An Intelligent Approach to Inverse Heat Transfer Analysis of Irradiative Enclosures

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Abstract

This is a thesis by publication for a PhD degree of engineering in the university of Adelaide. The current dissertation comprises five published/submitted journal articles. Three of these journal papers have already been published in the journal of "International Communications in Heat and Mass Transfer" and one has been accepted by the editorial board of "Chemical Engineering Communications". This study, based on research undertaken in the area of Inverse Heat Transfer Problems (IHTP), aims at analyzing the applicability of Intelligent Techniques (ITs) to solve sequential (real-time) heat flux estimation class of IHTPs, especially those involving in the most complicated form of heat transfer , radiation. Currently, several optimization based methods have been developed and applied to solve heat flux estimation problems. These methods normally require detailed and accurate information regarding physical properties. Often, the measurement of such physical properties is extremely difficult, if not impossible. Moreover, all optimization-based methods require that the direct problem must be solved first. This constraint of the need for iterated direct problem solutions can produce significant computing errors and calculations may be excessively time-consuming. This thesis offers new inverse models to estimate heat flux based on a sequence of measured temperatures. The offered models developed by ITs, in accordance with the achievement of this research, only requires a series of temperature-input heat data for a few minutes of operation; the dimensions and thermophysical properties are not needed. As another significant advantage, the estimation stage by the trained ITs only includes a small number of simple calculations excluding any recursive computation; this means the method is very fast-paced in comparison with classical avenues of numerical heat transfer for similar problems.

At the outset, the most general form of ITs in engineering applications, Artificial Neural Networks (ANNs), employed to formulate an inverse model in the studied furnace/dryer (see chapter 4). The promising results confirmed that ITs are sound candidates to create inverse models. In that study, some deficiencies in ANNs such as finding the relevant parameters by trial and errors motivated the authors to check GA-ANNs and ANFIS as the possible alternatives for ANNs. The comparison study between aforementioned methods (see chapter 5) provided good outlines to find the best method in different situation. As the ANNs

optimized by Genetic Algorithms (GA) discovered as the best method in the chapter 5, different types of ANNs were compared to find the best one (see chapter 6) in terms of accuracy and computation time. The results demonstrated that Multilayer Perceptron (MLP) optimized by GA can perform the best among all studied ANNs.

Since the literatures lack of a practical comparison between the proposed and optimization based methods, as the next phase of study, these two method were compared (see chapter 7) to reconfirm the superiority of inverse models developed by ITs. In the last stage (chapter 8), a two -input/ two-output problem defined to check the capability of the proposed method in the problems more closer to the real-world industrial applications.

In short, a series of very accurate methods for inverse heat transfer problems is proposed and successfully tested using experimental data.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, 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. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Preface

This thesis is submitted as a portfolio of publications according to the "*PhD Rules & Specifications for thesis*" of the University of Adelaide. The journals in which the papers were published or submitted are closely related to the research field of this work. The citation is listed and the journals are ranked in the order of the impact factor in reference to their scientific significance (Journal Citation Report 2007, Thomson ISI).

The main structure of this thesis is based on the following three published, one accepted and one submitted papers:

1. **Mirsepahi, A**., M. Mohammadzaheri, L. Chen, and B. O'Neill, "An artificial intelligence approach to inverse heat transfer modeling of an irradiative dryer". International Communications in Heat and Mass Transfer, 2012. 39(1): p. 40-45. Copyright of this paper belongs to Elsevier Ltd. (Chapter 4).
2. **Mirsepahi, A**., L. Chen and B. O'Neill, "A comparative artificial intelligence approach to inverse heat transfer modeling of an irradiative dryer". International Communications in Heat and Mass Transfer, 2013. 41: p. 19-27. Copyright of this paper belongs to Elsevier Ltd. (Chapter 5).
3. **Mirsepahi, A.,** L. Chen and B. O'Neill, "A comparative approach of inverse modelling applied to an irradiative batch dryer employing several artificial neural networks". International Communications in Heat and Mass Transfer, 2014. 53: p. 164-173.Copyright of this paper belongs to Elsevier Ltd. (Chapter 6).

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1. **Mirsepahi, A**., L. Chen and B. O'Neill, " An artificial intelligence solution for heat flux estimation using temperature history: a two-input/two-output problem". Submitted to Chemical Engineering Communications. Copyright of this paper belongs to Elsevier Ltd. (Chapter 6).

2. **Mirsepahi, A.,** Mehdizadeh, A., L. Chen and B. O'Neill, " Comparison of Inverse Modelling and Optimization-Based Methods in the Heat Flux Estimation Problem of an Irradiative Dryer/Furnace". Submitted to Journal of Computational Science. Copyright of this paper belongs to Elsevier Ltd (Chapter 7).

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Chapter 1

INTRODUCTION

1.1 Introductory background

Heat transfer involves the transport of energy due to temperature gradients. There are three different modes of heat transfer: Conduction in which temperature gradients arise in solid or fluid media; Convection where energy is transferred between a surface and a passing fluid that are not at thermal equilibrium; and radiation in which electromagnetic waves are emitted from surfaces at finite temperatures [1, 2].

Heat transfer remains a significant field of interest to engineering researchers, designers, developers, and manufacturers. Applications include a wide variety of systems and components of energy devices used in power plants, heat exchangers, high performance gas turbines and other power conversion systems. In addition, applications are ubiquitously found in chemical processes, general manufacturing, bio-heat transfer, electronic cooling, comfort heating and cooling towers [3].

Thermal processes play an important role in plethora engineering applications. Energy consumption resulting from thermal processes has always been a major concern in industry, hence a significant amount of research has been undertaken to devise the most efficient methods to minimize the energy consumption of thermal process [4-6]. The most important criterion which strongly influences our ability to reduce the energy consumption of thermal processes is the accuracy of the model of thermal processes. In other words, to what extent the model can reliably predict the behavior of thermal systems in order to avoid wasting energy, which can help to minimize the production of greenhouse gases and environmental footprints [4, 6]. Consequently, many investigations have been undertaken to improve and develop robust modeling strategies [7-9]

Each system needs an efficient and reliable method and model for process identification. The main purpose of process modeling is to predict plant behavior and to drive the process to operate at its optimal production rate [6].

Heat transfer modelling problems can be divided into two separate categories: direct and inverse problems [10]. Thermophysical properties, boundary, and initial conditions are all known in direct problems. The purpose of the solution of a direct problem is to determine the temperature distribution for a geometrically well-defined domain [11]. Direct heat transfer problems are usually considered to be “well-posed”. Conversely, inverse heat transfer problems are normally “ill-posed” [10]. In these problems, there is a lack of knowledge in boundary conditions, initial conditions or thermo-physical properties. These unknowns are to be estimated using measured temperature data at one or several locations within the domain. As a consequence of the ill-posed nature of the problem, unavoidable random errors (noise) in the measured data may induce errors which are amplified by several orders of magnitudes and the unknowns may be poorly estimated. Hence, inverse heat transfer problems are considered to be more “difficult” than direct heat transfer problems [10-13].

Industrial heat transfer processes are often highly complex and the modeling of such processes is a difficult task because of the large number of physical parameters for the heat transfer media [14, 15]. Optimization based (classical methods in some part of the current thesis) methods used for such modelling are primarily based on energy balances and rate equations which allow us to develop and solve the governing differential equations [16]. Unfortunately, these models are quite complex and the resulting highly non-linear differential equations are seldom solvable by analytical solutions [14]. As a consequence, numerical solutions normally have to be employed [17-22].

Additionally, existing mathematical models are predicated on many assumptions due to the complexity of heat transfer systems [18, 21] and many of these simplifications may conflict with the real conditions of operation. Further, many systems are not easily modeled mathematically [15] due to anisotropic properties, complex geometries, unknown thermodynamics, etc. and such difficulties mean that classical methods may not be suitable.

A significant body of research on inverse heat transfer problems has accumulated in the past thirty or so years [23]. A classical method for the solution of inverse design problems is to guess an input for heat flux and then employ mathematical models to check the accuracy of the desired temperature distribution. The guessed heat flux is then modified based on previous results. Such methods are known as trial-and-error methods. They are time consuming and computationally expensive, in addition, smooth and physically feasible solutions are exceedingly difficult to achieve [24].

Commonly applied techniques applied to solve inverse heat transfer problems are the least squares methods modified by the addition of regularization. Unfortunately, the regularization imposes more restrictions on the permissible solutions. These iterative algorithms require multiple solutions of the governing equations. In addition, a complete data base is required which makes them non-recursive [25].

In classical methods, detailed physical property data are normally required [23, 26, 27]. In many cases the measurement of such physical properties is extremely difficult - if not impossible. Moreover, in order to use all classical inverse models, the direct problem must be solved first. This constraint of repeated solutions of the direct problem can produce significant computing errors and calculations may be excessively time-consuming [10, 23, 24, 26-28].

In such situations, new methods such as "Intelligent Techniques" which are based on other forms of knowledge about the system may produce more accurate solutions in a reasonable time frame. Intelligent techniques exploit experimental data rather than mathematical equations, consequently detailed knowledge of physical properties may not be necessary. Intelligent techniques are able to model complex systems without the need for complex mathematical models. Input and output data are the sole requirement for the application of "Intelligent Techniques" to model systems. This is the principal reason that many researchers adopt intelligent techniques for the analysis of complex systems [29]. They can be also employed to avoid time consuming calculations.

1.2 Literature review and significance/contribution

1.2.1 Inverse heat transfer problems

Applications for a diverse array of inverse heat transfer problems (IHTP) have been increased in many branches of engineering especially in chemical, mechanical and aerospace engineering [30]. IHTPs are typically ill-posed in a mathematical sense and the solution of those problems are difficult, in contrast to the standard heat transfer problems which are normally well-posed [30].

The solution of a well-posed problem should satisfy three conditions: the solution must exist, unique and stable. Conversely, the existence of solution may be proved by physical reasoning but IHTPs are extremely sensitive to the existence of errors in measured data. Consequently, to satisfy stability condition, special techniques are needed in IHTPs [11, 31, 32]. An inverse problem can be solved when it is reformulated as an appropriate well-posed problem.

Application areas of inverse heat transfer:

- Estimation of thermo-physical properties of material [11, 26, 33, 34].
- Estimation of bulk radiation properties and boundary conditions in absorbing, emitting and scattering semi-transparent materials [11, 35-40].
- Control of the motion of the solid liquid interface during solidification [11, 41, 42].
- Estimation of inlet condition and boundary heat flux in forced convection inside ducts [11].
- Estimation of interface conductance between periodically contacting surfaces [11, 43].
- Monitoring the radiation properties of reflecting surfaces of heaters and cryogenic panels [11, 31, 32].
- Estimation of heat release during friction of two solids [11, 31, 32].
- Estimation of reaction function [11, 44].
- Control and optimization of the curing process of rubber [11].
- Estimation of the boundary shapes of bodies [11].
- Estimation of the temperature or heat rate distribution within the combustion region [23]
- Estimation of source term or temperature distribution in radiative heat transfer [23, 25, 27, 39, 45, 46].

1.2.2 Literature survey in classical (optimization based) methods

In this review, several classical methods in inverse heat transfer have been surveyed in order to find the most prominent methods employed in the literature:

Li [28] presented an approach for the estimation of the source term of two-dimensional cylindrical absorbing, emitting and scattering gray medium. Minimization of the square of errors was employed in order to solve inverse problems. Park and Yoo [37] considered an inverse radiation problem of determining the time-varying strength of a heat source. In their study radiation and conduction occurred simultaneously. A conjugate gradient method was employed to solve inverse problems. Fan et al. [23] presented a new inverse analysis in order to estimate the heat rate and temperature distributions in combustion region from the information of the temperature and heat flux profiles of wall elements in that system. They employed the Monte-Carlo method to solve direct problems and the conjugate gradient method for inverse use. Park and Lee [47] employed the modified conjugate gradient method to determine the time-varying strength of a heat source from temperature measurements in three dimension participating mediums where radiation and conduction occurred simultaneously. Lu and Hsu [40] conducted RMC (Reverse Monte Carlo method) for transient radiative transfer process within absorbing, scattering and non-emitting participating media. This method took up much less computational time than the Monte Carlo method. Chen and Wu [26] used the finite difference method in conjunction with the least-squares cubic spline and temperature measurements to predict the distribution of the heat transfer coefficient on a surface exposed to a moving fluid. Pourshaghagh et al. [36] presented an algorithm for inverse design of radiative furnaces filled by a scattering medium. Radiative heat flux solved the issues by means of Modified Discrete Transfer Method (MDTM) using the correction factors and for inverse designs, they employed conjugate gradient method. Kim and Baek [38] solved an Inverse Conduction-Radiation problem in a two-dimensional concentric cylindrical absorbing, emitting and isotropically scattering medium. They employed the finite-volume method for direction and Levenberg-Marquardt method for inverse problems. The direct problem was to calculate the total heat flux on one design surface and the inverse problem was to estimate boundary temperature on heater surface and resulting total heat flux on the heater and design surface. Rukolaine [27] presented the adjoint problem method in iterative regularization with Tikhonov and parametric inverse heat transfer problems in radiation. During their method, regularization is first applied to an original inverse problem and then regularization was fulfilled by solving the direct problem. The adjoint problem becomes linear, even if the original was nonlinear. Mossi et al. [48] worked on an inverse boundary design problem which involved convection and radiation heat transfer. They found the heat flux distribution required on heaters located on the top and side walls of a two-dimensional enclosure. Truncated Singular Value Decomposition (TSVD) was used in order to solve that inverse problem. Liu et al. [35] presented an inverse radiation analysis for determining the three dimensional temperature field. The forward Monte Carlo method was used to describe the radiative energy propagation. The inverse problem was formulated as an ill-posed matrix equation and was solved by the least square QR decomposition (LSQR) method. The direct problem was to find the exit radiation energy received by CCD cameras at the boundary surfaces for unknown temperature field and radiative properties. In the inverse problem, the temperature field was regarded as unknown. Wang et al. [49] presented a backward Monte Carlo method to determine the three-dimensional (3-D) temperature distribution in a large rectangular enclosure containing the participating medium. For the inverse problem, the temperature distribution was regarded as unknown and the inverse problem was solved by the least square conjunction gradient (LSQR) method.

Commonly used techniques to solve inverse heat transfer problems are the least squares methods modified by the addition of regularization. Regularization imposes more stringent restrictions on the permissible solutions. The iterative algorithms require repeated solutions of the governing energy transfer equations[25].

The classical non trial-error based methods such as conjugate gradient (CG) and Levenberg-Marquardt are capable of estimating the solution in short time in comparison to trial-error based methods [50] but the resulting mathematical problems are challenging and must be solved simultaneously. In addition, if the initial guess is poor, an infeasible solution may be obtained or in a worse case, the solution may not be convergent [51]. In such instances, non trial-error based methods can only provide a local minimum solution depending on the initial value [51]. As an alternative to classical non trial-error based methods, evolutionary methods, such as genetic algorithms have been received increased attention because of their ease of coding and superior convergence characteristics when applied in non-linear optimization problems. The results were promising but some deficiencies have been observed in genetic algorithms (GA). Moreover, GA and other evolutionary algorithms require large populations and involve long computing times for convergence which make them inappropriate for many inverse heat transfer problems [52].

1.2.3 More critical literature review in classical methods

A critical review has been conducted in Chapter 2, the great body of this section reviews four prominent classical methods to find their constraints and limitations.

1.2.4 The classical methods limitations

As mentioned previously, the problems involved in the use of classical methods can be categorized as follows:

- The solution procedure of some of classical methods is based on trial-and-error. The probability of error is extremely high for such methods and they are normally time-consuming [23].

- Iterative methods inherent in other classical methods also incur heavy penalty of long time for convergence [27, 28].
- Detailed and accurate physical properties are needed in many classical methods. Their unavailability makes the solution difficult to achieve (impossible in some cases) and necessitate simplified (and often physically unrealistic) assumptions given the complexity of heat transfer systems [23].
- In order to use classical methods, the direct problem must be solved first. The resulting inverse solution is susceptible to serious computing errors and time-consuming calculations are required [23].

1.2.5 A survey on employing intelligent techniques in heat transfer

Intelligent techniques are accepted as a technology offering an alternative way to tackle complex and ill-defined problems. Intelligent techniques have also been used in system modeling [23], control [23], robotics [53], forecasting [53, 54], power systems [53] and optimization [53].

Cortés et al. used an Artificial Neural Network (ANN) to solve an inverse heat transfer problem. The problem involved a heat conduction problem with internal heat source in cylindrical coordinates [55]. Mittal and Zhang used ANN for real-time calculations of the air properties required in drying of agricultural and food materials, and for ventilation of farm buildings [54]. Bhattacharjee and Kothari used ANN to predict of thermal residence of textile fabrics [56]. Spieker et al. used Neural Network for modeling of several thermal processes [6]. Radhakrishnan and Mohamed worked on developing a neural network based soft sensor for online estimation of the composition variables in the hot metal and slag in a blast furnace [57]. Fan et al. presented a new inverse radiation analysis for estimating the heat rate and temperature distributions in the combustion region from the information of the temperature and heat flux profiles of wall elements in the system [23]. Sablani and Shafiur Rahman presented an ANN model for the prediction of thermal conductivity of food as a function of moisture content, temperature and apparent porosity [58]. Hernández et al. proposed a predictive model for heat and mass transfer using ANN to obtain online predictions of temperature and moisture kinetics during the drying of cassava and mango [59]. Sablani et al. presented ANN models to allow prediction of the convective heat transfer coefficient at the surface of a cube and semi-infinite plate from measurement of the temperature-time history inside the solid body [60]. Pedreñ-Molina et al. applied neural architecture to model and predict the sample temperature and moisture content evolution in microwave assisted drying processes during a long time interval [16]. Shiguemori et al. used a NN based inverse procedure from satellite data, non-linear function estimation, to infer vertical temperature profiles [61]. Chen et al. proposed an overlapped type of local neural network to improve accuracy of the heat transfer coefficient estimation of the supercritical carbon dioxide [15]. Scalabrin et al. studied on the heat transfer modeling of flow boiling inside horizontal tubes at saturation conditions [62]. Yuzgec developed a non-linear predictive control technique to determine the optimal drying profile for a drying process [63]. Romeo and Gareta presented the methodology of NN design and application for a biomass boiler monitoring and pointed out the advantages of NN in these situations [53]. Hakeem et al. developed ANNs model for the prediction of temperature profiles and temperatures for a vertical thermo siphon reboiler [64]. Wu et al. employed an ANN to predict the performance of a gas cooler in a carbon dioxide trans-critical air conditioning system. The well-trained ANN was used to predict the effects of the five input parameters individually [65]. Agyare et al. employed ANN to estimate saturated hydraulic conductivity [66]. Sun presented an ANN for improving the accuracy of simplified hot-plate method used for measuring material thermal conductivity [67]. Tahavvor and Yaghoubi used an ANN to determine natural convection heat transfer and fluid flow around a cooled horizontal circular cylinder having constant surface temperature [68]. Varol et al. used an ANFIS temperature and flow field due to buoyancy-induced heat transfer in a partially heated right-angle triangular enclosure [69].

1.2.6 Advantages of intelligent technique based methods in heat transfer

Intelligent techniques allow computers to ‘make decisions’ by interpreting data and selecting amongst alternatives, and they may prove more useful and simpler to apply than numerical methods. What is required for setting up such a system is data that represent the past history and performance of the real system and a selection of a suitable model. The performance of the selected models should be tested with the data from the past history of the real system.

The reasons for the lead scientist to use intelligent techniques in heat transfer applications can be categorized as follows:

- Intelligent techniques are generic techniques for mapping non-linear relationships between inputs and outputs without knowing the details of these relationships

- Intelligent techniques are able to learn and generalize the relationship in complex data sets
- Intelligent techniques are much faster than classical methods
- Intelligent techniques can handle more than two variables to predict two or more outputs.

Intelligent techniques are good for tasks involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems.

In the past three decades, a large number of computer based algorithms have been developed. Many problems have been solved using these algorithms (especially in engineering) which were difficult to deal with using conventional mathematical algorithms. These algorithms are principally based on models of human intelligence; therefore, they are mainly known as intelligent technique methodologies. They generally involve very simple computational steps repeated over a very large number of computational cycles. Clearly, they present a different paradigm to conventional mathematical algorithms involving the numerical solutions to differential equations [70].

An important area of application of these soft computing tools lies in thermal engineering problems. These problems were usually solved by traditional hard computing methods. Unfortunately, traditional methods are often not robust and the resulting model error renders them inappropriate for the solution of new complex problems. New complex challenges are coming from the desire to solve intractable problems. Steady-state problems are rapidly replaced by dynamic ones thereby changing our needs for new solutions when dealing with control, optimization dynamics and system performance problems [70].

Many recent studies have confirmed that intelligent techniques show promising results to deal with many types of aforementioned complexities. Several significant reasons and advantages have stimulated this interest in the application of intelligent techniques to solve a diverse suite of problems [70], namely:

1. Pattern recognition: Inherent relationships between any set of input and output data can be recognized precisely by intelligent techniques. This ability is completely independent of physical models. Uncertain and noisy input output data, nonlinearity of relationships and multiple variables can not affect the exactness of intelligent techniques [70].

