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An artificial intelligence solution for heat flux estimation using temperature history; a two-input/two-output problem

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An Artificial Intelligence Solution for Heat Flux Estimation using Temperature History; A Two-Input/Two-Output Problem

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Abstract

In order to check the applicability of Artificial Intelligent (AI) techniques to act as reliable inverse models to solve the multi-input/multi-output heat flux estimation classes of Inverse heat transfer problems (IHTPs), In a newly reconstructed experimental setup, a two-input/two-two output (TITO) heat flux estimation problem was defined in which the radiation acts as the main mode of thermal energy. A simple three layer perceptron Artificial Neural Network (ANN) was designed, trained and employed to estimate the input powers (represent emitted heats-heat fluxes from two halogen lamps) to irradiative batch drying process.

To this end, different input power functions (signals) were input to the furnace/dryer's halogen lamps and the resultant temperature histories were measured and recorded for two different points of the dryer/furnace. After determining the required parameters, the recorded data were prepared and arranged to be used for inverse modelling purposes. Next, an ANN was designed and trained to play the role of the inverse heat transfer model. The results showed that ANNs are applicable to solve heat flux estimation classes of IHTPs.

1. INTRODUCTION

Direct and inverse problems are the two main classes of thermal modelling problems. In inverse problems, the temperature distribution is known and one of the following factors is missing: geometry, boundary conditions (i.e. heat flux), thermophysical parameters or initial conditions. On the other hand, direct problems deal with temperature estimation when all the aforementioned factors are known (Beck, et al., 1985, Kowsary, et al., 2006, Mirsepahi, et al., 2012, Mirsepahi, et al., 2013, 2014). In general, inverse heat transfer problems (IHTPs) are considered ill-posed problems (Necati Ozisik and R. B. Orlande, 2000). Two major approaches have been considered in heat flux estimation problems: whole domain and sequential approaches. The sequential approach should be used to solve a heat flux estimation problem in real time. Alternatively, the whole domain approach estimates heat flux for the entire operation time and requires temperature data for the duration of the operations. Tikhonov regularization is a prominent algorithm which was widely been used in whole domain heat flux estimations (Kowsary, et al., 2006). This study focuses on sequential heat flux estimation.

Optimisation-based methods and inverse modelling have been mainly used to estimate sequential heat fluxes. In inverse modelling, depending on the sequence of measured temperatures, a so called 'inverse' model is developed to estimate heat flux directly. Examples include linear filters (models). The development of inverse models using heat equations is challenging. Radiation, which adds non-linearity to the system (Howell, et al., 2003), further complicates this problem. On the other hand, in optimisation-based methods, the heat flux is guessed as input to the direct model of the system. Then, depending on the measured temperature of the system, the estimated heat flux is tuned (Kowsary, et al., 2006). The direct models are well posed; therefore, the same inverse modelling challenges do not apply to optimisation-based heat function estimation. Briefly, in inverse modelling, a model is identified to estimate heat flux in real time, whereas in the optimisation-based approach, using an optimisation method, heat flux values are estimated at each instant.

Many studies on irradiative thermal systems, which are characterized by the dominant heat transfer mode of radiation, confirm their complexity and importance in diverse engineering applications. A range of optimisation-based algorithms (e.g. conjugate gradient (Kowsary, et al., 2007), Levenberg–Marquardt (Payan, et al., 2015) and genetic algorithm (Kim, et al., 2004)) have been used in real-time heat flux estimations of irradiative thermal systems, whereas inverse modelling solutions are less addressed in the literature owing to their complexity (Chen and Wu, 2006, Erturk, et al., 2002, Fan, et al., 2002, Kowsary, et al., 2006, Li, 2001, Rukolaine, 2007).

In recent years, artificial intelligence (AI) techniques have been used to solve both direct (Ghanbari, et al., 2010) and inverse (Bertelli, et al., 2015) IHTPs. AI techniques do not use thermal equations in their algorithms. AI has triggered innovations in inverse models for real-time heat flux estimation in thermal systems (Chen, et al., 2011), including complex irradiative models (Mirsepahi, et al., 2013). Two advantages of AI inverse models make them superior to optimisation-based heat flux estimation methods. AI inverse models do not require prior knowledge of the thermophysical properties and numerical solutions of direct models of the system.

