospital data. Short-stay is a relative term and differs when applied to alternative types of care paradigms, for example, geriatric care services (see also long-stay patients).
WSSE	Weighted Sum Squared Error.