2. Fault tolerant: the large number of processing parts in the structure of intelligent techniques and benefits of parallel data processing make intelligent techniques a fault tolerant methodology [70].
3. Ease of extension to dynamic modeling: The learning procedure of intelligent techniques enables them to adapt to changes in parameter, as a result, intelligent techniques are able to deal with time-dependent dynamic modeling [70].
4. Ease of incorporating with other methodologies: This characteristic enables intelligent techniques to incorporate with fuzzy logic, GA to improve their ability to deal with significantly more complex thermal processes [70].

Three reasons have been proposed to explain this increased interest in using intelligent techniques in thermal and energy related process modeling:

1. Fundamental technical knowledge has lagged behind industrial requirements in the constantly increasing complexity of the field of application in thermal engineering processes. Thus intelligent techniques as new model-free paradigms are able to provide improved solution to meet the demand [70].
2. Industrially relevant thermal problems often involve a large number of state variables coupled with complex geometries and their interactions. Classical (optimization based) methods are often restricted to dealing with a small part of the broad spectrum of problems required in modern critical applications. Consequently experimentally based solutions have played important roles in the progress of thermal science and engineering [70].
3. Considerable recent advances in the application of various ANNs and their delivery excellent results has attracted the attention of a considerable number of thermal engineers to employ the ANN analysis to critical and challenging thermal problems [70].

1.2.7 Application to problems where radiation provides the dominant energy transfer mode

Despite the fact that thermal radiation is the most important heat transfer mechanisms in high-temperature equipment (e.g. furnaces, high temperature reactors, etc), inverse radiation problems are rarely addressed (in contrast to inverse heat conduction problems).

An obvious reason for this lack of attention is the fact that radiation is a significantly more complex phenomenon than conduction and convection. The nature of the integro-differential equation that governs radiative heat transfer defies easy solutions even for direct problems. Thus, inverse radiation problems that have been solved to date are rather simple cases.

Because of aforementioned characteristics of radiation, it was decided to focus on inverse radiation heat transfer as the key area for the current thesis..

1.3 Research gap

In this research, several issues were surveyed involving inverse heat transfer problems. First, analytical and numerical methods were observed to be time-consuming and the resulting solutions are not accurate in many instances, especially for radiation dominant problems.

The spectrum of classical (optimization based) techniques were investigated ; it was noted that the need for extensive and accurate physical property and repeated solutions of a direct problem as a mandatory step in the iterative solution process significantly increases the probability of error in classical methods especially for the radiation mechanism. Moreover, the recent application of intelligent techniques to a variety of heat transfer problems confirm their applicability, ease of use to solve the difficult inverse problems.

However, the above addressed issues did not consider “Intelligent Techniques” as alternative methods to solve inverse heat transfer problems, which would be crucial in the solution of those problems (specifically in radiation problems). Most studies focused on improvements to classical methods and focused on the use of intelligent techniques in other cases rather than inverse problems. The inverse heat transfer problems could be solved more efficiently with the aid of “Intelligent Techniques”.

1.4 Research questions

The goal of this study is to research and develop intelligent techniques as an alternative technique for the solution of inverse heat transfer problems, specifically those involving radiation as the dominant mode of heat transfer. In order to conduct this research, at least one experiment should be set up to verify the merit of the developed theory. The details of this setup is addressed in Chapter 3.

1.5 Aims/Objectives of the project

- To Build a furnace/dryer in which the experimental investigation will be conducted to assess the capability of the proposed solution methodologies.

- To define a complicated SISO (single-input single-output) inverse heat transfer problem and check the capability of different intelligent techniques to solve that.
- To define complicated MIMO (multi-input multi-output) inverse heat transfer problems and check the capability of different intelligent techniques to solve those.
- To find the best method among different intelligent techniques and find/devise an appropriate method in order to model/study inverse heat transfer problems dominated by the radiation mechanism using experimental data in both SISO and MIMO modes.
- To validate the merit of the developed theoris by comparison with experimental data.

1.6 Thesis organization

To achieve afore-mentioned objectives, the appropriate experimental set-up was constructed and is described in Chapter 3. The main body of the thesis is divided into three parts:

a. To check the possibility of intelligent techniques in the inverse heat transfer modeling problems of the dryer (Chapters 4 and 8),

b. To find the optimal intelligent techniques for the solution of the IHTPs of studied setup (Chapters 5 and 6), and to compare between classical methods and intelligent techniques in IHTPs of employed rig (Chapter 7).

The research can be also divided in two other categories:

The single input-single output (SISO) in chapters 4 to 7 and the two input- two output (TITO) study (Chapter 8).

In chapters 4 and 8 in SISO and TITO studies respectively, the possibility of Artificial Neural Networks (ANNs) was checked and promising results achieved. In chapters 5 and 6 the best possible intelligent techniques were tested to discover the optimal one in terms of accuracy and computation time. In chapter 7, a comparison study between intelligent techniques and optimization based method was conducted.

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Chapter 2

A Critical Review of Classical Solutions

2.1 Introduction

A quick review in Chapter 1 revealed that the complex nature of inverse heat transfer problem (IHTPs) was responsible for fewer studies the subject. Since the most common solutions for solving IHTPs are optimisation based methods, in the current chapter, a comprehensive literature review is conducted to find the deficiencies of such methods. The review demonstrates that some defects make these methods time consuming and inaccurate, especially for irradiative thermal systems.

2.2 General concept

When all information about a thermal model is known, including boundary and initial conditions, governing equations, thermophysical properties and all relevant forces, the corresponding mathematical problem is considered solvable. If any information is missing, the mathematical problem becomes ill-posed and is categorised as an indirect or inverse problem (IP) because its solution usually starts with the results, and the causes are calculated subsequently. IPs are solvable if sufficient additional information, such as measurement data, can be provided [1, 2].

2.3 Inverse heat transfer problems

When unknown quantities appear in the mathematical formulation of a heat transfer model, it results in an IHTP. Parameters such as temperature distribution, heat flux and radiation intensities are usually measured to find the unknown quantities to solve an IHTP [3, 4]. For instance, solving an inverse heat conduction problem (IHCP) usually involves estimating an unknown boundary condition (usually heat flux) by measuring the temperature history in the relevant domain. Thus, in a direct heat transfer problem, the cause (boundary condition) is known and the effect (temperature history) should be determined; however, in an IHTP, the cause should be estimated based on some knowledge of the effect [5].

2.4 Classification of IHTPs

IHTPs are grouped into two categories. The first category is based on the nature of the heat transfer process [3, 5]:

- inverse heat conduction problems,
- inverse heat convection problems,

- inverse heat surface radiation problems,
- inverse radiation problems in participating media,
- inverse heat transfer problems in conduction and convection simultaneously,
- inverse heat transfer problems in conduction and radiation simultaneously,
- inverse heat transfer problems of phase changing.

The second classification is based on the type of unknown quantity in the mathematical equation of the IHTP [3, 5]:

- inverse heat transfer of boundary conditions
- inverse heat transfer of thermophysical properties
- inverse heat transfer of initial condition
- inverse heat transfer of source term
- inverse heat transfer of geometric.

Inverse problems can be further subdivided into function estimation problems and parameter estimation problems. If information on the functional form of the unknown quantity is available, such as thermal parameters, a given IHTP can be solved by simply estimating a few unknown parameters. Conversely, if no information is obtainable on the functional form of the unknown quantity, the IHTP is considered a function estimation problem[6-8].

2.5 Four prominent techniques to solve IHTPs

In general, IHTPs are solved by minimising an objective function using some stabilisation techniques in the estimation part of the employed procedure:

$$S = (Y - T)^T (Y - T) \tag{2-1}$$

where S represents the objective function and Y and T represent the measured and estimated quantities (usually temperature). The estimated quantity is obtained from the solution of the corresponding direct problem [1, 3, 4, 9].

Several mathematical techniques have been proposed in the literature to solve IHTPs. This thesis describes four techniques that are sufficiently general, straightforward and vigorous to deal with the difficulties associated with solving IHTPs.

2.5.1 Levenberg–Marquardt Method

The Levenberg–Marquardt (LM) technique has been employed to solve a variety of inverse problems, including IHTPs [[6, 7, 10-15]. To use this technique, a sensitivity matrix J is calculated:

$$J_{ij} = \frac{\partial T_i}{\partial P_j} \tag{2-2}$$

where: J_{ij} is the sensitivity coefficient; i=1,2,…, I; j=1,2,…,N; I is the number of measurements; N is the number of unknown parameters; T_i is the i^{th} estimated quantity (usually temperature); and P_j is the j^{th} unknown parameter. The sensitivity matrix is also employed in a few other methods.

The LM method can be used for nonlinear parameter estimation problems, as well as linear problems that are too ill-conditioned to solve using typical linear methods. There are five steps involved in solving an IHTP using the LM method, including the direct problem, inverse problem, iterative procedure, stopping criteria and computational algorithms.

2.5.1.1 Direct problem

The direct problem is usually associated with the physical modelling of each thermal system, and it is the same as the inverse problem. However, in the direct problem, the unknown parameter is deemed to be known based on an initial guess, which is improved in an iterative procedure.

2.5.1.2 Inverse problem

The inverse problem is the same as the direct problem, but the unknown quantity remains unknown. To solve an IHTP using this method, Equation 2-1 should be reformulated as follows:

$$S(P)=\sum_{i=1}^{I} [Y_i - T_i(P)]^2 \tag{2-3}$$

here, S is the sum of the squares error or objective function, P=[P1,P2,…,PN] is the vector of unknown parameters, T_i (P)=T (P, t_i) is the estimated unknown quantity at time t_i (from the solution of the direct problem), where $I \geq N$. The matrix form of Equation 2-3 is:

$$S(P)=[Y-T(P)]^T[Y-T(P)] \tag{2-4}$$

2.5.1.3 Iterative procedure

To minimise the least squares norm in Equation 2-1,we find the derivatives of $S(P)$ with respect to the unknown parameters:

$$\frac{\partial S(P)}{\partial P_1} = \frac{\partial S(P)}{\partial P_2} = \cdots = \frac{\partial S(P)}{\partial P_N} = 0 \tag{2-5}$$

The matrix format of Equation 2-5 is:

$$\nabla S(P) = 2[-\frac{\partial T^T(P)}{\partial P}][Y - T(P)] = 0 \tag{2-6}$$

$$[\frac{\partial T^T(P)}{\partial P}] = \begin{bmatrix} \frac{\partial}{\partial P_1} \\ \frac{\partial}{\partial P_2} \\ \vdots \\ \frac{\partial}{\partial P_N} \end{bmatrix} [T_1 \quad T_2 \quad \cdots \quad T_I] \tag{2-7}$$

The sensitivity matrix is:

$$J(P) = \left[\frac{\partial T^T(P)}{\partial P}\right]^T = \begin{bmatrix} \frac{\partial T_1}{\partial P_1} & \frac{\partial T_1}{\partial P_2} & \frac{\partial T_1}{\partial P_3} & \cdots & \frac{\partial T_1}{\partial P_N} \\ \frac{\partial T_2}{\partial P_1} & \frac{\partial T_2}{\partial P_2} & \frac{\partial T_2}{\partial P_3} & \cdots & \frac{\partial T_2}{\partial P_N} \\ \frac{\partial T_3}{\partial P_1} & \frac{\partial T_3}{\partial P_2} & \frac{\partial T_3}{\partial P_3} & \cdots & \frac{\partial T_3}{\partial P_N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial T_I}{\partial P_1} & \frac{\partial T_I}{\partial P_2} & \frac{\partial T_I}{\partial P_3} & \cdots & \frac{\partial T_I}{\partial P_N} \end{bmatrix} \tag{2-8}$$

Thus, Equation 2-6 becomes:

$$-2J^T(P)[Y - T(P)] = 0 \tag{2-9}$$

The abovementioned equation needs to be solved iteratively. To this end, we employ the Taylor series expansion to linearize the vector of the estimated parameters:

$$T(P) = T(P^k) + J^k(P - P^k), \tag{2-10}$$

where $T(P^k)$ and J^k are the estimated unknown quantities and the sensitivity matrix calculated in iteration k, respectively. Equation 2-10 can then be substituted into Equation 2-9:

$$P^{k+1} = P^k + [(J^k)^T J^k]^{-1}(J^k)^T[Y - T(P^k)] \tag{2-11}$$

The Gauss method (Equation 2-11) is the iterative procedure of the LM method. Actually, it is an approximation of the Newton–Raphson method. In Equation 2-11, $J^T J$ should not be singular or:

$$|J^T \mathrm{J}| \neq 0 \tag{2-12}$$

The equation (2-12) is called the identifiability condition. If this condition exists, the unknown parameter P cannot be determined using the iteration procedure of Equation 2-11, and the problem is ill-conditioned. Obviously, all IHTPs are ill-conditioned. The LM method is an alternative to the iterative procedure to overcome the aforementioned constraint:

$$P^{k+1} = P^k + [(J^k)^T J^k + \mu^k \Omega^k]^{-1} (J^k)^T [Y - T(P^k)] \tag{2-13}$$

where μ^k is a damping parameter and $\Omega^k$is a diagonal matrix. The matrix of $\mu^k \Omega^k$ is used to decrease instabilities caused by the ill-conditioned nature of IHTPs. At the start of the iterative procedure, after the first guess, the abovementioned matrix is made larger. In this step, $J^T J$ does not need to be non-singular[3, 4]; therefore, the LM tends to be the steepest decent method. After some initial iterations, μ^k is gradually reduced; the LM method then tends to act as the Gauss method (Equation 2-13).

2.5.1.4 Stopping criteria

As the stopping criteria for the LM method, Dennis and Schnable [16] suggested the following criteria:

$$S(P^{k+1}) < \varepsilon_1 \tag{2-14.a}$$

$$\|(J^k)^T [Y - T(P^k)]\| < \varepsilon_2 \tag{2-14.b}$$

$$\|P^{k+1} - P^k\| < \varepsilon_3 \tag{2-14.c}$$

where $\varepsilon_1, \varepsilon_2$ and ε_3 are user-prescribed tolerances and $\|x\| = (x^T x)^{1/2}$. Details of the stopping criteria can be found in [16].

2.5.1.5 Computational algorithms

Several diagonal matrices have been described in the literature[5, 16]. As such, the LM method can be configured in various ways to solve an IHTP. In this study, we selected the MRQMIN (details in [17]) method:

$$\Omega^k = diag[(J^k)^T J^k] \qquad (2\text{-}15.a)$$

The corresponding computational algorithms are shown in Figure 2-1.

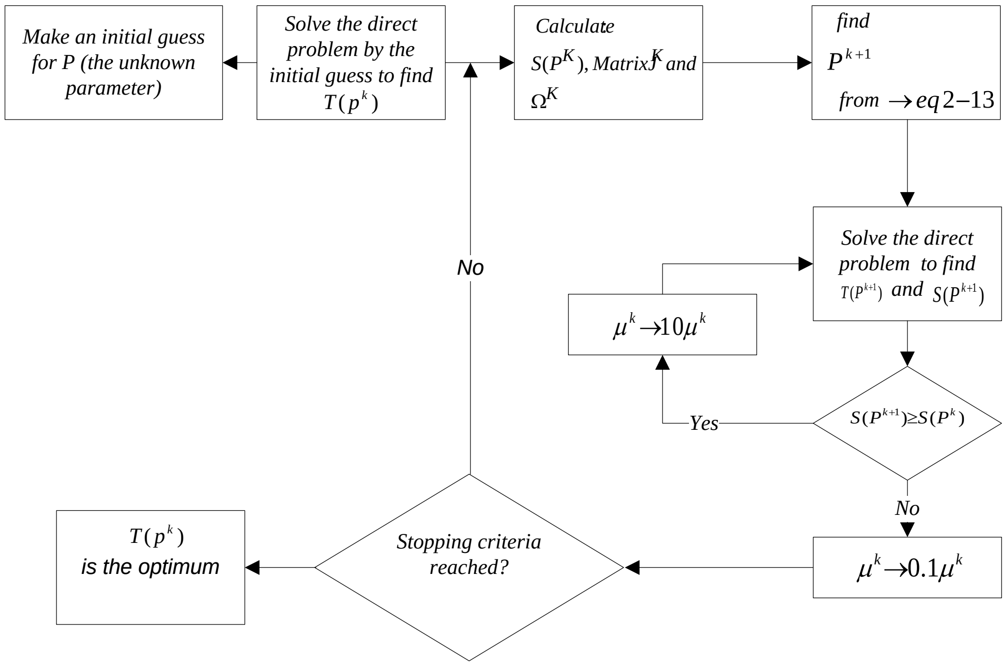

Figure 2-1: Computational algorithms of the LM method

2.5.2. Conjugate gradient method

The conjugate gradient (CG) method is another powerful method for solving IHTPs—especially those involving parameter estimation. In the CG method, a suitable step size is selected in each iteration[18-21]. This step size helps the method minimise the objective function. The step size is taken along a descent, and the descent can be calculated as a linear combination of the negative gradient in one iteration with the direction of descent in the previous iteration [5]. The linear combination should be made such that the consequential angle is less than 90°. Many convergence methods have been described in the literature[22-25]. Similar to the LM method, the CG method involves five steps, including the direct problem, inverse problem, iterative procedure, stopping criterion and computational algorithms, which are described below.

2.5.2.1. Direct problem

The direct problem is related to the physical nature of the problem. There is a time-varying unknown parameter in all direct problems, which makes the problems ill-posed. The unknown parameter should be determined using an iterative procedure.

2.5.2.2 Inverse problem

Similar to the LM method, to solve the inverse problem, parameter estimation can be performed by minimising the ordinary least squares norm:

$$S(P) = [Y - T(P)]^T[Y - T(P)] \qquad (2\text{-}4)$$

2.5.2.3 Iterative procedure

To minimise $S(P)$ using the CG method, we employ the following iterative procedure:

$$P^{k+1}=P^k-\beta^k d^k, \qquad (2\text{-}15.b)$$

where β^k is the search step size, d^k is the direction of descent and k is the number of iterations. To find the direction of descent, we conjugate the gradient direction $[\nabla S(P^k)]$ and the direction of the previous iteration (d^{k-1}) as follows:

$$d^k=\nabla S(P^k) + \gamma^k d^{k-1} \qquad (2\text{-}16)$$

Many different expressions are available in the literature for expressing the conjugate coefficient (γ^k). Two such expressions are Polak–Ribiere[26] and Fletcher–Reeves[23], which are given by Equations 2-17 and 2-18, respectively:

$$\gamma^k = \frac{\sum_{j=1}^{N}\left\{[\nabla S(P^k)]_j[\nabla S(P^k)-\nabla S(P^{k-1})]_j\right\}}{\sum_{j=1}^{N}[\nabla S(P^k)]_j^2}, \qquad (2\text{-}17)$$

$$\gamma^k = \frac{\sum_{j=1}^{N}[\nabla S(P^k)]_j^2}{\sum_{j=1}^{N}[\nabla S(P^{k-1})]_j^2}, \qquad (2\text{-}18)$$

where $\gamma^0 = 0$ for K=0. To obtain the gradient direction using Equation 2-4 with respect to the unknown parameter P, this equation can be rewritten as follows:

$$\nabla S(P^k)=-2(J^k)^T[Y-T(P^k)] \qquad (2\text{-}19)$$

where J^k is one component of the sensitivity matrix in Equations 2-7 and 2-8:

$$[\nabla S(P^k)]_j = -2\sum_{i=1}^{I} \frac{\partial T_i^k}{\partial P_j}\left[Y_i\text{-}T_i(P^k)\right] \tag{2-20}$$

A review of the literature shows that, for nonlinear problems, the Polak–Ribiere expression provides better convergence. Most, if not all, IHTPs are nonlinear; thus, we selected the Polak–Ribiere in this study [17, 22].

The *steepest descent* method can be acquired if we substitute $\gamma^k = 0$ in Equation 2-15 in all iterations. This method is considerably simpler than the CG method, but its convergence time is substantially higher[3, 4, 9, 27].

By minimising the function $S(P^{k+1})$ with respect to β^k in Equation 2-15, β^k can be found as follows:

$$min_{\beta^k}^{S(P^{k+1})} = min_{\beta^k}^{[Y-T(P^{k+1})]^T[Y-T(P^{k+1})]} \tag{2-21}$$

By substituting P^{k+1} in Equation 2-20, we obtain:

$$min_{\beta^k}^{S(P^{k+1})} = min_{\beta^k}^{[Y-T(P^k-\beta^k d^k)]^T[Y-T(P^k-\beta^k d^k)]} \tag{2-22}$$

After linearising the vector $T(P^k - \beta^k d^k)$ using the Taylor series, we obtain:

$$\beta^k = \frac{\sum_{i=1}^{I}\left[\left(\frac{\partial T_i}{\partial P^k}\right)^T d^k\right][T_i(P^k)-Y_i]}{\sum_{i=1}^{I}\left[\left(\frac{\partial T_i}{\partial P^k}\right)^T d^k\right]^2} \tag{2-23}$$

where:

$$\left(\frac{\partial T_i}{\partial P^k}\right)^T = \left[\frac{\partial T_i}{\partial P_1^k}, \frac{\partial T_i}{\partial P_2^k}, \cdots, \frac{\partial T_i}{\partial P_N^k}\right] \tag{2-24}$$

and the matrix form:

$$\beta^k = \frac{[J^k d^k]^T[T(P^k)-Y]}{[J^k d^k]^T[J^k d^k]} \tag{2-25}$$

2.5.2.4 Stopping criterion

The discrepancy principle is employed to stop the iterative procedure of the CG method. The CG method is stopped when:

$$S\left(P^{k+1}\right) < \varepsilon \tag{2-26}$$

The value of ε should be selected such that satisfactory stable solutions are obtained. The iterative procedure should be stopped when residuals between the measured and estimated unknown quantities are of the same order of magnitude as the measurement errors:

$$|Y(t_i) - T(x_{means}, t_i)| \approx \sigma_i \tag{2-27}$$

where σ_i is the standard deviation of the measurement errors at time t_i. If σ_i is constant, we obtain:

$$\varepsilon = \sum_{i=1}^{I} \sigma_i^2 = I\sigma^2 \tag{2-28}$$

Details of the aforementioned assumption can be found in [5, 28].