Mirsepahi et al. employed an ANN as an inverse model to estimate input power of (Heat flux) an irradiative furnace (Mirsepahi, et al., 2012). In their next study, some different AIs were compared to find the best AI (Mirsepahi, et al., 2013) and then several ANNs were compared in terms of accuracy and computational time (Mirsepahi, et al., 2014). All aforementioned studies have solely focused on single-input, single-output problems with promising results. To date, multiple input, multiple output (MIMO) applications have not been considered. However, real-world industrial applications of heat flux control areas suggest that a majority of industrial problems, especially in terms of inverse radiative solutions, are normally highly non-linear and multivariable with MIMO nature.

This study determines the applicability of AI to address TITO heat flux estimation problems, especially those involving radiation. To this end, an experimental setup was constructed to define the TITO heat flux estimation problem in an irradiative furnace/dryer. Then, an ANN was developed to serve as the inverse model. Details are described below.

2. TITO INVERSE MODELLING PROBLEM

For a system with two sources and two temperature sensors with input powers q_1 and q_2 and measured temperatures of T_1 and T_2, respectively, an inverse model for heat flux (input power) estimation is defined as follows:

$$\left(\hat{q}1\left(k-\frac{\tau_{d1}}{\tau_s}\right),\hat{q}1\left(k-\frac{\tau_{d2}}{\tau_s}\right)\right)=F_I\left[T_1\ \ k\ \ ,T_1\ \ k+1\ ,\ldots,\ T_1\ \ k+r_1\ \ ,T_2\ \ k\ \ ,T_2\ \ k+1\ ,\ldots,T_2\ \ k+r_2\ \right]$$

, (1)

In eq.1 τ_{d1} and τ_{d2} are the dead times for lamp 1 and 2 respectively when τ_s is the sampling time. The time needed for heat sources to influence the temperature is called delay r_1 and r_2 are the orders of the inverse model, the number of temperature samples used in the real time heat flux estimation. Variables with the hat symbol are estimated values. Obviously, real-time estimation includes a reasonable estimation delay $=t_d+r_I.t_s$. The problem is how to identify F_I.

3. EXPERIMENTAL SETUP

The irradiative dryer/furnace had enough capacity for two radiation heat sources (halogen lamps) and several temperature sensors (T type thermocouples). Both the lamps and thermocouples are arranged non-symmetrically to ensure that more complicated modelling/control problems can be employed to check different methodologies.

In this study (Fig. 1a), the system included two radiative heat sources(lamps) and two temperature sensors. The lamps were hung above the top surfaces in two different chambers. The chambers were connected through a hole (the large red coloured point) on the divider surface. The thermocouples were at the bottom and on the left surface of the two chambers (two small red coloured points). The lamps and thermocouples were non-symmetrically arranged to provide a more complex modelling challenge. Owing to this lack of symmetry, the effects from either lamp on the temperature sensors were unique.

The resulting TITO control problem is strongly coupled, strongly interactive and highly non-linear.

The dryer body was constructed using insulation boards(20mm thick) and a steel frame(Fig. 1b). An amplifier was employed to increase the output voltages of the thermocouples and to direct this signal to a digital input-output card connected to the computer. The control command was sent to the power amplifier unit from the MATLAB program. The power controller (power amplifier) varied the input voltages to the lamps depending on the magnitude of the signal received from the computer (Fig. 2).

In the MATLAB environment, the real time windows target (RTWT), which is a prototyping toolbox, was employed to connect the furnace/dryer to the computer to facilitate data gathering. RTWT employs a single computer as both host and target PC(Fig. 2).

4. SOLUTIONS TO A REAL PROBLEM USING ARTIFICIAL INTELLIGENCE

The problem is the heat flux estimation of an infrared dryer (Fig. 1) using the measured temperatures of two points at two shown surfaces. To identify F_I in Eq_1, the delay time, orders, sampling time and dead times should be found first. Then, the appropriate AI should be trained and checked. The accomplishment of the aforementioned tasks is reported in the following subsections.

4.1. Identifying The Inverse Model, FI

The orders r1 and r2 (Eq. 1) are 5 and 3, respectively. The delays τ_{d1} and τ_{d2} are 1 and 0.8 seconds, respectively, and the sampling time τ_s, is 2 seconds. An ANN network with three layers of neurons was designed to be trained using the prepared data. Input and output layers have 8 (Equation 5) and 2 (two lamps input power) neurons respectively with linear activation functions having a slope of one. The hidden layer has 17 neurons. The number of neurons were determined by trial and error , the initial guess was 17 ($= 2\times 8+1$) (Nguyen and Widrow, 1990). The training method is Levenberg-Marquardt batch error back propagation. The ANN has been trained in 78 epochs (iterations) and the performance function is the mean of squared errors (MSE). Among the available series data, 30% was used for training and the rest for validation (to avoid overfitting) on a random basis.

4.1.1. Data Preparation

The experimental data for the transient mode are stored in a matrix with four columns:

$$A=\begin{bmatrix} q_{11} & q_{21} & \cdots & T_{11} & T_{21} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ q_{1n} & q_{2n} & \cdots & T_{1n} & T_{2n} \end{bmatrix}, \qquad (2)$$

n is the number of collected data points, A is the matrix of raw recorded/sensed data and q_{1i} and q_{2i} (first and second columns) are input powers for the first and second lamps, respectively. T_{1i} and T_{2i} (third and fourth columns) are the recorded temperatures for the first and second thermocouples, respectively.

As mentioned before, the delay or dead time of the system were determined to be 1and 0.8s for the first and second thermocouples, respectively. The sampling time (2s in this study) and the orders are 5 and 3 for the first and second sensed temperatures, respectively. The method of finding aforementioned variables can be found in (Mirsepahi, et al., 2012):

$$B=\begin{bmatrix} q_{1(1)} & q_{2(1)} & T_{1(d)} & T_{2(D)} \\ \vdots & \vdots & \vdots & \vdots \\ q_{1(n-D+1)} & q_{2(n-D+1)} & T_{1(n-D+d)} & T_{2(n)} \end{bmatrix}, \tag{3}$$

where B is a matrix of data with consideration of dead time; $d=\frac{\tau_{d1}}{\tau_s}$ and $D=\frac{\tau_{d2}}{\tau_s}$ and D > d.

For an inverse model with the order of R for the first thermocouple and r for the second, where R > r, the data should be arranged in a matrix as shown below:

$$C=\begin{bmatrix} \overbrace{\begin{matrix} T_{1(d+1)} & \dots & T_{1(d+R)} & T_{2(d+1)} & \dots & T_{2(d+r)} \end{matrix}}^{Input} & \overbrace{\begin{matrix} q_{1(1)} & q_{2(1)} \end{matrix}}^{Output} \\ \begin{matrix} \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{matrix} & \begin{matrix} \vdots & \vdots \end{matrix} \\ \begin{matrix} T_{1(n-R+1)} & \dots & T_{1(n)} & T_{2(n-r-R+1)} & \dots & T_{2(n-R)} \end{matrix} & \begin{matrix} q_{1(n-d-r-R+1)} & q_{2(n-d-r-R+1)} \end{matrix} \end{bmatrix}, \tag{4}$$

where C is a matrix of the prepared data.

The predicted/estimated variables are shown with a hat. After applying two dead times and orders, a set of 1000 pieces of recorded data were prepared as shown in (5):

$$PD=\begin{bmatrix} \overbrace{\begin{matrix} T_{1\,6} & T_{1\,7} & T_{1\,8} & T_{1\,9} & T_{1\,10} & T_{2\,5} & T_{2\,6} & T_{2\,7} \end{matrix}}^{\text{Input}} & \overbrace{\begin{matrix} q_{11} & q_{21} \end{matrix}}^{\text{Output}} \\ \begin{matrix} T_{1\,7} & T_{1\,8} & T_{1\,9} & T_{1\,10} & T_{1\,11} & T_{2\,6} & T_{2\,7} & T_{2\,8} \end{matrix} & \begin{matrix} q_{22} & q_{22} \end{matrix} \\ \begin{matrix} \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{matrix} & \begin{matrix} \vdots & \vdots \end{matrix} \\ \begin{matrix} T_{1\,995} & T_{1\,996} & T_{1\,997} & T_{1\,998} & T_{1\,999} & T_{2\,994} & T_{2\,995} & T_{2\,996} \end{matrix} & \begin{matrix} q_{1\,990} & q_{2\,990} \end{matrix} \end{bmatrix} \tag{5}$$

5. EXPERIMENTAL RESULTS

After training the recorded data, the ANN model was designed to study heat flux estimation problem. To validate the proposed model, four different temperature functions in both points (i.e. different from those used ones in the training part) were chosen. Their resultant temperature functions were prepared in the same manner as the training data and applied to the ANN. The resultant input heat/power functions were then calculated by the ANN. Next, the estimated input heat/power functions were compared with the real input heat/power functions set for the furnace/dryer (Fig. 3 & 4).