2.5.2.5 Computational algorithms

Figure 2-2 shows the computational algorithms for the CG method.

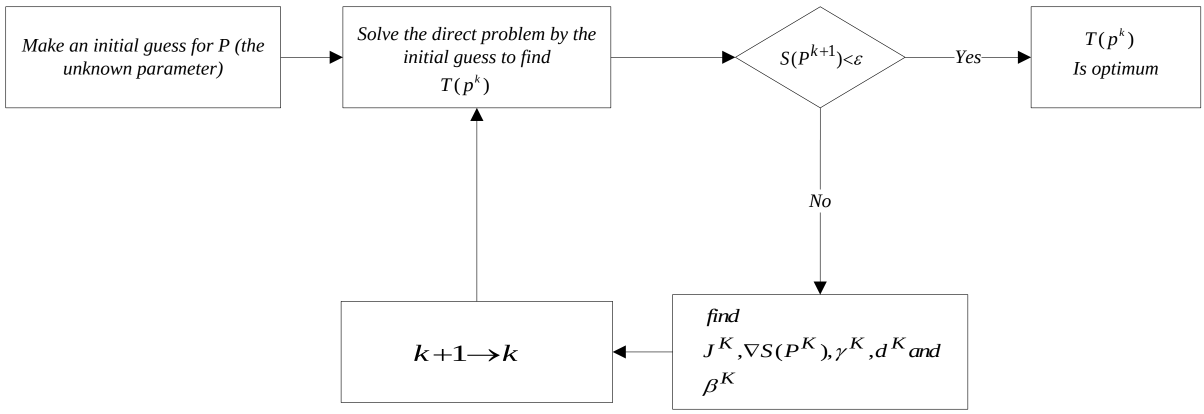

Figure 2-2: Computational algorithms for the CG method

2.5.3 Conjugate gradient method with adjoint problem for parameter estimation

This method is suitable for the function estimation class of IHTPs, which usually involve the estimation of coefficients in a function. In continuous problems, Equation 2-4 can be rewritten as:

$$S(P) = \int_{t=0}^{t_f} [Y_m(t) - T(x_{meas}, t; P)]^2 dt \quad (2\text{-}29)$$

where $Y(t)$ is the measured parameter (such as temperature), $T(x_{meas}, t;P)$ is the estimated parameter at the single measurement location x_{meas} and t_f is the experiment duration.The direct problem is the same as those in the aforementioned methods.

2.5.3.1 Inverse problem

The inverse problem deals with the estimation of a function's unknown parameters by employing measured data received from a measurement device (such as a sensor) at $x = x_{meas}$. The unknown function is called $g_p(t)$ and is parameterised in a general linear form given by:

$$g_p(t) = \sum_{j=1}^{N} P_j C_j(t). \quad (2\text{-}30)$$

2.5.3.2 Sensitivity problem

The sensitivity function $\Delta T(x, t)$ is defined as the directional derivative of the known parameter or function (such as $T(x, t)$) in the direction of the perturbation of the unknown function [28, 29]. It is needed when computing the search step size β^k in this method.

To formulate the sensitivity problem, we assume that $T(x, t)$ is perturbed by an amount $\Delta T(x, t)$ when the unknown function $g_p(t)$ is perturbed by $\Delta g_p(t)$; hence, we obtain:

$$\Delta g_p(t) = \sum_{j=1}^{N} \Delta P_j C_j(t). \quad (2\text{-}31)$$

The sensitivity problem can be obtained by replacing $T(x, t)$ with $\Delta T(x, t)$ and $g_p(t)$ with $\Delta g_p(t)$ in the direct problem.

2.5.3.3 Adjoint problem

To minimise the $S(P)$ function in Equation 2-29, a Lagrange multiplier $\lambda(x, t)$ needs to be included because the measured parameters $T(x_{meas}, t; P)$ in such a function are required to satisfy a constraint (the solution of the direct problem). To derive the adjoint problem, the following extended function should be written as:

$$S(P) = \int_{t=0}^{t_f} [Y_m(t) - T(x_{meas}, t; P)]^2 \mathrm{dt} + \int_{x=0}^{l} \int_{t=0}^{t_f} \lambda(x, t) F(x, t) dx dt \quad (2\text{-}32)$$

where $F(x,t)$ is the direct problem equation:

$$\Delta S(P) = \int_{t=0}^{t_f}\int_{x=0}^{l} 2[Y_m(t) - T(x_{meas}, t; P)]\, \Delta T(x,t)\, \delta(x - x_{meas})\mathrm{dt}$$
$$+\int_{x=0}^{l}\int_{t=0}^{t_f} \lambda(x,t).\, \Delta F(x,t) dx dt \quad (2\text{-}33)$$

After some simplification [5], we obtain:

$$\Delta S(P) = \int_{t=0}^{t_f}\int_{x=0}^{l} \{\frac{\partial^2 \lambda(x,t)}{\partial x^2} + \frac{\partial \lambda(x,t)}{\partial t} + 2[T(x,t;P) - Y(t)]\, \delta(x - x_{meas})\Delta T(x,t)\; dx\; dt\; \Delta T(x,t)\; dx$$
$$+ \int_{t=0}^{t_f} \frac{\partial \lambda(0,t)}{\partial x} \Delta T(0,t) dt$$
$$+ \int_{t=0}^{t_f} \frac{\partial \lambda(1,t)}{\partial x} \Delta T(1,t) dt$$
$$- \int_{t=0}^{t_f} \lambda(x,t_f)\Delta T(x,t_f) dx + \int_{t=0}^{t_f} \lambda(0.5,t)\Delta g_p(t) dt. \quad (2\text{-}34)$$

2.5.3.4 Gradient equation

By substituting $\Delta g_p(t)$ in the parametric form given by Equation 2-31 into Equation 2-34 after eliminating $\Delta T(x,t)$ as described in [5], we obtain:

$$\Delta S(P) = \int_{t=0}^{t_f} \lambda(0.5,t)\; \Delta g_p(t) dt. \quad (2\text{-}35)$$

The parametric form of this equations:

$$\Delta S(P) = \sum_{j=1}^{N} \int_{t=0}^{t_f} \lambda(0.5,t) C_j(t) \Delta g_p(t)\; dt\;\; \Delta P_j, \quad (2\text{-}36)$$

where:

$$\Delta P = [\Delta P_1, \Delta P_2, \cdots, \Delta P_N]. \quad (2\text{-}37)$$

The j^{th} component of the gradient vector $\nabla S(P)$ can be obtained as:

$$[\nabla S(P)]_j = \int_{t=0}^{t_f} \lambda(0.5,t) C_j(t) dt \text{ for } j = 1 \text{ to } N. \quad (2\text{-}38)$$

2.5.3.5 Iterative procedure of the CG method with adjoint problem

The iterative procedure can be obtained in the same manner as the CG method. However, the gradient vector components should be computed using Equation 2-38. The search step size β^k is chosen by minimising $S(P)$ at each iteration k:

$$min_{\beta^k}^{S(P^{k+1})} = min_{\beta^k}^{\int_{t=0}^{t_f}[Y(t)-T(x_{meas},t;P^k-\beta^k d^k)]^2 dt}, \tag{2-39}$$

with the aid of the Taylor series expansion:

$$\beta^k = \frac{\int_{t=0}^{t_f}[T(x_{meas},t;P^k)-Y(t)]\Delta T(x_{meas},t;d^k)dt}{\int_{t=0}^{t_f}[\Delta T(x_{meas},t;d^k)]^2\, dt}. \tag{2-40}$$

2.5.3.6 Stopping criterion for the CG method with adjoint problem

Similar to the procedure for the CG method, the stopping criterion is based on the discrepancy principle. The standard deviation σ is given by:

$S(P) < \epsilon$

Then:

$|Y(t) - T(x_{meas}, t; P)| \sim \sigma$

The tolerance ε is determined as:

$\varepsilon = \sigma^2 t_f$

2.5.3.7 Computational algorithms for the CG method with adjoint problem

The computational algorithms are shown in Figure 2-3.

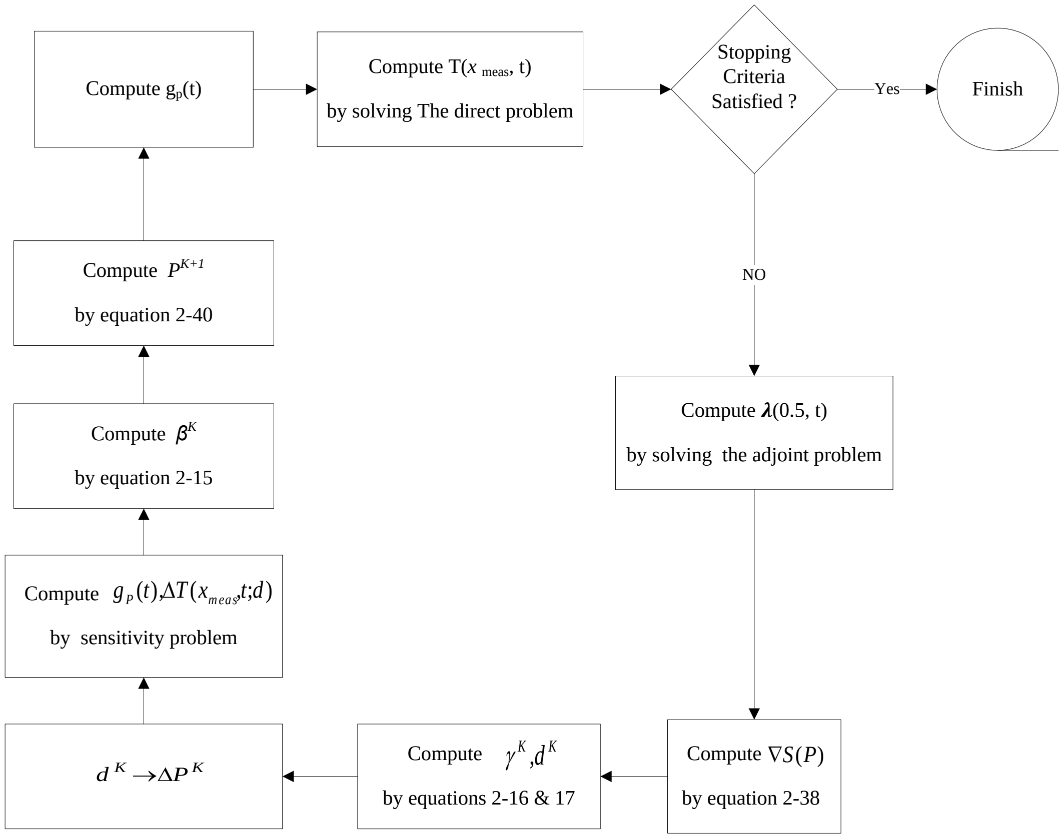

Figure 2-3: Computational algorithms for the CG method with adjoint problem

2.5.4 Conjugate gradient method with adjoint problem for function estimation

This method is appropriate for IHTPs involving function estimation with no available information about the functional form of the unknown function, except for the functional space it belongs to [5, 23, 27-35].

To describe this technique, we assume $g_P(T)$ of a plane energy source, which is recorded by a sensor located at x_{meas}. It is assumed that the unknown function belongs to the Hilbert space of square-integrable functions[28, 36]. The functions in the aforementioned space satisfy:

$$\int_{t=0}^{t_f} [g_P(t)]^2 \, dt < \infty. \tag{2-41}$$

To solve the problem, we define the functional $S(g_P(t))$ as:

$$S(g_P(t))=\int_{t=0}^{t_f}\{Y(t)-T[x_{meas},t;g_P(t)]\}^2\,dt. \qquad (2\text{-}42)$$

2.5.4.1 Inverse problem

In this technique, the source term $g_P(t)$ is an unknown function of time. However, the measured data $Y(t)$ are known. To implement the iterative procedure, we need the sensitivity function $\Delta T(x,t)$ and the Lagrange multiplier $\lambda(x,t)$.Therefore, we develop the sensitivity problem and the adjoint problem. The derivations of these two problems are similar to those of the previous method (CG for parameter estimation).

2.5.4.2 Sensitivity problem

This is similar to the previous method (CG for parameter estimation). When $g_P(t)$ undergoes an increment $\Delta g_P(t)$, the temperature changes by $\Delta T(x,t)$. In the direct problem, $T(x,t)$ and $g_P(t)$ are replaced by $[T(x,t)+\Delta T(x,t)]$ and $g_P(t)+\Delta g_P(t)$, respectively, to obtain the sensitivity problem.

2.5.4.3 Adjoint problem

In line with the CG method, the direct problem is multiplied by a Lagrange multiplier $\boldsymbol{\lambda}$(x, t). The resulting expression is then integrated over the spatial domain and the time domain. The expression obtained is then added to the functional $S[g_p(t)]$ given by Equation 2-42:

$$S[g_p(t)]=\int_{t=0}^{t_f}\{Y(t)-T[x_{meas},t;g_P(t)]\}^2dt+\int_{x=0}^{1}\int_{t=0}^{t_f}\lambda(x,t)\,F(x,t) \qquad (2\text{-}43)$$

For $\Delta S[g_p(t)]$, we obtain:

$$\Delta S(P)=\int_{t=0}^{t_f}\int_{x=0}^{l}2\{T[x,t;g_P(t)]-Y(t)\}\,\Delta T(x,t)\,\delta(x-x_{meas})dxdt$$

$$+\int_{x=0}^{l}\int_{t=0}^{t_f}\lambda(x,t).\Delta F(x,t)dxdt \qquad (2\text{-}44)$$

where$F(x,t)$ is the direct problem and $\partial(.)$ is the Dirac delta function.

2.5.4.4. Gradient equation

Using the same process as in the CG method, we obtain:

$$\Delta S[g_p(t)] = \int_{t=0}^{t_f} \lambda(0.5, t).\,\Delta g_p(t)dt \tag{2-45}$$

Equation 2-31 is substituted into the above equation to obtain the components of Equation 2-45:

$$\Delta S[g_p(t)] = \int_{t=0}^{t_f} \nabla S[g_p(t)]\Delta g_p(t)\; dt. \tag{2-46}$$

It can be concluded that:

$$\nabla S[g_p(t)] = \lambda(0.5, t) \tag{2-47}$$

2.5.4.5 Iterative procedure

We obtained the direct and adjoint problems for computing the functions $T(x,t)$, $\Delta T(x,t)$ and $\boldsymbol{\lambda}$(x, t). The measured data ($Y(t)$) are available. The unknown function is estimated by minimising $S[g_p(t)]$, which is given in Equation 2-38. This can be achieved using the iterative procedure as follows:

$$g_p^{k+1}(t) = g_p^k(t) - \beta^k d^k(t), \tag{2-48}$$

where β^k is the search step size and $d^k(t)$ is the direction of descent, defined as:

$$d^k(t) = \nabla S[g_p^k(t)] + \gamma^k d^{k-1}(t), \tag{2-49}$$

γ^k can be calculated from the Polak–Ribiere expression (2-50) or the Fletcher–Reeves expression (2-51):

$$\gamma^k = \frac{\int_{t=0}^{t_f} \nabla S[g_p^k(t)]\{\nabla S[g_p^k(t)] - \nabla S[g_p^{k-1}(t)]\}dt}{\int_{t=0}^{t_f}\{\nabla S[g_p^k(t)]\}^2 dt} \quad \text{for } k=1,2,\ldots, \tag{2-50}$$

$$\gamma^k = \frac{\int_{t=0}^{t_f}\{\nabla S[g_p^k(t)]\}^2 dt}{\int_{t=0}^{t_f}\{\nabla S[g_p^{k-1}(t)]\}^2 dt} \quad \text{for } k=1,2,\ldots, \tag{2-51}$$

where $\gamma^0 = 0$ for k=0. By minimising $S[g_p^{k+1}(t)]$ in Equation 2-42 with respect to β^k,the step size $\beta^k$is obtained as follows:

$$min_{\beta^k}^{S[g_p^{k+1}(t)]} = min_{\beta^k}^{\int_{t=0}^{t_f}\{Y(t)-T[x_{meas},t;g_p^k(t)-\beta^k d^k(t)]\}^2 dt} \tag{2-52}$$

Using the Taylor expansion equation, we obtain:

$$min_{\beta^k}^{S[g_p^{k+1}(t)]} = min_{\beta^k}^{\int_{t=0}^{t_f}\{Y(t)-T[x_{meas},t;g_p^k(t)]+\beta^k \Delta T[x_{meas},t;d^k(t)]\}^2 dt} \tag{2-53}$$

After a few manipulations, we obtain:

$$\beta^k = \frac{\int_{t=0}^{t_f}\{T[x_{meas},t;g_p^k(t)]-Y(t)\}\Delta T[x_{meas},t;d^k(t)]dt}{\int_{t=0}^{t_f}\{\Delta T[x_{meas},t;d^k(t)]\}^2 dt} \tag{2-54}$$

2.5.4.6 Stopping criterion

Similar to the two previous methods, the stopping criterion is given by:

$$S[g_p(t)] < \epsilon \tag{2-55}$$

The solution accuracy is sufficient when:

$$|Y(t) - T[x_{meas}, t; g_P(t)]| \approx \sigma \tag{2-56}$$

where σ is the standard deviation (see [5] for more details) and ε can be calculated as:

$$\varepsilon = \sigma^2 t_f \tag{2-57}$$

2.5.4.7 Computational algorithms

The computational algorithms for the CG method with adjoint problem for function estimation are shown in Figure 2-4

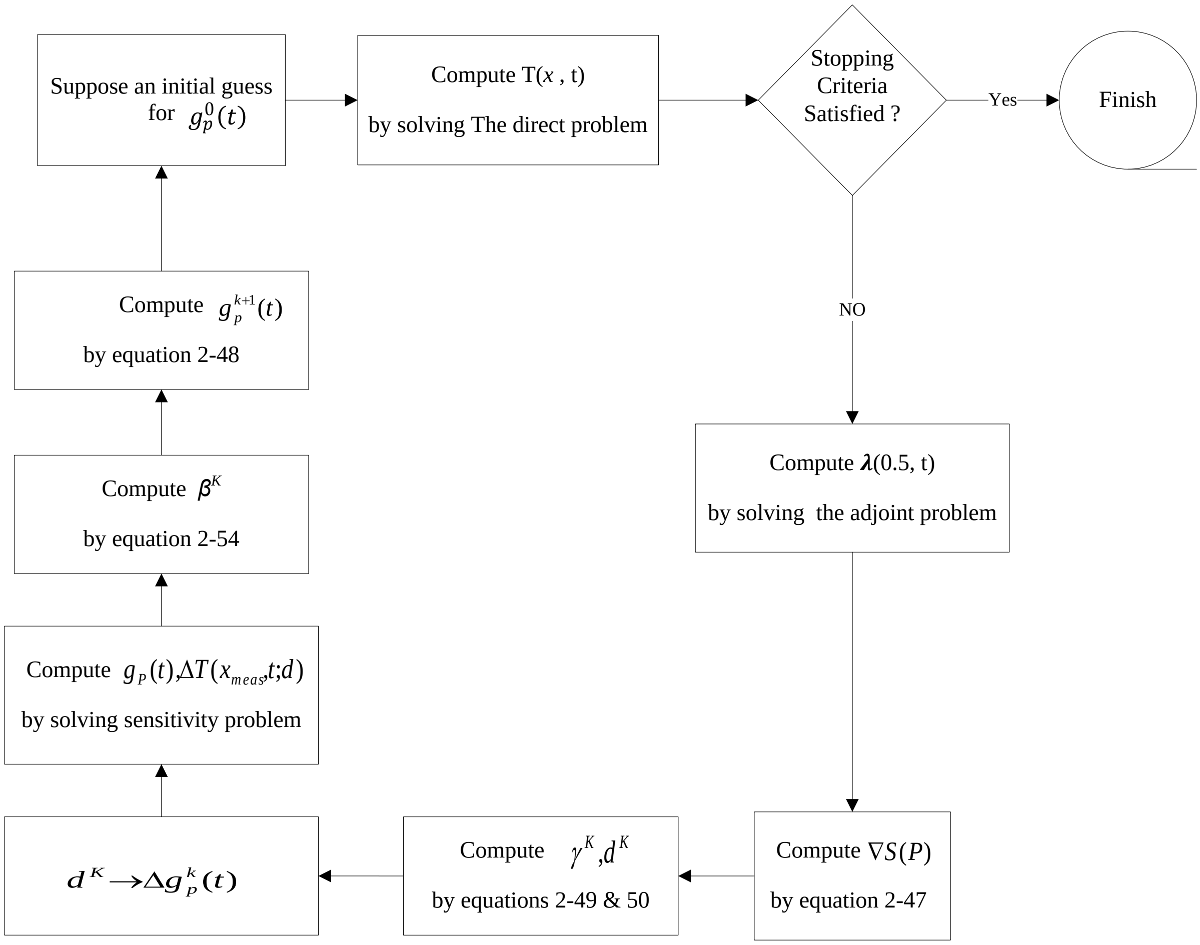

Figure 2-4: Computational algorithms for the last method

2.6 Aims of introducing the four prominent methods

A survey of the literature on irradiative systems showed that, with the exception of scattering media problems [37] (which are not the focus of the current study), almost all classical methods have been derived from the methods mentioned in this chapter.

By introducing these methods, it can be concluded that the procedures for all classical methods (optimisation-based algorithms) include the solution of direct problems, and that the procedures are iterative. The first method adds the complexity of the direct problem to inverse algorithms, and the last method makes their procedures time-consuming.

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Chapter 3

Experimental Set Up and Implementation

3.1 Introduction

In the current chapter , The experimental setup is introduced. At the first stage , the main structure is illustrated , then the differences of two experimental setups are described. Finally, the details of any components are introduced.

3.2 General description

The main structure of the experimental setup is shown in Figure 3-1.

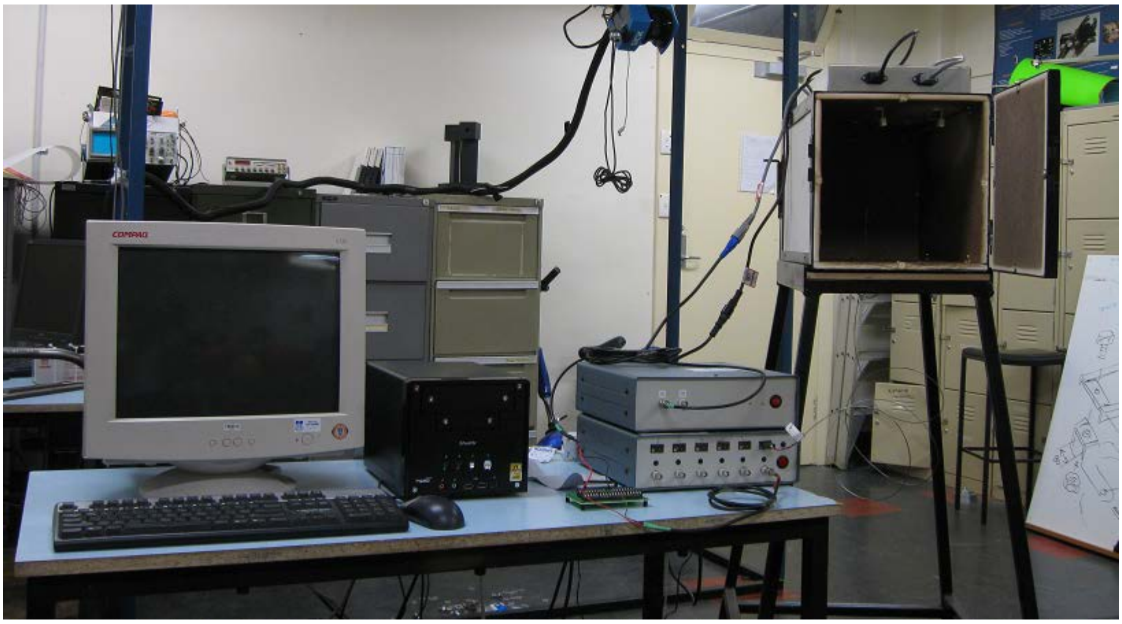

Figure 3-1: The furnace/dryer experimental setup

The infrared dryer has two radiational heat sources (lamps) and the capacity of many temperature sensors (thermocouples). Both lamps and thermocouples can be arranged asymmetrically to generate more complicated modeling/control problems to test different methodologies. As a result of this asymmetry, the effect of any of the lamps on any of the temperature sensors is unique. For instance, if we have two lamps and five sensors, ten single-input/single-output control problems, and then two-input two-output control problems can be defined with this system, each of which may have different features because of the various positions of the sensors with regard to the lamps and furnace walls [1-3].

In current research, two different modeling/control problems have been considered: a SISO (Single input-Single output) system and a TITO (Two inputs–Two outputs) system. For the

SISO problem, one lamp and one sensor are involved. In the TITO problem, to make a more complicated modeling/control problem, a partition was located inside the dryer/furnace with a hole in the middle, two lamps, and two sensors were involved in the data gathering (Figure 3-2).

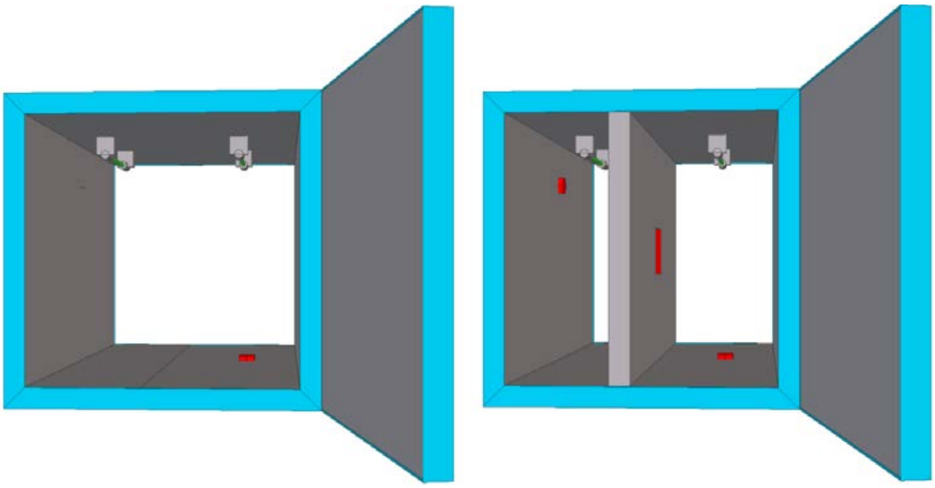

Figure 3-2: SISO and TITO studied furnace structures

3.3 Required resources

In order to make a control loop, two methods can be employed. In the first one, as shown in Figure 3-3, two computers are needed: the first one, the host PC with operation system, can be used to control our system using MATLAB fuzzy and neural networks Simulinks. The second computer, the target PC without an operation system, will act as a bridge between our software and the furnace.

In the host PC, MATLAB software has been installed. By using MATLAB Simulink software, the coming data from the target PC will be processed in order to find the best intelligent techniques from the possibilities for the modeling of our system in both direct and inverse modes [4].

Consequently, the required program for controlling our system will be compiled to C++ by the Real-time workshop Simulink (RTW). Finally the xPC target Simulink will be installed on the Target PC. The Target PC will communicate with our hardware (the furnace) in order to receive and send data.

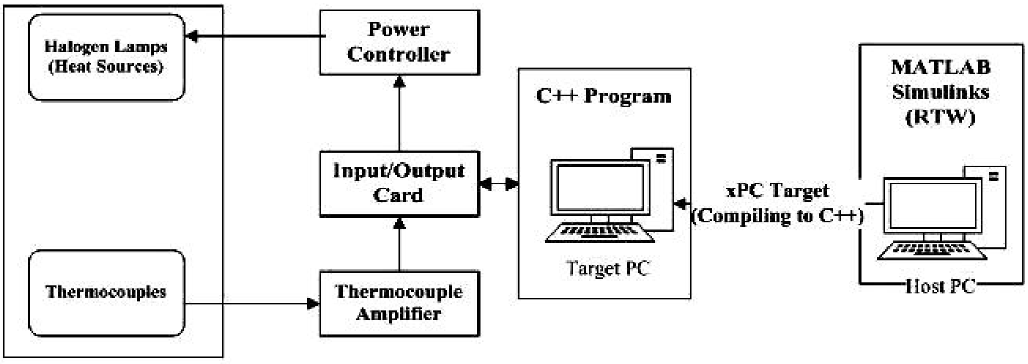

Figure 3-3: The first probable Software process needed to set up our experiment

In the first method, the xPC target has been used in MATLAB software as a bridge between the Real-time workshop Simulink and the hardware part of our control loop. In order to use the xPC target, two computers are needed (the host and target computers). During our investigations, it was found that the xPC target is normally used for high bandwidths, whereas, in our application; a sampling time of 0.01s is used, which is appropriate for our temperature control purposes. It means the frequency of sending data from the sensors to the computer/controller or from the computer/controller to the actuator (lamps) is 100 Hz. Consequently, it was decided to expand the study to find an alternative method, which might be simpler for this application.

Real-time Windows Target, the chosen method for the current research, is another "Links and Targets", like the xPC target which is appropriate for lower bandwidths (less than 1 KHz), moreover it works in a single PC and simultaneously uses that PC as both the host and target (Figure 3-4) [4].

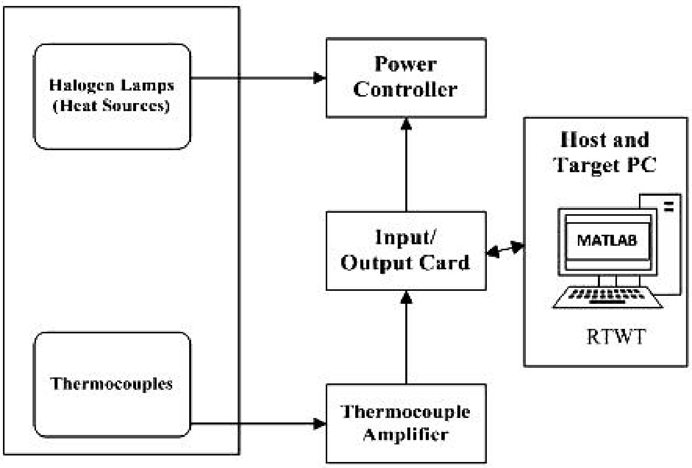

Figure 3-4: Connecting signals in the experimental setup

RTWT, prototyping software, is a PC solution in order to prototype and test real-time systems. RTWT employs a single computer as both host and target PC. In this computer, the MATLAB environment, Simulink software can be used to produce models using Simulink blocks and State flow diagrams.

After producing a model and simulating it with the aid of Simulink software, an executable code can be generated by the RTWT code generation software and the Open Watcom C/C++ compiler. This application can be run in real time by the Simulink external mode [5].

3.4 The furnace/dryer body

Figure 3-5 shows the furnace/dryer body dimensions. The furnace/dryer body is made of steel frame and insulation boards (Figure 3-6).

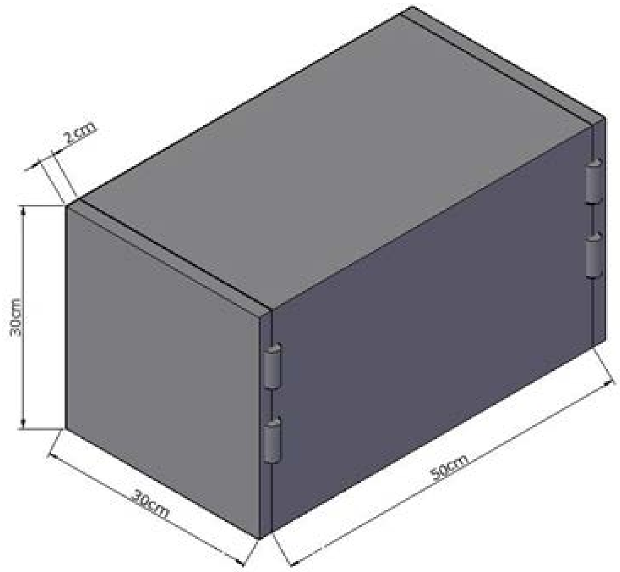

Figure 3-5: The size of the dryer body

The insulation boards are made from inorganic insulation glass fibers. They are bonded using thermosetting materials and manufactured in various thicknesses from 3 up to 75 millimeters . These boards are normally used for electrical insulation and heat protection.

Figure 3-6: The walls of the dryer made by insulation boards and steel sheets

A SUPERWOOL 607 insulation board with a thickness of 20 millimeters, made by the Morgan Crucible Company in South Australia, was used in this project.

3.5 Thermocouples

A thermocouple is generally utilized to convert heat into electrical power, based on the discrepancy between the electrical potential generated in two wires made of different metals, forming the thermocouple. There is a nonlinear relationship between the temperature change (ΔT) and output voltage (V), as shown in Equation 3-1:

$$\Delta T = \sum_{n=0}^{N} a_n \; V^n \qquad (3\text{-}1)$$

where a_n is a constant available in the manual for n from zero to nine for different thermocouples. Thermocouples are quick sensors (with very short time delays), which are able to measure a wide range of temperatures.

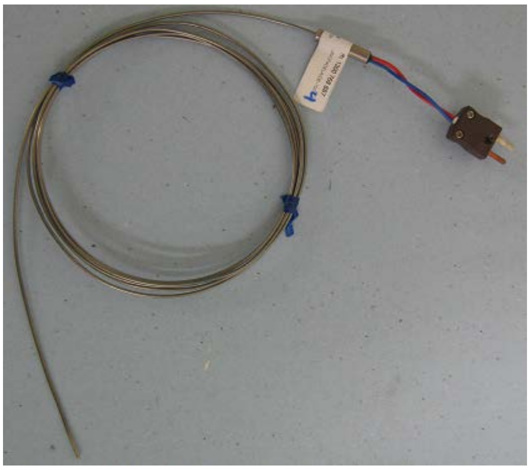

Figure 3-7: A type T thermocouple

Among different kinds of thermocouples, type T (Figure 3-7) was selected for this application (see Table 3-1).

Table 3-1: Thermocouple type T characteristics

Type	Temperature range °C (continuous)	Tolerance class one (°C)	Tolerance class two (°C)
T	−250 to +400	±0.5 between −40 & 125 ±0.004×T between 125 and 350	±1.0 between −40 & 133 ±0.0075×T between 133 & 350

3.6 The thermocouple amplifier

In the thermocouple amplifier (Figures 3-8), the signal coming from the thermocouple (43 µV/°C) is amplified to 10 $^{\mathrm{mV/°C}}$. This signal is sent to the computer. The thermocouple amplifier type is AD595 and was purchased from the ANALOG DEVICES Company [6]. This amplifier has six input and output channels which make the experimental setup appropriate for several SISO and MIMO problems.

Figure 3-8: Thermocouple Amplifier

Figure 3-9 shows the location of the thermocouple amplifier in the experimental setup.

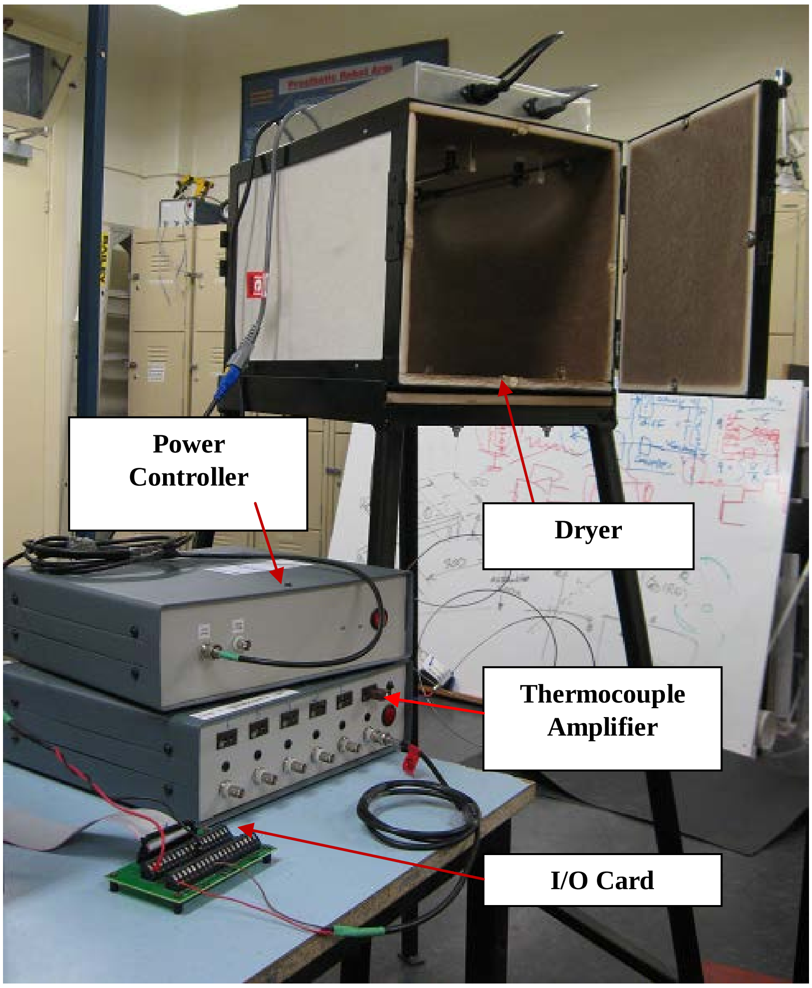

Figure 3-9: Thermocouple amplifier located between the I/O card and the dryer

3.7 The Input/output card

In this project, the selected I/O card (Figure 3-10) converts analog signals coming from the thermocouple amplifier to digital signals and sends them to the computer (Figure 3-11). At the same time, the I/O card converts digital signals coming from the computer to analog ones and send them to the power controller, then to the halogen lamp(s). I/O card type MF624 was selected, which is compatible with the RTWT toolbox of the MATLAB software and was specifically produced for thermal processes. The MF 624 has an 8-channel 14-bit A/D converter with a simultaneous sample/hold circuit, eight independent 14-bit D/A converters, an 8-bit digital input port and an 8-bit digital output port, 4 quadrature encoder inputs, and 5 time counters.

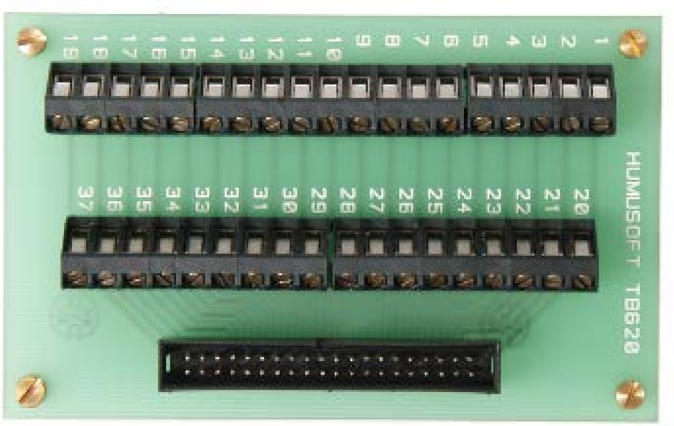

Figure 3-10: MF 624 Multifunction I/O Card

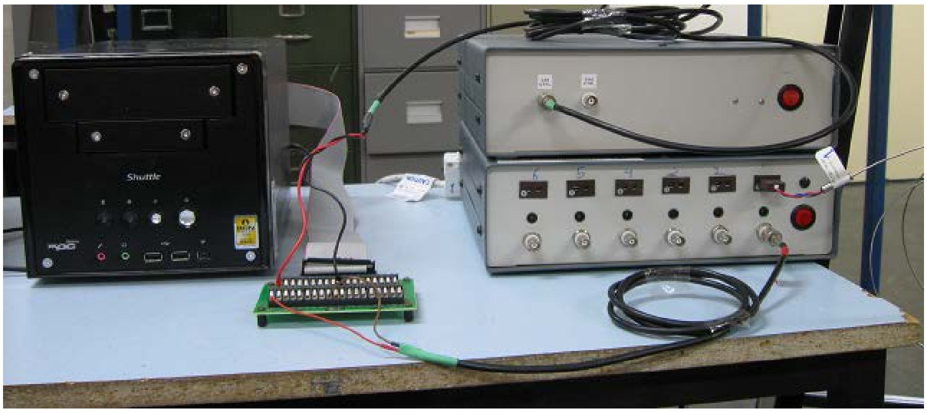

Figure 3-11: The I/O card connects the computer to the power and thermocouple amplifiers

3.8 The power controller unit

Power controllers (Figure 3-12) provide circuit breaker functions such as protection of the load and wiring from overload conditions. In addition, the power controller provides an on/off control of the conduction of the load circuit and is used to protect an AC wire harness against damage if the power controller experiences a short circuit failure caused by over-current or short-circuiting.

Figure 3-12: The power controller for the dryer lamps

The load (output) voltage of the power controller is adjusted by varying the time within each electrical half-cycle. The AC electrical current and a control signal is entered in to a power controller; if the electrical half-cycle is T, for a portion of T, the power controller is ON and allows the current to pass through. For the rest of the electrical half-cycle the power controller is OFF. This portion is defined by the control signal. We used an FCAL/2 power controller manufactured by the UNITED AUTOMATION Company [6]. In fact, our power control unit has two power controllers for two lamps.

3.9 The lamps

There were two important factors for the radiation sources. They need to have a quick response to the control command (the voltage coming from the computer) and also they need to change the emitted heat flux continuously. Halogen lamps could meet the criteria.

From a variety of options, two 2^{kW} halogen lamps were selected. Figures 3-13 and 3-14 show lamps and their support clamps.

Figure 3-13: Halogen lamps in the dryer

Figure 3-14: TITO furnace/dryer structure

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Name of Principal Author (Candidate)	Ali Mirsepahi
Contribution to the Paper	Data gathering, Analyze the data, Data preparation, Data Training, Finding the ANN model, make the comparison, writing the draft
Overall percentage (%)	
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature	Date 1/10/2015

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Supervising, Editing the writing
Signature	Date 1/12/2015

Chapter 4

AN ARTIFICIAL INTELLIGENCE APPROACH TO INVERSE HEAT TRANSFER MODELING OF AN IRRADIATIVE DRYER

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4.1 Abstract

In this chapter/publication, a new solution approach was developed for heat flux estimation class of inverse heat transfer problems where radiation provides the dominant mode thermal energy transport. An Artificial Neural Network (ANN) was designed, trained and employed to estimate the heat emitted to the irradiative batch drying process.