Estimated inputs obtained from the optimisation method resulted in a mean absolute error of 6.045 W over the four chosen benchmarks.

$$E_{mean} = \frac{\sum_{i=1}^{N} \left| \hat{Q}\ i\ - Q\ i\ \right|}{N} \qquad (6)$$

In eq. 6, N is the number of data points after the data preparation process and Q is the amount of heat input. The accuracy of the estimation is considered to be acceptable with a temperature sensing error of ±1°C. Figures 3 and 4and Table 1 show the accuracy of the proposed ANN model.

Here is a summary of advantages of the proposed method:

- The solution procedures for optimization based methods are iterative. The possibility of error is tremendously high for such methods and they are usually time-consuming (Chen and Wu, 2006, Dul'kin and Garas'ko, 2008, Fan, et al., 2002, Park and Jung, 2001), but in the proposed method this constraint does not exist. In ANN the only iterative part is in training which is containing simple mathematical relations, therefore proposed method is much faster than optimization based methods.

- In almost all optimization based methods, detailed and accurate physical properties are needed. The unavailability of such properties makes the solution so difficult (impossible in many cases) and require simplified unrealistic assumptions (Chen and Yang, 2007, Chen, et al., 2007, Chen, et al., 2008, Dantas, et al., 2003, Dul'kin and Garas'ko, 2002, 2008, Fan, et al., 2002, Gejadze and Jarny, 2002, Huang and Yeh, 2002, Huang, et al., 2003, Huang and Tsai, 2005, Park and Jung, 2001, Park and Lee, 2002, Rukolaine, 2007). The introduced method does not need physical properties as it is only based on input and output data.
- In many optimization based methods, the direct problem must be solved first. Therefore, the resulting solution will be subject to serious computing errors and time-consuming calculations(Chen and Jaluria, 2007, Chen, et al., Dul'kin and Garas'ko, 2008, Rukolaine, 2007). Conversely, in introduced method, there is no need to solve the direct problem.

6. CONCLUSIONS

MIMO problems are more applicable for industrial purposes. When using an irradiative batch dryer, a new TITO problem in real-time heat flux estimation problems is defined. For this purpose, heat was applied through two halogen lamps hung from the top surface of the dryer and temperature functions were measured by the two thermocouples. After processing the recorded data, an ANN was designed and trained to directly check the applicability of AI techniques to estimate heat fluxes (input powers). This model was capable of receiving the temperature function histories of the points used to estimate the input heat/power functions applied to the system. It was confirmed that the energy input functions estimated by the proposed ANN matched the real heat/power functions applied during the experiment.

To validate an accurate ANN model for power/heat source estimation, only one series of temperature distribution functions and input heat/power data are required. Neither knowledge of dimensions nor thermos-physical properties are required. An additional advantage is that the training part of the ANN design process only consists of a limited number of basic mathematical calculations apart from any recursive computation. It can be concluded that heat transfer modelling using AIs is very quick when compared with classical optimisation-based methods.

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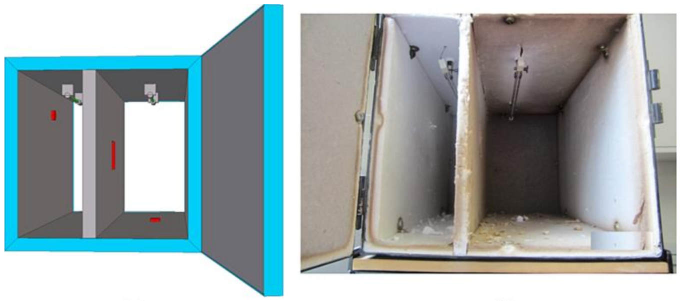
Table 1 Errors associated with the model for four different functions

	Error Series1		Error Series 2		Error Series 3		Error Series 4	
	Lamp1	Lamp2	Lamp1	Lamp2	Lamp1	Lamp2	Lamp1	Lamp2
E_{mean} (W)	3.0	3.5	4.0	5.0	4.5	4.8	11.20	12.36
E_{max} (W)	16.0	17.0	28.0	29.0	22.0	21.8	26.42	27.46

Figure 1. The experimental setup a) The arrangement of lamps and thermocouples in the studied dryer/furnace b) Two halogen lamps with their clamps



(a) (b)