In a simple laboratory drying furnace, various input signals (different input power functions) were applied to the dryer's halogen lamp and the resulting temperature history were measured and recorded for a point on the bottom surface of the dryer. After estimating the order, the sampling time and the dead-time of the system, the recorded data were arranged 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 inverse heat estimation problems of irradiative batch drying process. An important advantage of this method in comparison with classical inverse heat transfer modelling approaches, in that detailed knowledge of the geometrical and thermal properties of the system (such as wall conductivity, emissivity , etc.) is not necessary. Such properties are difficult to measure and may undergo significant changes during the temperature transient.

4.2 Introduction

Thermal processes dominated by radiative transport of energy play an important role in a plethora of engineering applications such as furnaces, dryer and reactors. Such systems are significantly more difficult to model compared to processes dominated by conduction and convection. Radiation is a highly non-linear phenomena and the effects of geometry need to be carefully considered. In industrial practice, designers wish to develop steady state and dynamic models to optimize the processes, ensure a quality product and increase production rates [1]. Current heat transfer modeling methods for thermal processes (particularly those involving radiation) rely on broad assumptions and simplifications that fail to adequately account for the real conditions of operation [2].

Heat transfer modelling problems can be divided into two separate categories: direct and inverse problems [3]. In direct problems, all relevant thermophysical properties, boundary, and initial conditions are specified. Direct problems are normally considered to be "well-posed". By contrast, for inverse problems, there is lack of knowledge of the boundary conditions, initial conditions or thermophysical properties and such problems are normally "ill-posed" [3]. The unknown conditions must be estimated using measured temperature data at one or several locations within the domain. As a consequence of the ill-posed nature of the problem, inevitable random errors in the measured data result in error magnification by several orders of magnitudes and the unknown boundary conditions or thermophysical parameters may be poorly estimated. Consequently, inverse heat transfer problems are known to be considerably more "difficult" compared to the corresponding direct heat transfer problems [3-6].

Heat function estimation in radiative problems is an important type of IHTPs [6]. A variety of trial-error-based methods based on iterative solution guessing a value for heat flux and then employing conventional mathematical models to check satisfaction of the desired temperature distribution have been used to solve such problems. Faulty solutions are common and the methods are time consuming due to heavy computational requirements [7-11].

Other applied techniques to solve inverse heat transfer problems involve least squares optimizations modified by the addition of regularization. Regularization imposes more restrictions on the permissible solutions [12]. Optimization methods such as conjugate gradient (CG) and Levenberg-Marquardt have also been used to improve the initially guessed values of heat flux to solve heat flux estimation problems.

These iterative algorithms require multiple solutions of governing equations. However, they are capable of estimating the solution in significantly shorter time than the trial and error based methods [12]. Iterative methods of solution also incur a heavy penalty due to the long time to convergence [13,14]. If the initial guess is poor, an infeasible solution may be obtained or in the worst case, the solution may not converge [15]. In such instances, non trial-error based methods can only provide a local minimum solution depending on the initial value [15]. As an alternative, evolutionary methods, such as genetic algorithm (GA), have received increased attention because of their ease of coding and superior convergence characteristics when applied in non-linear optimization problems. The results were promising but some deficiencies have been observed in GA [12,15]. Moreover, GA and other evolutionary algorithms require large populations and involve long computing times for convergence which make them inappropriate for many inverse heat transfer problems [16].

In all aforementioned conventional methods, detailed physical property information is normally required [7,10,13]. In many cases the measurement of such physical properties is extremely difficult, if not impossible. Moreover, in order to use all conventional inverse methods, the direct problem must be solved first. This constraint of repeated direct problem solutions can produce significant computing errors and calculations may be excessively time-consuming [3,7,9,10,13,14].

The aim of the present work is to check the applicability of artificial neural networks (ANNs) to solve heat flux estimation class of IHTPs especially those involving presence of the most complicated form of heat transfer, radiation. The nature of the integro-differential equation that governs radiative heat transfer defies easy solution even for direct problems. Thus, inverse radiation problems that have been solved to date are rather simple cases. ANN solutions are based on experimental data rather than mathematical governing equations; consequently, detailed knowledge of physical properties may not be necessary. Input and output data are the sole requirement for the application of ANNs to model systems.

4.3 Experimental setup

Figure 1 presents a schematic of experimental rig used in the study. A single halogen lamp was attached to the top surface to provide the heat source and a thermocouple sensor was attached at the base is used as the sensor; both were located asymmetrically (Figure 4-1). All connected through an electronic I/O card, a power controller, an amplifier and Real Time Windows Target (RTWT) Toolbox of MATLAB/Simulink software.

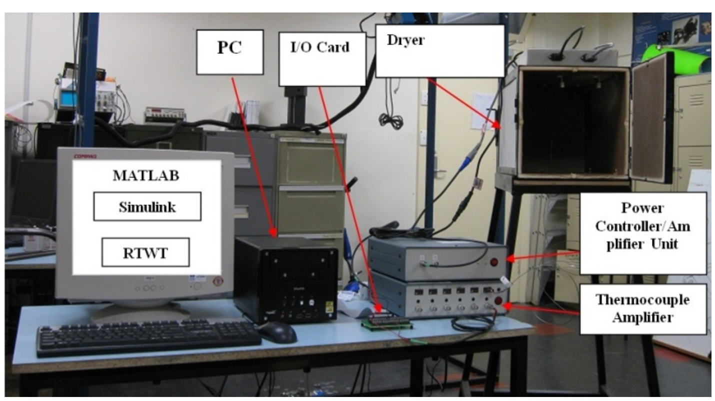


Figure 4-1: The dryer experimental setup

4.4 Problem Statement

This research is aimed to propose a new approach to estimate the input irradiative heat to an enclosure using the history of temperature distribution on one of the surfaces of the enclosure. It will be discussed later that the temperature history of a single point is enough to estimate the emitted heat by a single heat source. In this work, this latter case was experimentally studied.

A mathematical model of such a system can be achieved by the first law of thermodynamics. The furnace can be assumed as an enclosure with Diffuse-Gray Surfaces. The following assumptions are considered for thermo-dynamics-based modeling [18]:

1. The surfaces' properties are non-uniform
2. ε_k (emissivity factor of each surfaces) is independent of the wavelength and the direction of radiation.
3. All energy is emitted and reflected diffusely.

Incident and reflected energy flux is non-uniform; as a result, the enclosure (dryer/furnace) boundary must be subdivided into infinitesimal areas.

In order to find the mathematical model of the dryer, an infinitesimal element on the bottom surface is considered (Figure 4-2):

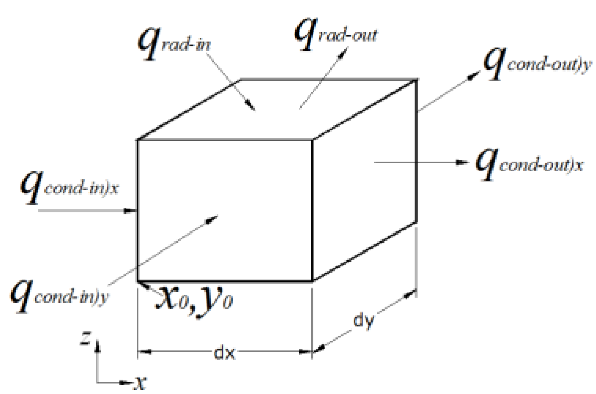


Figure 4-2: An element at the bottom side of the studied furnace

In general:

Input Energy –Output Energy+ Generated Energy-Consumed Energy= Energy Accumulation (4-1)

The input energy to this element comes from the conduction in *x* and *y* directions, the radiation from the halogen lamp and the radiation from other surfaces:

$$\text{Input Energy}= -K_{cond}\left.\frac{\partial T(x,y,t)}{\partial x}\right|_{x=x_0}.l.dy\ -K_{cond}\left.\frac{\partial T(x,y,t)}{\partial y}\right|_{y=y_0}.l.dx+q_{lamp}(x,y,t) \tag{4-2}$$

Where k_{cond} is the heat conduction coefficient (W/mK), t is time (s), l is the thickness of dryer body (m), T is temperature (K), q is input heat energy (W), j is the index of elements on the surfaces where the studied element is not located on them, and N is the number of these elements.

$F_j\,(x, y)$ is the exchange factor of the inner surface of j^{th} element and the element located at (x, y) .$q_{o,j}$ is the output radiation heat of j^{th} element on the surfaces where the studied element is not located on them .

The output energy can be divided in three categories: output energy through conduction, radiation due to high temperature of the element and reflecting radiation

$$\text{Output Energy}= -K_{cond}\left.\frac{\partial T(x,y,t)}{\partial x}\right|_{x=x_0+dx}.l.dy\ -K_{cond}\left.\frac{\partial T(x,y,t)}{\partial y}\right|_{y=y_0+dy} ldx\ +\varepsilon_k\sigma\overline{T}^4 dxdy+$$

$$\left(\left(1-\varepsilon_k\right)\sum_{i=1}^{n} q_{o,j}\ \left.F_j(x,y)\right|_{(x,y)=(x_o,y_o)}\right)dx.dy \tag{4-3}$$

Where σ is the Stefan-Boltzmann Constant=5.6703×10^{-8} W/m^2K^4 and T is the average temperature of the inner side of the element.

According to Taylor's series:

$$\left.\frac{\partial T(x,y,t)}{\partial x}\right|_{x=x_0+dx} \cong \left.\frac{\partial T(x,y,t)}{\partial x}\right|_{x=x_0} + \left.\frac{\partial^2 T(x,y,t)}{\partial x^2}\right|_{x=x_0} \tag{4-4}$$

$$\left.\frac{\partial T(x,y,t)}{\partial y}\right|_{y=y_0+dy} \cong \left.\frac{\partial T(x,y,t)}{\partial x}\right|_{y=y_0} + \left.\frac{\partial^2 T(x,y,t)}{\partial y^2}\right|_{y=y_0} \tag{4-5}$$

Also

$$\text{Generated Energy}=\text{Consumed Energy}=0 \tag{4-6}$$

and,

$$\text{Accumulated Energy}=\rho VC_p\frac{\partial T(x,y,t)}{\partial t}=\rho(l.dx.dy)C_p\frac{\partial T(x,y,t)}{\partial t} \tag{4-7}$$

Where V is the volume of the element and C_p is the specific heat capacity at a constant pressure. After considering Equation 4-7 to Equation 4-2 in Equation 4-1:

$$K_{cond}\frac{\partial^2 T(x,y,t)}{\partial x^2}\bigg|_{x=x_0}+K_{cond}\frac{\partial^2 T(x,y,t)}{\partial y^2}\bigg|_{y=y_0}-\frac{\varepsilon_k}{l}\sigma\overline{T}^4+\frac{\varepsilon_k}{l}F_j(x,y)\Big|_{(x,y)=(x_o,y_o)}+q'''_{lamp}(x,y,t)=\rho C_P\frac{\partial T(x,y,t)}{\partial t} \qquad (4\text{-}8)$$

Due to insulation, following known boundary conditions can be considered for the dryer (Figure 4-3):

$$T(x,y,0)=T_o \qquad \frac{\partial T(l_1,y,t)}{\partial x}=0 \qquad \frac{\partial T(x,l_2,t)}{\partial y}=0 \qquad (4\text{-}9)$$

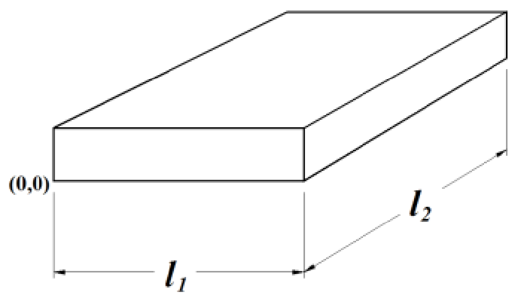


Figure 4-2: bottom surface of the studied furnace

Emitted heat to the system= $\int q'''_{lamp}(x^*,y^*,t)\,dx^*\,dy^*$ (In transient situation) is subject to estimation in this research, where x^* and y^* represent the coordinates of the surfaces of the enclosure (i.e. *x* and *y* in Figure 2). Having the solution of this problem, one can estimate the emitted heat that will lead to a special temperature distribution.

4.5 ANN approach to the proposed IHTP

As previously stated, the inverse model is often used as a controller to generate the input heat that leads to a special temperature distribution. In control, the number of controlled variables (e.g. temperature of points on the surface) cannot exceed the number of control actuators (e.g. heat sources). In order to impose a desired temperature distribution on a surface in a batch infrared dryer we need to control a large number of heat sources simultaneously using an accurate inverse model. This research addresses the initial step of this task. An accurate inverse model was generated through this work. This model is able to estimate the transient input heat that has led to a specific temperature history. A general form of this inverse model is shown in Equation 4-10:

$$\widehat{Q}\left(k-\frac{\text{Dead time}}{\text{Sampling time}}\right)=F[T(k),T(k+1),\ldots,T(k+r)] \tag{4-10}$$

where $\widehat{Q}$ represents estimated input heat (hat sign represents estimated). Dead time is the time needed for the input heat to affect the temperature at a particular point, the system dead time calculated by a step function in the MATLAB environment; sampling time is the time interval between two consequent measurements and *r* (or the order) shows how long the temperature of the particular point is affected by the input heat emitted at any moment. Sampling time and order are both calculated by trial and error. F is a function which is to be estimated by an ANN.

4.6 Data Preparation

During the experiments, data were recorded and stored as a matrix with two columns of the input heat and the temperature. Q represents the input heat and T represents the temperature.

$$\text{Matrix of raw recorded/sensed data} = \begin{bmatrix} Q_1 & T_1 \\ Q_2 & T_2 \\ Q_3 & T_2 \\ \vdots & \vdots \\ Q_n & T_n \end{bmatrix} \tag{4-11}$$

where n is the number of collected data. It was found experimentally that the delay or dead time of the system is 1.4 seconds. Sampling time of $T_s = 0.2$ second was considered due to the nature of the system. Raw data matrix after considering of the dead time is:

$$\text{Matrix of data after considering the dead time}=\begin{bmatrix} Q_1 & T_{d+1} \\ Q_2 & T_{d+2} \\ Q_3 & T_{d+2} \\ \vdots & \vdots \\ Q_{n-d} & T_n \end{bmatrix} \tag{4-12}$$

where $\quad d=\frac{\text{dead time}}{\text{sampling time}}$

For an inverse model with the order of r; the data should be arrange as shown below:

$$\text{Prepared Data}=\begin{bmatrix} \overbrace{\begin{matrix} T_{d+1} & \cdots & T_{d+r} \\ \vdots & \ddots & \vdots \\ T_{n-r+1} & \cdots & T_n \end{matrix}}^{\text{Input}} & \overbrace{\begin{matrix} Q_1 \\ \vdots \\ Q_{n-d-r+1} \end{matrix}}^{\text{Output}} \end{bmatrix} \tag{4-13}$$

The order was found five based on several trial and errors.

4.7 Neural Network Modeling of the radiating furnace

In this research, the input to the inverse model is temperature history in Kelvin and the output is input heat in kilo Watt. The dead time is 1.4 seconds or Equation 4-10 can be written in the following form:

$$\widehat{Q}(k\text{-}7)=F[T(k),T(k+1),T(k+2),T(k+3),T(k+4)] \tag{4-14}$$

Variables with a hat are the estimated/predicted ones. After applying the dead time and the order, a set of 1000 pieces of recorded data were prepared as below:

$$\text{Prepared data}=\begin{bmatrix} \overbrace{\begin{matrix} T_8 & T_9 & T_{10} & T_{11} & T_{12} \\ T_9 & T_{10} & T_{11} & T_{12} & T_{13} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{996} & T_{997} & T_{998} & T_{999} & T_{1000} \end{matrix}}^{\text{Input}} & \overbrace{\begin{matrix} Q_1 \\ Q_2 \\ \vdots \\ Q_{989} \end{matrix}}^{\text{Output}} \end{bmatrix} \tag{4-15}$$

An ANN network with three layers of neurons was designed to be trained using the prepared data. Input and output layer has five and one neurons respectively with linear activation functions with the slope of one. The hidden layer has five neurons with sigmoid activation functions. The training method is Levenberg-Marquardt batch error back propagation .The ANN has been trained in 83 epochs (iterations) and the performance function is the mean of squared errors (MSE).

4.8 Experimental Results

After achieving the ANN model, four different functions different from one used in training process were used to verify the method. Their resultant temperature were arranged (as explained in data preparation section) and given to the proposed ANN and the corresponding input heat functions were estimated by the ANN (shown in Figure 4-5).

The estimation process for each datum of input heat takes 0.023 seconds (a for loop employed to calculate this time); due to the fact that training and estimation process are apart and the estimation process solely includes simple non-recursive mathematical operations.

The mean of absolute error is 43.00245 watt in average for four data series for the input heat in the range of 0~2 KW.

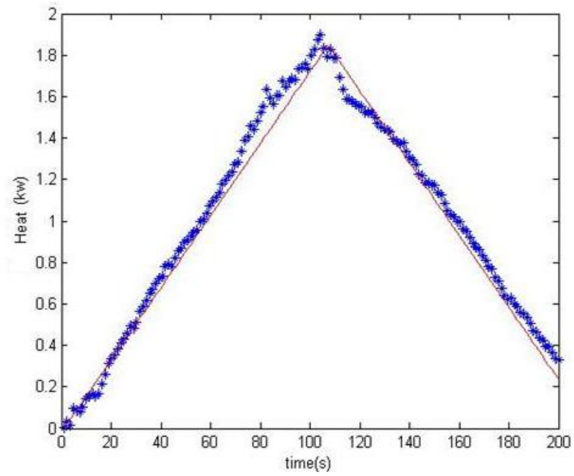
$$\mathrm{mae} = \frac{\sum_{i=1}^{N} \left| \hat{Q}(i) - Q(i) \right|}{N} \tag{4-16}$$

where,

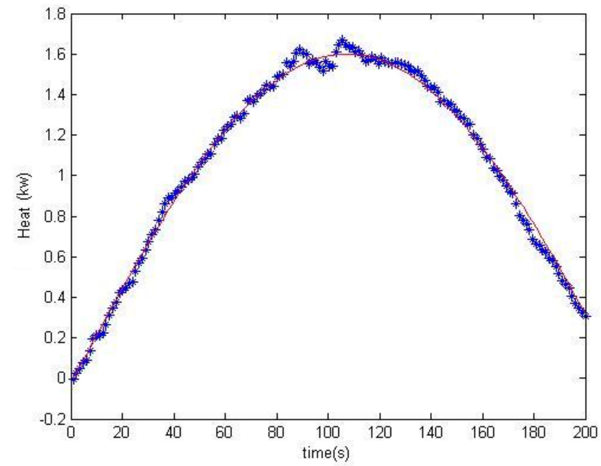
N: the number of data after data preparation process,

Q: input heat.

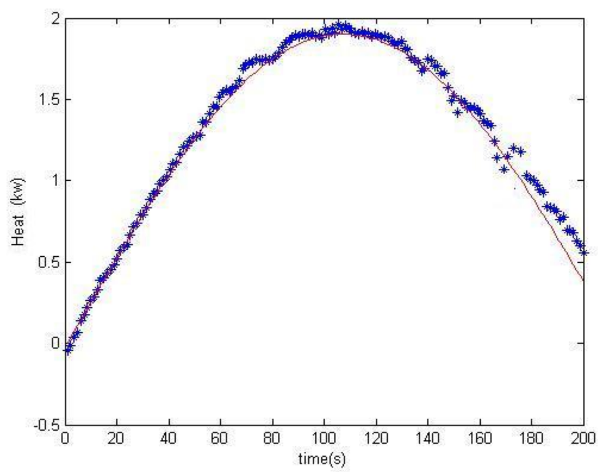
The accuracy of the estimation is completely acceptable with temperature sensing error of ±1°C.



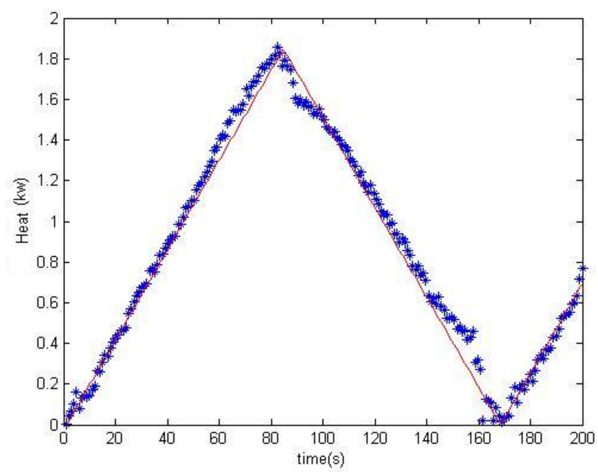
(a)



(b)



(c)



(d)

Figure 4-3 : Actual and estimated input heat data for four checking data series (blue stars show estimated input heat by the proposed ANN and red lines show real input heat applied to the system)

Table 4-1: Prediction accuracy for different trained models (mae and maximum of error)

Criterion	mae (W)				Maximum of error (W)			
Checking data	1st series	2nd series	3rd series	4th series	1st series	2nd series	3rd series	4th series
Error (W)	52.0675	27.8197	44.6249	47.4982	169.4966	91.7501	380.4250	177.3014

4.9 A summary of advantages of the proposed method

- The solution procedure for conventional inverse methods is based on trial-and-error. The probability of error is extremely high for such methods and they are normally time-consuming [8, 9, 11, 12] but in the proposed method this restriction does not exist.
- Iterative methods inherent in other conventional inverse methods also incur heavy penalty of long time to convergence [14, 15]. In ANN the only iterative part is in training which is containing simple mathematical relations, therefore proposed method is much faster than conventional iterative methods.
- Detailed and accurate physical properties are needed in many inverse methods. Their unavailability makes the solution difficult to achieve (impossible in some cases) and necessitate simplified (and often physically unrealistic) assumptions given the complexity of heat transfer systems [9, 11, 12, 14, 19-28]. The proposed method does not need physical properties as it is only based on input and output data.
- In order to use many conventional inverse methods, the direct problem must be solved first. Hence, the resulting inverse solution will be subject to serious computing errors and time-consuming calculations are required [9, 11, 12, 14, 19-28]. However, in proposed method, there is no need to make and solve the direct model.

4.10 Conclusion

In this paper, for an irradiative batch dryer, an Artificial Neural Network model was designed and successfully trained and utilized as an appropriate alternative for conventional methods for input irradiative heat estimation. This ANN model was trained using experimental data. For this purpose, heat was applied through a halogen lamp hung from the top surface of the dryer, and the temperature was measured by a thermocouple at the bottom surface. All these data were recorded, processed and employed to make an inverse ANN model of the system. This model receives temperature history of a point and estimates the input heat to the system. It was demonstrated that the heat estimated by the designed neural network were consistent with the real heat applied during the experiment

From a practical point of view, in accordance with the achievement of this research, the only requirement to make a highly accurate neural network model for a heat estimation problem is a series of Temperature-Input heat data for a few minutes of operation and the dimensions and thermophysical properties are not needed. As another significant advantage, the estimation stage by the trained neural networks only included a small number of simple calculations excluding any recursive computation; this means the method is very fast-paced in comparison with classical techniques of numerical heat transfer for similar problems

In short, a very accurate method for the inverse heat transfer problems was proposed and successfully tested using experimental data.

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Overall percentage (%)	
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Supervising, Editing the writing
Signature	Date 1/12/2015

Chapter 5

A COMPARATIVE ARTIFICIAL INTELLIGENCE APPROACH TO INVERSE HEAT TRANSFER MODELING OF AN IRRADIATIVE DRYER

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5.1 Abstract

In this chapter, a variety of new approaches is developed and results are compared for solving inverse heat transfer problems where radiation is the dominant mode of thermal energy transport. An artificial neural network ANN), two hybrid methods of genetic algorithms and artificial neural networks (GA-ANNs), and an adaptive neuro-fuzzy inference system network (ANFIS) were designed. These were trained and then employed to estimate the required input power in an irradiative batch drying process. A comparison of the results shows that the most accurate method is ANFIS but the number of parameters in ANFIS is larger than that of ANNs. Consequently, the ANFIS solution is time consuming in this application; however other neuro-fuzzy techniques may require fewer parameters and these will be considered in future studies. For the studied ANNs, the hybrid method of GA-ANN is optimal (using the Levenberg-Marquardt as the optimization algorithm during back propagation) in terms of accuracy and network's performance.

5.2 Introduction

Heat transfer involves the transport of thermal energy. Fundamental methods in engineering include conduction, convection, and radiation. Conduction refers to the heat transfer that occurs across the medium. The medium may be solid or a fluid. Convection refers to the heat transfer that will occur between a surface and a moving fluid when they are at different temperatures. Finally in radiation, energy is transported by electromagnetic waves emitted from surfaces at finite temperatures [1,2].

Heat transfer is a significant field of interest for engineering researchers, designers, developers and manufacturers. Industrial applications include a wide variety of systems and components for energy devices used in power plants, heat exchangers, high performance gas turbines and other power conversion systems. A diverse range of applications occurs in chemical processing, general manufacturing, biological- heat transfer, electronic cooling, comfort heating and cooling towers [3].

Thermal processes dominated by the radiative transport of energy play an important role in a plethora of engineering applications such as furnaces, dryer and reactors. Such systems are significantly more difficult to model when compared to processes dominated by conduction and convection as radiation is a highly non-linear phenomenon and the effects of geometry need to be carefully considered. In industrial practice, designers wish to develop steady state and dynamic models to optimize these processes, ensure a quality product and increase production rates [4,5]. Current heat transfer modeling methods for thermal processes (particularly those involving radiation) rely normally on broad assumptions and simplifications that do not adequately account for the real conditions of operation [6-9].

In heat-transfer modeling problems when all thermophysical properties, and initial and boundary conditions are specified the energy balance equations are "well-posed". Such problems are known as direct heat transfer problems [10]. By contrast, inverse heat transfer problems (IHTPs) frequently lack detailed knowledge of relevant parameters and subsequently derived equations are normally "ill-posed" [4,7]. For inverse heat transfer problems, the unknown conditions, inputs and parameters must be estimated using measured temperature data at one or several locations within the domain. As a consequence of the ill-posed nature of the problem, random errors inevitable in the measured data may be accumulated and result in error magnification by several orders of magnitude and the unknown boundary conditions and/or thermophysical parameters are often poorly estimated [4,6-9].

Estimation of the energy input and fluxes for radiative heat-transfer problems is clearly an important type of IHTPs [4,8]. Several trial-error and iterative based methods have been developed and applied to solve indirect problems, such as input power estimation (e.g. Mirsepahi et al. [4]). A plethora of optimization algorithms have been introduced to solve such IHTPs [11,12].

Unfortunately, these methods normally require detailed and accurate physical property information [13,14]. Normally, measurement of such physical properties is extremely difficult, if not impossible. Moreover, all conventional inverse methods require an initial solution of the direct problem [15]. This constraint requiring the solution of a large number of iterated direct problems may produce significant computing errors and/or calculations may be excessively time-consuming [7,14,16-18]. Mirsepahi and his co-workers developed a number of popular ANNs as an alternative solution methodology which was based on gathering and examining experimental data rather than developing and solving the complex mathematical energy transport equations. Consequently, detailed knowledge of the system's physical properties is no longer necessary. Likewise, the ANNs are able to model complex systems without the need for complex mathematical models involving energy balances [19]. Accurate input and output test data are the sole requirement for the application of ANNs to model these systems. Such methods provide an additional benefit by avoiding time-consuming calculations [20]. In a previous study [4], an ANN was designed, trained and then employed to estimate the input power in a batch drying process where radiation provides the dominant mode of thermal energy transport. This ANN allowed simple development of the inverse heat transfer model and promising results were reported. The ANN was a simple three layer perceptron whose key parameters (number of neurons in the hidden layers, the momentum and the learning rates) were ascertained by trial and error. This type of ANN has been widely applied to solve a diverse range of modeling tasks but the earlier study was the first time that such simple ANNs were applied to an application dominated by radiative transfer of thermal energy. Subsequently, it was hypothesized that if the structure of employed ANN was optimized, the aforementioned parameters could be determined more quickly and with higher accuracy. A search of the literature suggested that an improved method known as a genetic-algorithm artificial neural net (GA-ANN) could optimize the parameters of the ANNs using a genetic algorithm (GA) [21-24]. Hence, a study of GA-ANN to solve power input estimation for this class of IHTPs was performed and the results were compared with those from the previous work. The class of simple ANNs used initially [4] is very efficient in adapting and learning but an inherent disadvantage of these tools is that they provide an empirical 'black box' solution. An alternative, experimentally based method which in part overcomes this weakness is the application of fuzzy logic (FL) modeling originally introduced by Lofti Zadeh [25]. FL deals with reasoning which is approximate rather than fixed and exact. Variables are assigned a truth value ranging from 0 to 1 and such analysis mimics to some degree normal human reasoning. It allows the designer to develop more robust solutions and utilize approximate values and inferences as well as incomplete or ambiguous data rather than relying on crisp data. Unfortunately, fuzzy logic learning is a time consuming process; however, the trade off is that it provides the advantage of approximate reasoning [4,26-28]. Furthermore, literature review suggests that the combination of ANNs with fuzzy methods may provide an efficient approach for various modeling dynamic systems, as each method mitigates the other method's weakness and deficiencies thereby increasing the combined efficiency of the resulting neuro-fuzzy (NF) system. A NF system uses learning methods derived from ANN in order to determine the optimal parameters of fuzzy model including appropriate membership functions and fuzzy rules. Numerous investigations have been performed applying ANFIS modeling to solve significant engineering problems [29-33].

The aim of the present study is to compare these three intelligent technique methods (ANNs, GA-ANN and ANFIS) to solve power input estimation for a class of IHTPs, specifically, a process dominated by the most complex form of heat transfer, namely radiation.

5.3 Experimental setup

Figure 5-1 presents a schematic of the experimental rig used in the study. A single halogen lamp was attached to the top surface of a simple furnace to provide the required radiative heat source and temperature measurements were obtained using a thermocouple sensor attached to the base; both items were located asymmetrically (Figure 5-2). An I/O card, a power controller, an amplifier and Real Time Windows Target (RTWT) Toolbox of MATLAB/Simulink software were used. The dryer body was insulated and enclosed in a steel frame. T-type thermocouples with the accuracy of 1 °K were selected as sensors. A thermocouple amplifier was used to increase the output voltage of thermocouples and direct signals to a digital input-output card; the control command was generated in the computer and sent to the power control (power amplifier) unit which amplifies input voltage to the lamp(s) based on received signal form the computer.

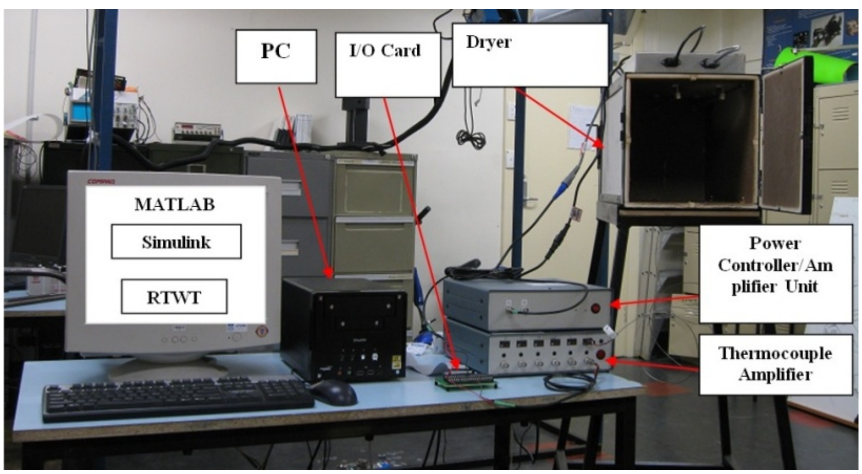


Figure 5-1: The dryer experimental setup

5.4 Problem statement

The goal of this work is to compare the aforementioned intelligent techniques to determine the optimal method for estimation of the input power to an enclosure using the experimental data in terms of accuracy and computing time. The required experimental data was gathered from a model infrared dryer/furnace.

It was also assumed that the furnace is an enclosure with diffuse-gray surfaces. A mathematical model of the energy balance for such a system can be determined. Some simplifying assumptions are necessary in order to model such a system: the non-uniformity of the prosperities of the surfaces, the independency of the emissivity factor (ε_k) from the wavelength and the direction of radiation from each surface. As the last assumption it was assumed that all energy has been emitted and reflected diffusely [34].

As incident and reflected energy flux is non-uniform; in order to find the mathematical model of the dryer, an infinitesimal element on the bottom surface is considered (Figure 5-2).

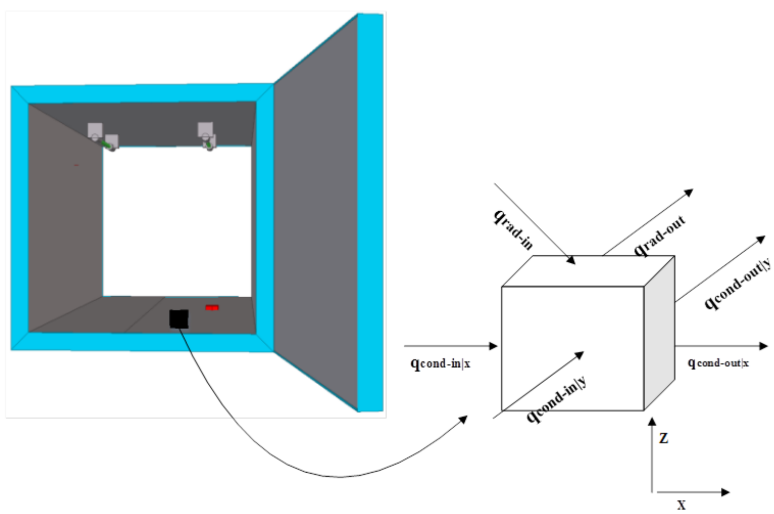


Figure 5-2: An element at the bottom side of the studied furnace (conduction in z direction is negligible)

The procedure of finding Equation 5-1 was described in [4]:

$$K_{cond}\left.\frac{\partial^2 T(x,y,t)}{\partial x^2}\right|_{x=x_0}+K_{cond}\left.\frac{\partial^2 T(x,y,t)}{\partial y^2}\right|_{y=y_0}-\frac{\varepsilon_k}{1}\sigma\overline{T}^4+\frac{\varepsilon_k}{1}F_j(x,y)\Big|_{(x,y)=(x_o,y_o)}+q'''_{lamp}(x,y,t)=\rho C_P\frac{\partial T(x,y,t)}{\partial t} \quad (5\text{-}1)$$

Where k_{cond} is the heat conduction coefficient (*W/m°K*), *t* is time (*s*), *l* is the thickness of dryer body (*m*), *T* is temperature (°*K*), *q* is input heat energy (*W*), *j* is the index of elements on the surfaces where the studied element is not located on them, and *N* is the number of these elements.

Due to insulation, following known boundary conditions can be considered for the dryer (Figure 5-3):

$$T(x,y,0)=T_o \qquad \frac{\partial T(l_1,y,t)}{\partial x}=0 \qquad \frac{\partial T(x,l_2,t)}{\partial y}=0 \tag{5-2}$$

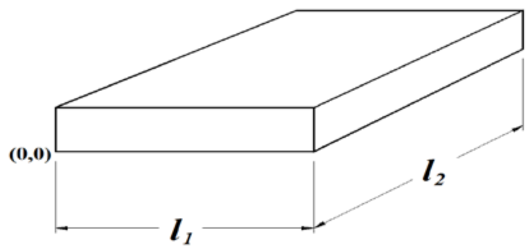


Figure 5-3: Bottom surface of the studied furnace

Emitted heat to the system= $\int q'''_{lamp}\left(x^*,y^*,t\right) dx^* dy^*$ (In transient situation) is subject to estimation in this research, where x^* and y^* represent the coordinates of the surfaces of the enclosure (i.e. *x* and *y* in Figure 5-2). Having the solution of this problem, one can estimate the emitted heat that will lead to a special temperature distribution.

5.5 Intelligent techniques approach for the proposed IHTP

As previously stated, an inverse model is often used as a controller to regulate the input power that produces the desired temperature distribution within the furnace or dryer. A perfect inverse would negate the requirement for feedback control. In control, the number of controlled (measured) variables (e.g. temperature at points on the surface) cannot exceed the number of control actuators (manipulated variables) (e.g. the input power). In order to impose a desired temperature distribution on a surface in a batch infrared dryer we need to control a large number of heat sources simultaneously using an accurate inverse model. This research addresses the initial step of this task namely the development of accurate high fidelity inverse model.

This model will enable the designer to estimate the transient input voltage to produce a desired temperature history. The general form of the required inverse model is shown below:

$$\hat{Q}\left(k - \frac{\tau_d}{\tau_s}\right) = F[T(k), T(k+1), \dots, T(k+r)] \qquad (5\text{-}3)$$

where $\hat{Q}$ is the estimated input heat, τ_d is the dead time and τ_s is the sampling time. r is the order of the model and characterizes how long the temperature at a particular point is affected by the input thermal energy emitted at any moment. F is a function to be estimated.

5.6 Data preparation

Experimental data for the transient is stored as a matrix with two columns of containing the input power (Q) and temperature (T).

$$A = \begin{bmatrix} Q_1 & T_1 \\ \vdots & \vdots \\ Q_n & T_n \end{bmatrix} \qquad (5\text{-}4)$$

where n is the number of collected data and A is the matrix of the raw recorded data.

It was found experimentally that the delay or dead time of the system is 1.4 seconds. The sampling time (0.2 seconds in current job) and order (5 in this research) should be guessed [4]

B is the matrix of raw data and prepared data:

$$B = \begin{bmatrix} Q_1 & Q_2 & \cdots & Q_{n-d} \\ \vdots & \vdots & \vdots & \vdots \\ T_{d+1} & T_{d+2} & \cdots & T_n \end{bmatrix} \qquad (5\text{-}5)$$

where B is matrix of data after considering the dead time and d = $\frac{\tau_d}{\tau_s}$

For an inverse model of order of r; the data should be arranged as shown below:

$$C = \begin{array}{c} \begin{array}{cc} \overbrace{\hphantom{T_{n-r+1} \quad \dots \quad T_{d+r}}}^{\text{Input}} & \overbrace{\hphantom{Q_{n-d-r+1}}}^{\text{Output}} \end{array} \\ \left[\begin{array}{cccc} T_{d+1} & \dots & T_{d+r} & Q_1 \\ \vdots & \vdots & \vdots & \vdots \\ T_{n-r+1} & \dots & T_n & Q_{n-d-r+1} \end{array}\right] \end{array} \qquad (5\text{-}6)$$

C is the matrix of prepared data.

5.7 Intelligent modeling of the Irradiative furnace/dryer

In this work, the input to the inverse model is temperature history in °K and the output is input power in kW. Equation 5-1 and the model function may be summarized in the following form:

$$\widehat{Q}(k+7) = F[T(k),T(k+1),T(k+2),T(k+3),T(k+4)] \tag{5-7}$$

Variables with a hat are the estimated/predicted ones. After applying the dead time and the order, a set of 1000 pieces of recorded data were prepared as below:

$$\text{Prepared data} = \begin{array}{c} \begin{array}{cc} \overbrace{\hspace{14em}}^{\text{Input}} & \overbrace{\hspace{2em}}^{\text{Output}} \end{array} \\ \begin{bmatrix} T_8 & T_9 & T_{10} & T_{11} & T_{12} & Q_1 \\ T_9 & T_{10} & T_{11} & T_{12} & T_{13} & Q_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{996} & T_{997} & T_{998} & T_{999} & T_{1000} & Q_{989} \end{bmatrix} \end{array} \tag{5-8}$$

5.8 GA-ANN modeling for the proposed IHTP

The back propagation ANNs (BPN) used in previous study [4] are widely applied in various engineering applications. Their solution is not robust and their parameters are highly sensitive and lack robustness, hence slight changes in the value of ANN's parameters may cause significant change in the ANN's performance [22].

In the absence of any accurate and defined theory to calculate parameter settings such as the number of hidden layers, momentum rate and learning rate must be determined heuristically and by trial and error methods. This fact makes the procedure of finding structure of the simple conventional ANNs time and effort consuming. In this new study, a GA is used to find the optimal values of aforementioned parameters.

The Levenberg-Marquardt (LM) optimization algorithm was used in our initial study[4]. In order to investigate the effectiveness of GA-ANN, we compared the performance of two popular optimization algorithms (LM and the Momentum Algorithm) and the parameters of both networks were optimized using the evolutionary GA. The commercially available NeuroSolutions software was used in order to optimize effectively aforementioned parameters. This software allows us to optimize the number of neurons in hidden layer using the Levenberg Marquadt algorithm and if the Momentum algorithm is employed the number of hidden layers, momentum rate and learning rate can be optimized.

GA is an optimization method based on evolutionary principles. NeuroSolutions software™ permits the user to employ the genetic algorithm as a learning algorithm for training multilayer perceptron ANNs. In this study, three parameters are used for the ANNs using the Momentum algorithm for training (the number of hidden layers, the momentum rate and the learning rate) whilst a single parameter (number of neurons in hidden layer) was used with the LM algorithm. These parameters form the genes in a chromosome for the evolution algorithm.

The fitness of a chromosome can be quantified as the fitness is inversely related to the Mean Absolute Error (MAE) of the ANNs outputs. An initial population of chromosomes was determined in a random manner; the algorithm is initiated and continues in a "survival of the fittest" mode to develop a better population. The key operations that commonly employed include selection, crossover and mutation [3, 35, 36].

Chromosomes with higher fitness numbers were chosen in the selection step. In the crossover step, two chromosomes are selected randomly, then cut at a random position and the binary values are exchanged to create two new chromosomes. The genes of a chromosome are changed in the mutation step with a low probability. This procedure is repeated to finally reach a population of chromosomes with an accurate fitness number.

In this study, the ANNs previously tested by Mirsepahi et al.[4] were optimized by applying the evolutionary algorithm. As the optimization method in the back propagation BP part was LM the number of hidden layers and input columns were optimized by GA. Another well-known method of optimization called momentum algorithm was tested and its parameters were optimized by GA.

In NeuroSolutions software for both networks in the GA optimization process, the number of epochs was set to 1000, maximum generation was 100 and maximum evolution time was set to

60 minutes. The lower and upper bonds for both step size and momentum algorithm were 0 and 1. Roulette was selected for the selection method, one point for crossover and the uniform method for mutation part.