Figure 2. Connected signals in the experimental setup

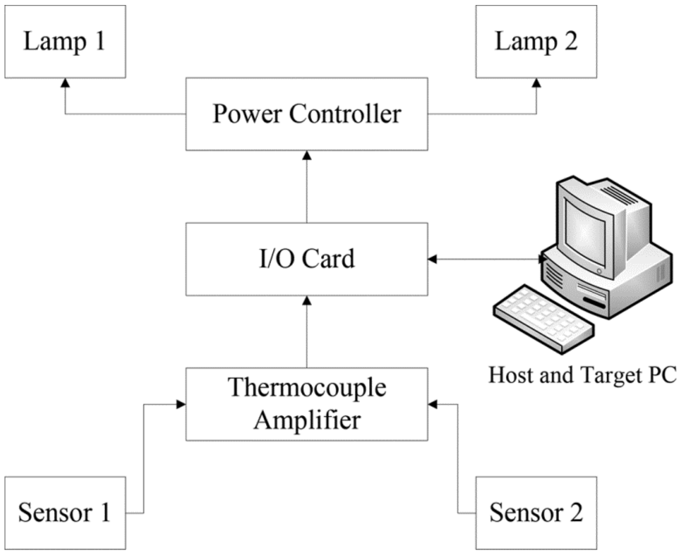


Figure 3. The accuracy of proposed AI (inverse) model (the first two sets of checking data)

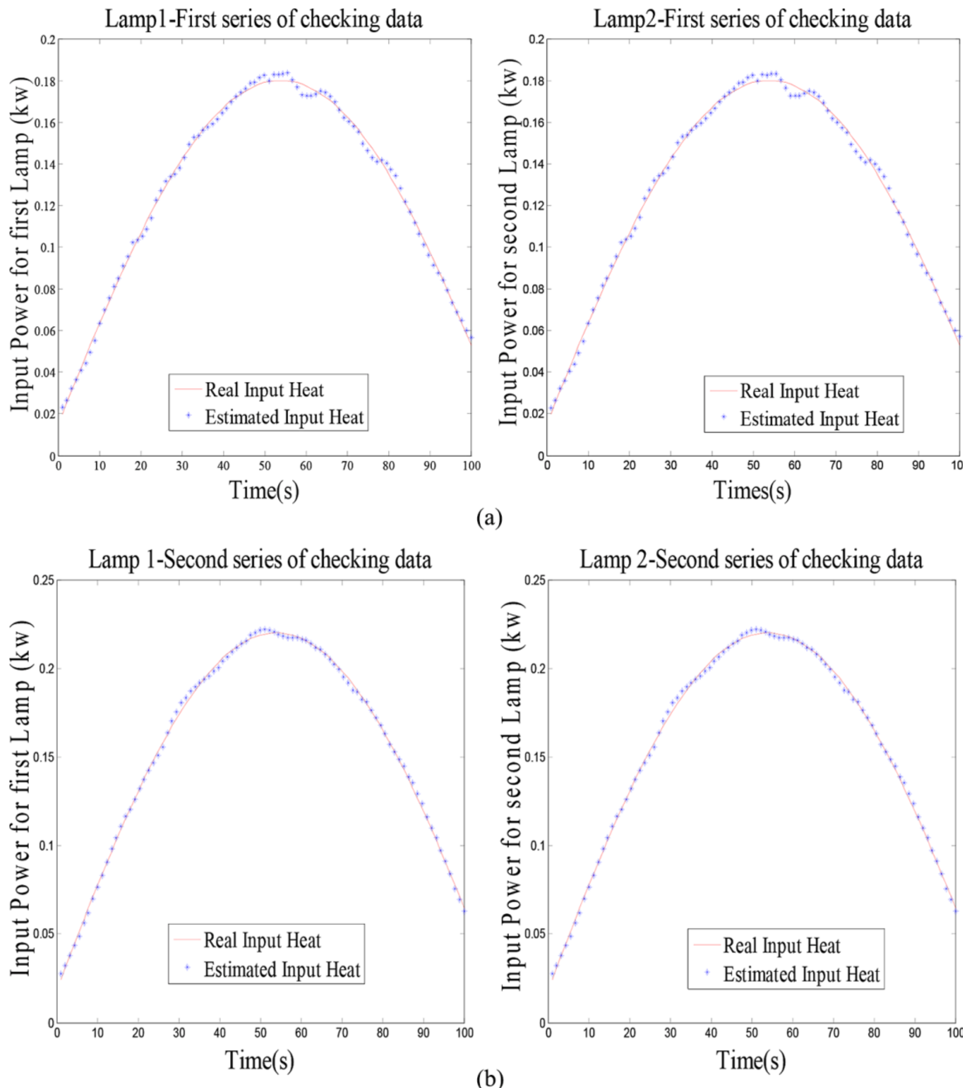


Figure 4. The accuracy of proposed AI (inverse) model (the second two sets of checking data)