Table 5-1 summarizes the results of four networks based on cross validation and training data (from training input 80% of data used as cross validation data).

Table 5-2: Summary of results (a) Back Propagation (BP) using LM to determine neurons number by trial and error (b) BP using LM to determine the number of neurons using GA (c) BP using momentum algorithm with the parameters fixed by trial and error (d) BP using momentum algorithm with the parameters determined using GA

Best Networks	*Training*	*Cross Validation*
Epoch #	202	103
Minimum MSE	0.0011	0.0014
Final MSE	0.0012	0.0015

(a)

Optimization Summary	*Best Fitness*	*Average Fitness*
Generation #	42	53
Minimum MSE	0.001	0.001
Final MSE	0.001	0.001

(b)

Best Networks	*Training*	*Cross Validation*
Epoch #	10000	10000
Minimum MSE	0.0017	0.0022
Final MSE	0.0017	0.0022

(c)

Optimization Summary	*Best Fitness*	*Average Fitness*
Generation #	99	84
Minimum MSE	0.0015	0.0017
Final MSE	0.0015	0.0026

(d)

Figure 5-4 shows that the optimal method for back propagation is the LM algorithm and the optimal network's performance is attained using optimization of relevant parameters by the genetic algorithm (GA).

For the momentum back propagation the optimized step size is 0.515 and the momentum rate is 0.769. The number of neurons in hidden layer for previous study was 5 (Levenberg-Marquadt BP). The optimal number of neurons in hidden layer using the GA is 4, whilst, the optimal number of neurons using the Momentum BP method was 10 with the GA and 7 without GA optimization.

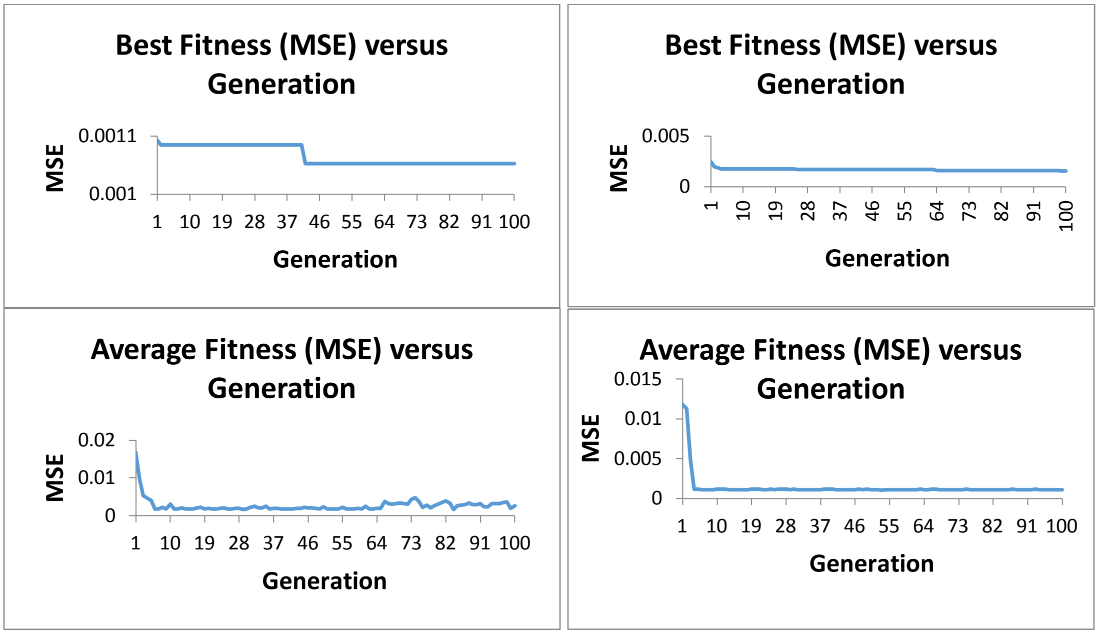


Figure 5-4: Average and best fitness in each generation for after optimization the parameters by GA for two BP methods (LM right-hand graphs and Momentum left-hand graphs)

5.9 ANFIS Architecture

In recent years, two prominent intelligent techniques (artificial neural networks and fuzzy logic), have been applied to solve a wide variety of highly non-linear heat transfer problems in various applications. ANNs possess basic computational structures which allow them to perform well when dealing with raw data. Fuzzy logic deals with reasoning on a higher level and uses linguistic information obtained from domain experts. The aforementioned abilities make the ANN and fuzzy logic combination a very powerful tools for solving numerous difficult non-linear modeling problems, especially instances where data may be complex or where a limited or an insufficient amount of accurate data is available [26, 27, 37].The combination of ANNs coupled with a fuzzy logic modeling method provides an efficient approach for various modeling systems. Each method compensates for the others weakness. A neuro-fuzzy (NF) system employs learning methods derived from ANNs in order to discover the parameters of fuzzy system including appropriate membership functions and fuzzy rules as shown in Figure 5-5 [26, 27, 37] (Table 5-2).

The NFs normally compute the node outputs up to the preceding layer in each period of instruction. Thus, the resulting parameters are calculated by the least squares error (LSE) method. When the error has been calculated in the backward route, the ratios of error have been distributed on condition parameters and their values are corrected by error descending gradient method. A variety of formations have been recommended to establish a NF model. One of the most powerful of those which have been introduced by Jang is known as adaptive neuro-fuzzy inference system (ANFIS). The key approach in this structure is error back propagation which scatters the error value towards inputs by algorithm of the gradient descent and corrects the parameters [26, 27, 37].

5.10 ANFIS Modeling for the Proposed IHTP

In this study one of the most common structures of NF network identified as adaptive neuro-fuzzy inference systems (ANFIS) has been employed. In this method, a fuzzy inference system is designed based on system specifications. This initial model is transformed to a neuro-fuzzy network and then trained using the recorded experimental data from the system. The training procedure involves both gradient error back propagation to adjust membership function coefficients and LSE to adjust linear output parameters.

Following determination of the ANFIS model using training, four input functions significantly different from those used in training process were utilized to verify predictive capability of the method. The resultant temperature profiles were arranged (as explained in data preparation section) and given to the proposed ANFIS and the corresponding input heat functions were estimated by the ANFIS [38]. In fuzzy inference systems, the number of fuzzy rules is equal to number of membership functions powered by the number of inputs. To cover the complete input space, many rules are needed. Training such FIS's is too time consuming or sometimes impossible. In order to reduce fuzzy rules number whilst incurring the minimum accuracy loss, a method known as *subtractive clustering* is applied [1, 7]. In this method, rules with the most probable antecedents in the recorded data from the actual system are selected. The model derived from subtractive clustering is then used as initial model for training. The training procedure involves both gradient error back propagation (to adjust membership function coefficients) and

LSE (to adjust linear output parameters). Figure 5-5 shows the architecture of proposed ANFIS model.

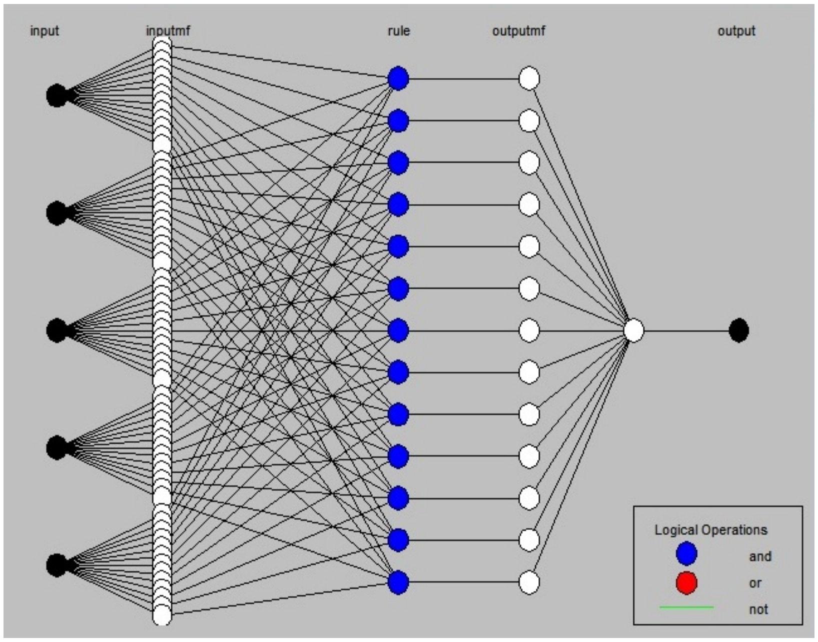


Figure 5-5: The architecture of proposed ANFIS model

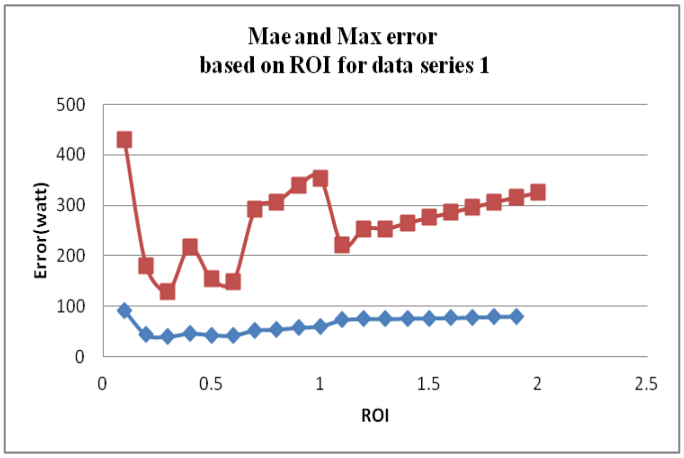
A key parameter in the subtractive clustering method is Range Of Influence (ROI). In this study, for the first time, the effect of changes in the initial ROI guess was studied using four different sets of test data. Surprisingly, for all the aforementioned data sets of data, a constant value = 0.3 provided the best guess in terms of accuracy measured using the mean of the absolute error (Mae) and the maximum error (Max error). Figure 5-6 shows this criterion versus different ROI as the initial guess. where,

$$\mathrm{mae} = \frac{\sum_{i=1}^{N} \left| \hat{Q}(i) - Q(i) \right|}{N} \tag{5-9}$$

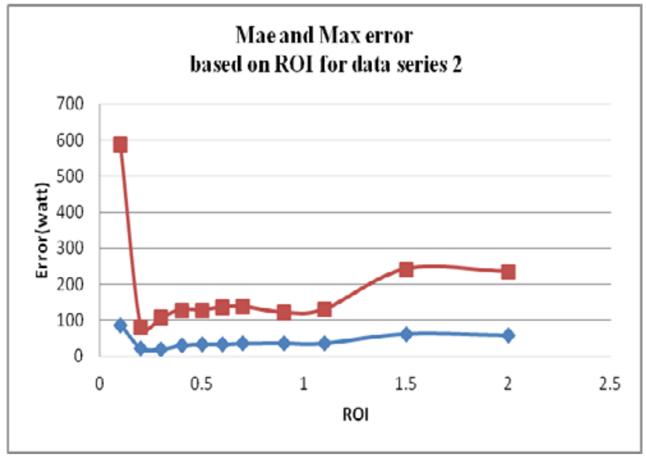
where N: the number of data after data preparation process, Q: real input power

$\hat{Q}$: predicted input power

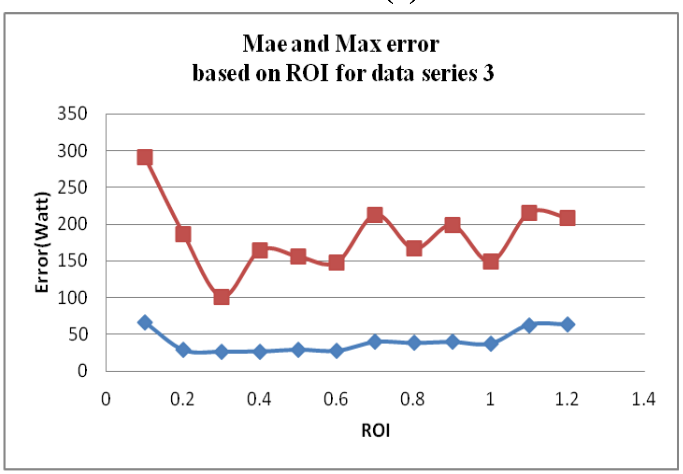
In order to determine the optimal Range of Influence, training data was trained with different ROIs and check with each sets of checking data.

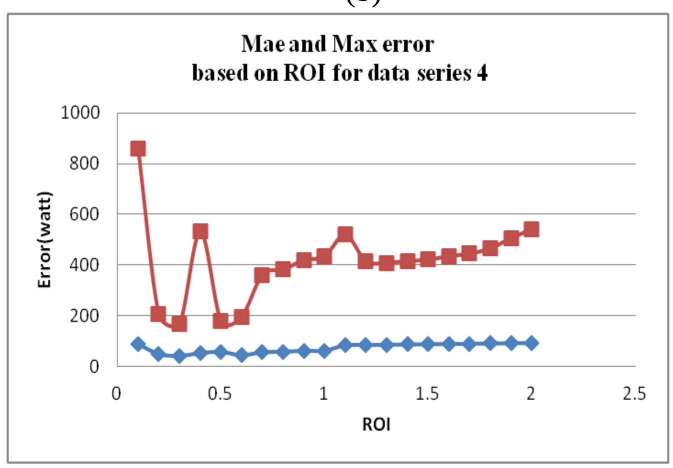


(a)



(b)





(c) (d)

Figure 5-6: Range of Influence (ROI) vs. errors for testing data sets which are completely separate from training data

Table 5-2: Fuzzy rule base for inverse modeling

Number of rules	Rule description
1	If (T_1 is T_1cluster1) and (T_2 is T_2cluster1) and (T_3 is T3cluster1) and (T_4 is T4cluster1) and (T_5 is T_5cluster1) then (q_1 is $q_1$cluster1)
2	If (T_1 is T_1cluster2) and (T_2 is T_2cluster2) and (T_3 is T3cluster2) and (T_4 is T4cluster2) and (T_5 is T_5cluster2) then (q_1 is $q_1$cluster2)
3	If (T1 is T1cluster4) and (T2 is T2cluster4) and (T3 is T3cluster4) and (T4 is T4cluster4) and (T5 is T5cluster4) then (q1 is q1cluster4)
4	If (T1 is T1cluster4) and (T2 is T2cluster4) and (T3 is T3cluster4) and (T4 is T4cluster4) and (T5 is T5cluster4) then (q1 is q1cluster4)
5	If (T1 is T1cluster5) and (T2 is T2cluster5) and (T3 is T3cluster5) and (T4 is T4cluster5) and (T5 is T5cluster5) then (q1 is q1cluster5)
6	If (T1 is T1cluster6) and (T2 is T2cluster6) and (T3 is T3cluster6) and (T4 is T4cluster6) and (T5 is T5cluster6) then (q1 is q1cluster6)
7	If (T1 is T1cluster7) and (T2 is T2cluster7) and (T3 is T3cluster7) and (T4 is T4cluster7) and (T5 is T5cluster7) then (q1 is q1cluster7)
8	If (T1 is T1cluster8) and (T2 is T2cluster8) and (T3 is T3cluster8) and (T4 is T4cluster8) and (T5 is T5cluster8) then (q1 is q1cluster8)
9	If (T1 is T1cluster9) and (T2 is T2cluster9) and (T3 is T3cluster9) and (T4 is T4cluster9) and (T5 is T5cluster9) then (q1 is q1cluster9)
10	If (T1 is T1cluster10) and (T2 is T2cluster10) and (T3 is T3cluster10) and (T4 is T4cluster10) and (T5 is T5cluster10) then (q1 is q1cluster10)
11	If (T1 is T1cluster11) and (T2 is T2cluster11) and (T3 is T3cluster11) and (T4 is T4cluster11) and (T5 is T5cluster11) then (q1 is q1cluster11)
12	If (T1 is T1cluster12) and (T2 is T2cluster12) and (T3 is T3cluster12) and (T4 is T4cluster12) and (T5 is T5cluster12) then (q1 is q1cluster12)
13	If (T1 is T1cluster13) and (T2 is T2cluster13) and (T3 is T3cluster13) and (T4 is T4cluster13) and (T5 is T5cluster13) then (q1 is q1cluster13)

The proposed ANFIS model was composed of 164 nodes, 130 nonlinear parameters and 13 fuzzy rules as summarized in Figure 5-7:

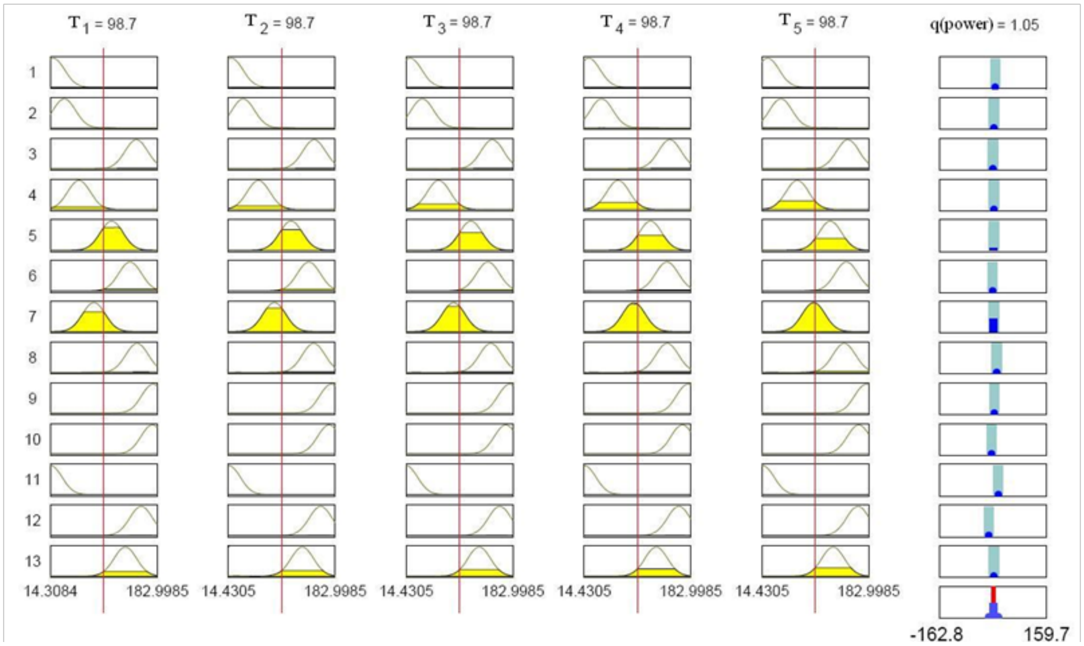


Figure 5-7: the proposed ANFIS rules

5.11 Experimental Results

After completing the training using the aforementioned methods, four functions different from those used in training process employed to compare each method's effectiveness as shown in Figure 5-8. Their resultant temperature were arranged (as explained in data preparation section) and given to the proposed techniques and the corresponding input energy functions were estimated by the each method (Table 5-3).

Results show that for the back propagation (BP) section of the ANN, the LM optimization proved to be more accurate when compared with results from the momentum algorithm. As well, the performance of ANNs can be improved and optimized by use of the genetic algorithm (GA). However, the ANFIS algorithm provided better predictions than the results derived by application of any of the other methods.

Without GA-ANN optimization, the neural net's parameters must be discovered by trial and error. Use of the GA allows the designer to determine the optimal parameters for the net. Its benefits are twofold, namely a more accurate solution with the additional bonus that the structure of the networks is simplified (providing, for instance, a reduced number of hidden layers). This simplification result in a faster response for the network.

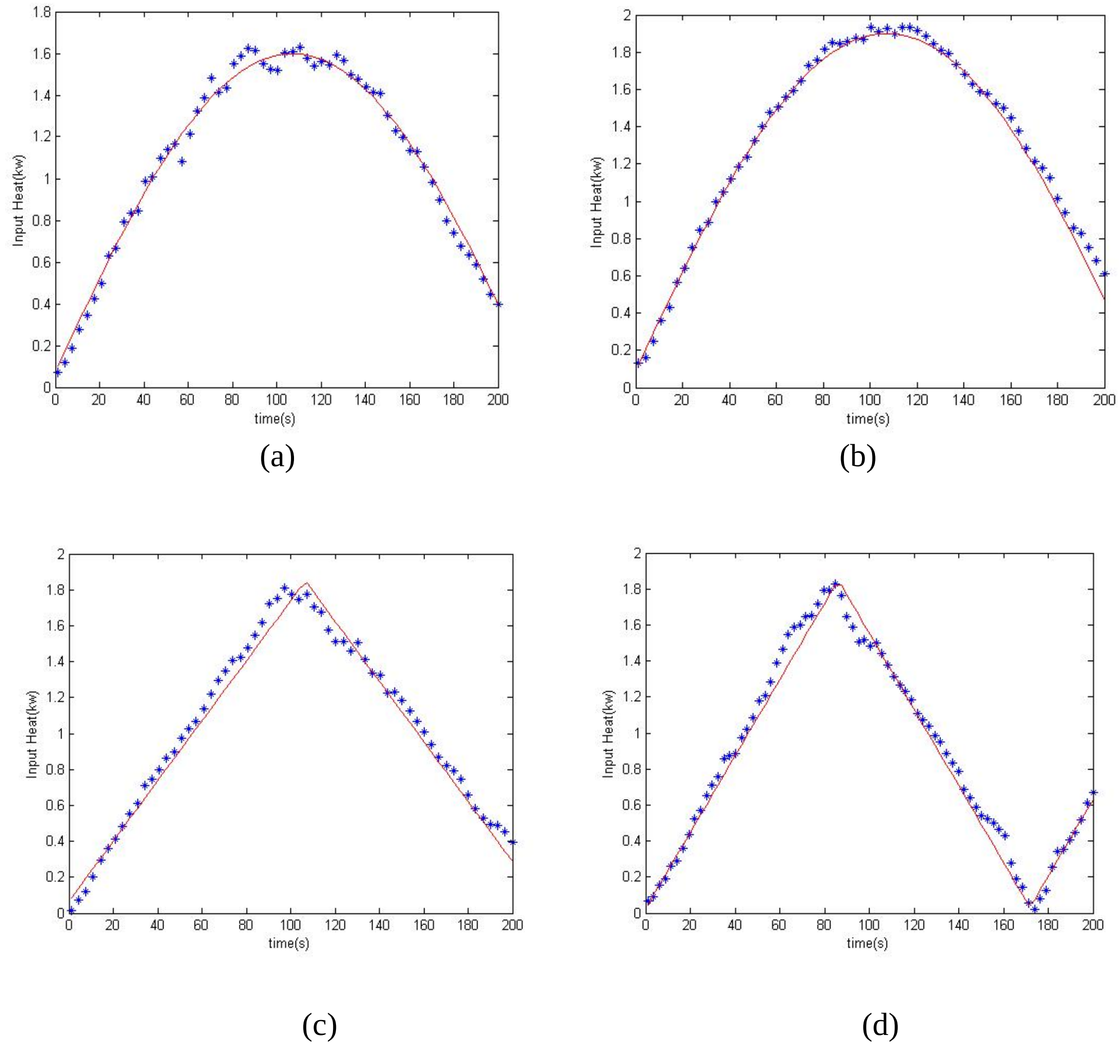


Figure 5-8: Actual and estimated input power data (average of all proposed techniques) for four checking data series (blue stars signify estimated input power by the proposed ANFIS and red lines show real input power applied to the system)

In general, as the number of parameters increases so does the training time. Training times for the ANFIS method exceed those for an ANN structure. This could result from use of a standard ANFIS structure which is not very flexible. Other NFs methods may be checked to determine if this penalty can be significantly reduced.

Table 5-3: Prediction accuracy for different trained models and techniques (minimum absolute error (MAE) and maximum error)

Int. Tech.	**Criterion**	**MAE (W)**				**Maximum Error (W)**			
LM	**Checking data**	**1st series**	**2nd series**	**3rd series**	**4th series**	**1st series**	**2nd series**	**3rd series**	**4th series**
	Error (W)	52	27.8	44.6	47.4	169.4	91.7	380.4	177.3
MOMENTUM		65.4	72.4	49.2	48.4	286.1	246	172.4	161
GA-LM		40.2	22.4	35.6	42	156.2	86.2	143.4	167.3
GA-MOMENTUM		51.1	44	42.9	44.5	223	179	167	139.7
ANFIS with the optimal ROI		40	20.3	27.2	32.4	129.4	81.1	101.5	149.2

5.12 Advantages and Comparisons

As mentioned in a previous study of multi-layer perceptron (MLP), the proposed intelligent methods are not plagued by time consuming trial-and-error calculations in their procedures that impede the use of classical methods. The sole iterative section of the proposed methods occurs during training and as this involves simple mathematical relations the problem solution can be derived must faster when compared with classical solutions.

Detailed physical properties and solution of direct problem are not required in the proposed methods. The sole requirement is high quality, input-output data. There is a substantial time saving and the resulting solutions are more accurate compared with the solutions derived by classical methods.

For the classical ANN methods employed in a previous study, the key parameters were found using a trial-and-error method. The use of evolutionary algorithms such as GA-ANN provides an optimized solution, consequently less effort is expended.

When using GA-ANN, the training phase requires a slightly longer time but this trade-off is acceptable as an optimal structure is defined. Furthermore, following training to produce an improved network, the solution time to determine the inverse is significantly reduced as the key parameters are optimized and the resulting structure is much simpler.

For the back propagation phase of MLPs, the Levenberg-Marquardt method provides a more accurate solution when compared to Momentum algorithm's solution. This observation is reasonable because LM uses a quadratic method for updating the weights and consequently would be expected to outperform linear methods.

As noted in the introduction, the inverse model is routinely used to develop a controller to generate the input power profile that produces the desired temperature distribution. The black box nature of the ANN solution is often cited as weakness as some control problems require human expertise or linguistic knowledge. The proposed ANFIS can address this deficiency and this procedure provided the best results in terms of fitted responses among all the methods considered in this work.

The number of parameters and training time are significantly increased using the ANFIS methodology. However, this trade-off is also acceptable given the improvement in prediction accuracy. The NF solution methodology was chosen because of its popularity efficacy for in solving a broad range of engineering problems. Other NFs may be applied in future studies to determine if this furnace can be modelled inversely with fewer parameter and improved structures.

In this study only MLP checked, Other ANNs can also be checked to find if they can perform better or not in this application.

5.13 Conclusion

In this paper, four different intelligent techniques were designed, successfully trained and then utilized as an appropriate alternative to conventional methods to predict the input power required by an irradiative batch dryer. The intelligent technique models were developed by training using experimental data. For this purpose, input electrical power was applied to a halogen lamp attached to the dryer's top surface and the resulting temperature was measured by a thermocouple fixed to the bottom surface. Data was recorded, processed and employed to produce an inverse ANN model of the system. This model can then take the transient temperature history of a point and from this data estimate the input electrical power to the system. The results demonstrate that the power estimated by the designed intelligent technique methods was consistent with the real power applied during the experiment.

From a practical point of view, the only requirement to make a highly accurate intelligent technique models for a heat estimation problem is a series of input temperature data for a few minutes of operation and the dimensions and thermophysical properties are not needed.

Comparisons show that application of a GA-ANN simplifies the structure of ANNs by optimizing key parameters and the resultant GA-ANN solves faster than a simple ANNs.

For the backward-propagation step in defining the ANN, the level Levenberg-Marquadt algorithm provides more accurate results than the Momentum algorithm.

The most accurate method for inverse model development was ANFIS which was included human expertise and linguistic knowledge, but significant increase in the number of parameters and training time was required. Other ANNs and NF methods are open for study in this application.

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Contribution to the Paper	Data Gathering, Data Analyzing, Data preparation, Training data for more than 16 ANNs, Analysing the results, make comparison, writing the draft
Overall percentage (%)	
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature	Date 1/10/2015

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Supervising, Editing the writing
Signature	Date 1/12/2015

Chapter 6

A COMPARATIVE APPROACH OF INVERSE MODELLING APPLIED TO AN IRRADIATIVE BATCH DRYER EMPLOYING SEVERAL ARTIFICIAL NEURAL NETWORKS

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6.1 Abstract

The present chapter has focused on a comparison between commonly employed Artificial Neural Networks (ANNs) in engineering applications to identify the most efficient ANN for inverse modeling of an irradiating furnace/dryer in terms of accuracy and computing time. To this end, several ANNs were designed, trained and employed to estimate the heat emitted during the irradiative batch drying process with the aid of NeuroSolution®.

As part of the study, different ANNs were designed and trained to play the role of the inverse heat transfer model. The reasons for exploiting these ANNs were derived from various studies in the literature, in which ANNs were employed for engineering modelling purposes. The results showed that the Multi Layer Perceptron (MLP) with the Levenberg-Marquadt (LM) in the Back Propagation (BP) was the best ANN among the methods evaluated to solve the inverse heat estimation problems used in irradiative batch drying processes. An important advantage of the ANNs method in comparison with classical inverse heat transfer modelling approaches is that a detailed knowledge of geometrical and thermal properties of the system (such as wall conductivity, emissivity, etc.) are not required. Such properties are difficult to measure and may undergo significant changes during the temperature transient mode.

In this study, Genetic Algorithms (GA) has been employed to determine key parameters of the employed ANNs. These parameters are normally found heuristically or by a trial and error brute force process. The results demonstrate that the parameters may be estimated much more accurately and faster by GA. The performance of the networks has been improved and the number of required hidden layers has been discovered using a non trial-error method, which also eliminated time-consuming re-testing procedures and produced more accurate results.

6.2 Introduction

Thermal processes dominated by radiation, play important roles in a plethora engineering applications. The most important criterion that influences our ability to control thermal processes, is the extent to which the designed model can reliably predict the behaviour of thermal systems in order to maximize energy efficiency and to minimize the production of greenhouse gases and relevant environmental footprints [1, 2]. Consequently, many investigations have been undertaken to improve and develop more robust modelling strategies [3-5].

Each system needs an efficient and reliable method, and a model for process identification. The main purpose of process modelling is to predict plant behaviour and drive the process to operate at its optimal production rate [2].

In the modelling of a thermal process, if there is a lack of knowledge of the system's boundary conditions, initial conditions or thermophysical properties, then the derived equations are "ill-posed". These unknowns are estimated using measured temperature data at one or several locations within the domain. As a consequence of the ill-posed nature of the problem, unavoidable random errors (noise) in the measured data may induce significant errors amplified by several orders of magnitudes and the unknowns may be poorly estimated. Hence, inverse heat transfer problems (IHTPs) are normally considered to be complex and "difficult to solve" [6]. On the contrary, if all aforementioned properties are known and the derived equations are well-posed, these problems are called "direct". The purpose of the solution of a direct problem, is to find the temperature distribution for a geometrically well-defined domain [7].

Applications of inverse heat transfer schemes occur in numerous application including: the estimation of thermophysical properties of material [7-10], estimation of bulk radiation properties and boundary conditions in absorbing, emitting and scattering semi-transparent materials [7, 11-13], control of the motion of the solid liquid interface during solidification [7, 14, 15], estimation of inlet condition and boundary heat flux in forced convection inside ducts[7], estimation of interface conductance between periodically contacting surfaces [7, 16], monitoring the radiation properties of reflecting surfaces of heaters and cryogenic panels [7, 17, 18], estimation of heat release during friction of two solids [7, 17, 18], estimation of reaction function [7, 19], control and optimization of the curing process of rubber [7], estimation of the boundary shapes of bodies[7], estimation of the temperature or heat rate distribution within the combustion region [20], and estimation of source term or temperature distribution in radiative heat transfer [20-25].

Radiation processes are strongly non-linear, highly complex and the accurate modelling of such processes is a difficult and time consuming task as a consequence of the large number of physical parameters defined for the heat transfer media [26, 27]. Conventional modelling methods used for such systems are normally based on a solution of energy balances and rate equations which allow us to develop and solve the governing differential equations [28].

Unfortunately, these models are rather complex and the resulting differential equations that are highly non-linear [26].

Despite the fact that thermal radiation is the dominant and most important heat transfer mode in high-temperature equipment (e.g. furnaces, high temperature reactors, etc), the solution of inverse radiation problems is rarely addressed in the literature (in contrast to inverse heat conduction problems which are widely studied).

An obvious reason for this lack of attention is the fact that radiation is a significantly more complex phenomenon than conduction and convection. The nature of the integro-differential equation that governs radiative heat transfer defies simple solutions even for direct problems. Hence, the inverse radiation problems that have been solved to date are generally simplistic and rather elementary cases [29].

Heat function estimation in radiative problems is an important type of IHTPs [7, 30]. Several trial-error and iterative based methods have been developed and applied to solve indirect problems, such as heat function estimation introduced by Mirsepahi et al.[30].

These methods normally require detailed and accurate information regarding physical properties [10, 20, 22]. Often, the measurement of such physical properties is extremely difficult, if not impossible. Moreover, all conventional inverse methods require that the direct problem must be solved first. This constraint of the need for iterated direct problem solutions can produce significant computing errors and calculations may be excessively time-consuming [6, 10, 20, 22, 31, 32].

Mirsepahi *et al.* proposed and applied a common ANN as an alternative method, based on the gathering and examination of experimental data, instead of the development of complex mathematical equations. Consequently, detailed knowledge of the system's physical properties is no longer necessary. ANNs are able to model complex systems without the need for complex mathematical models. Accurate input and output test data are the sole requirement for the application of ANNs to model the system. These methods provide an additional benefit by avoiding time-consuming calculations [33].

In their study, an ANN was designed, trained and then employed to estimate the input power to a batch drying process where radiation provides the dominant mode of thermal energy transport [30]. In that study, the authors employed MLP (Multi-layer perceptron), as conventional wisdom suggests that in engineering applications, this type of ANNs often works best, in terms of accuracy and quick response. Additionally, the number of neurons in hidden layer was found by trial-and-error (the number of hidden layers is a key parameter in MLP).

A variety of ANNs are able to solve function approximation problems. In order to determine if the ANNs proposed by Mirsepahi et al. provide a superior tool for the modelling of inverse radiation problems, this study has employed the NeuroSolutions® software to generate selections based on fitness and rapidity of the solution among those possible ANNs.

All ANNs possess a number of key parameters. These parameters are normally determined by trial and error. This method makes the procedure time consuming and inaccurate. For example, there is no criterion to specify key parameters such as the number of neurons in hidden layer(s).

Mirsepahi et al. in their study found the number of hidden layers heuristically using a trial-and-error procedure. In contrast to that work, here the key parameters are developed with the aid of a GA, in order to determine if the results may be improved in terms of reduced computing time and accuracy.

6.3 Experimental setup

Figure 6-1 illustrates a simple schematic of the experimental rig used in this study. A single halogen lamp was attached to the top surface of the furnace/dryer to provide the heat source and a thermocouple sensor was attached to the bottom surface as the sensor. Both items were located asymmetrically. An I/O card, a power controller, an amplifier and the Real Time Windows Target (RTWT) Toolbox of MATLAB/Simulink software were used.

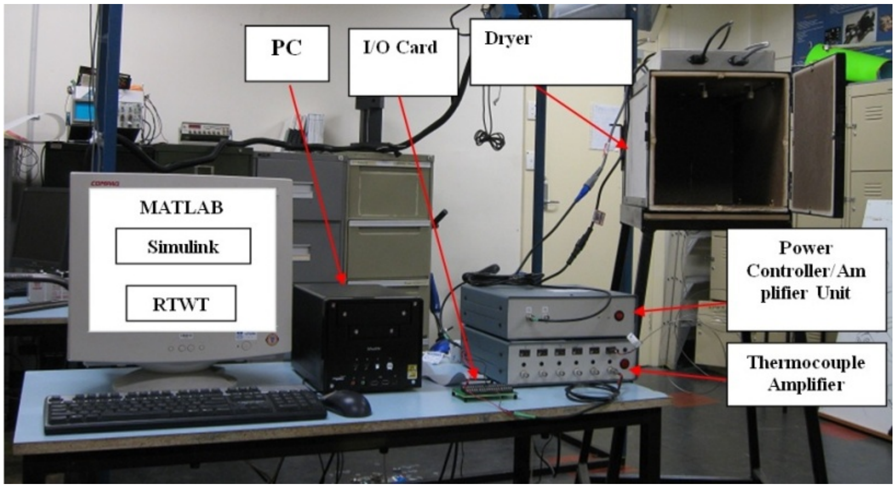


Figure 6-1: Setup for experimental dryer

The dryer body was built using insulation boards and a steel frame. A T-type thermocouple with an accuracy of $1^{o}K$ was selected as the sensor. A thermocouple amplifier was used to amplify the output power from the thermocouples. This signal was sent to a digital input-output card and the control commands were generated in the computer and then sent to the power control (power amplifier) unit which amplifies input voltage to the lamp based on the received signal from the computer.

6.4 Problem Statement

The objective of this work is to find the best ANN among those employed in the literature in terms of accuracy and computing time, then optimize the relevant key parameters to determine the optimal method for the estimation of the input power to an enclosure using experimental data. The required experimental data were gathered from a model infrared dryer/furnace (Figure 6-2).

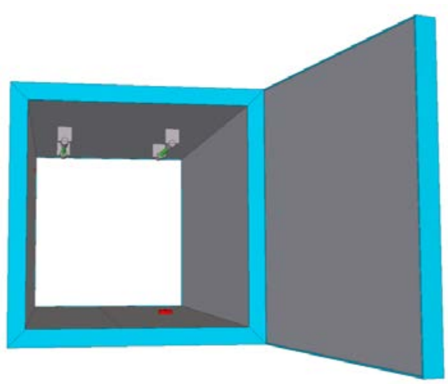


Figure 6-2: A simplified model of the dryer/furnace

It was also assumed that the furnace is an enclosure with diffuse-gray surfaces. A mathematical model of the energy balance for such a system can be determined. Some simplifying assumptions are necessary in order to model such a system which includes non-uniformity of the relevant thermal properties of the surfaces, the independency of the emissivity factor (ε_k) from the wavelength and the direction of radiation from each surface. As a final assumption, it was assumed that all the energy was emitted and reflected diffusely [34].

6.5 Intelligent techniques approach to the proposed IHTP

An inverse model is often used to develop a controller to regulate the input power that produces the desired temperature distribution. In control problems, the number of controlled (measured) variables (e.g. temperature at points on the surface) cannot exceed the number of control actuators (manipulated variables) (e.g. input power). In order to produce a desired temperature distribution on a surface in a batch infrared dryer, it is necessary to control a large number of heat sources simultaneously using an accurate inverse model. This research addresses the initial step of this task. An accurate inverse model was generated in this work. This model is able to estimate the transient input power to produce a desired temperature history. The general form of this inverse model is shown below:

$$\hat{Q}\left(k-\frac{\tau_d}{\tau_s}\right)=F[T(k),T(k+1),\dots,T(k+r)] \qquad (6\text{-}1)$$

where F is a function which is to be estimated, τ_d is the dead time (that is needed for input heat to affect the temperature at a practical point), τ_s is the sampling time (time interval between two consequent measurements), r is the order (which shows how long the temperature of the practical point is affected by the input heat emitted at any moment), T is the measured temperature and $\hat{Q}$ is the estimated/predicted input power.

6.6 Data preparation

Experimental data for the transient mode is stored in a matrix with two columns as:

$$A=\begin{bmatrix} Q_1 & T_1 \\ \vdots & \vdots \\ Q_n & T_n \end{bmatrix} \qquad (6\text{-}2)$$

Where n is the number of collected data, A is the matrix of raw recorded/sensed data, Q is input power and T is recorded temperature.

It was determined experimentally that the delay or dead time of the system is 1.4 seconds. The sampling time of 0.2 seconds and the order of 5 were guessed [30].

$$B=\begin{bmatrix} Q_1 & T_{d+1} \\ \vdots & \vdots \\ Q_{n\text{-}d} & T_n \end{bmatrix} \tag{6-3}$$

where B is a matrix of data after considering the dead time and $d=\frac{\tau_d}{\tau_s}$

For an inverse model with an order of r; the data should be arranged in a matrix as shown below:

$$C=\begin{bmatrix} \overbrace{\begin{matrix} T_{d+1} & \cdots & T_{d+r} \\ \vdots & \vdots & \vdots \\ T_{n\text{-}r+1} & \cdots & T_n \end{matrix}}^{\text{Input}} & \overbrace{\begin{matrix} Q_1 \\ \vdots \\ Q_{n\text{-}d\text{-}r+1} \end{matrix}}^{\text{Output}} \end{bmatrix} \tag{6-4}$$

where C is the matrix of prepared data.

6.7 Intelligent modeling of the radiating furnace

In this study, the input to the inverse model is the temperature history in degrees Kelvin and the output is input power in kW. Equation 6-1 may be written in the following form:

$$\widehat{Q}(k+7)=F[T1(k),T1(k+1),T1(k+2),T1(k+3),T1(k+4),T2(k),T2(k+1),T2(k+2)] \tag{6-5}$$

The variables with a hat are the estimated/predicted ones. After applying the dead time and the order, a set of 1000 pieces of recorded data were prepared as below:

$$\text{Prepared data}=\begin{bmatrix} \overbrace{\begin{matrix} T_8 & T_9 & T_{10} & T_{11} & T_{12} \\ T_9 & T_{10} & T_{11} & T_{12} & T_{13} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{996} & T_{997} & T_{998} & T_{999} & T_{1000} \end{matrix}}^{\text{Input}} & \overbrace{\begin{matrix} Q_1 \\ Q_2 \\ \vdots \\ Q_{989} \end{matrix}}^{\text{Output}} \end{bmatrix} \tag{6-6}$$

6.8 Comparison of a number of ANNs to discover the best one

One objective of this study is to compare different ANNs to find the optimal one to provide an inverse model of the furnace/dryer (Figure 6-2). Accordingly, a set of training data and four completely different testing data sets were gathered from the experimental setup. There are 80% of training data used for training and 20% used for cross validation. After determining the delay, sampling time and the order, the prepared matrices of data, as the input and output of ANNs, were entered into the NeuroSolutions for Excel 6®. Training data used to train ANNs and after completing this training, the sets of testing data were used to validate ANNs model. The results are presented in the Appendix A.

This comparison indicates that the ANN employed by Mirsepahi et al. [35] is optimal for the studied IHTP (MLP with LM optimization method in the back propagation section).

Table 6-1 contains the result of the four different testing data used to validate the model.

Table 6- 1: Result of four sets of testing data by MLP (LM as the optimization method). Key parameters were determined by trial-and-error

	Training	Cross Val.	Testing
Number of Rows	477	105	118
MSE	0.006	0.004	0.004
Correlation (r)	0.992	0.994	0.994
Min Absolute Error	0.000	0.002	0.001
Max Absolute Error	0.227	0.126	0.199
Mean Absolute Error (MAE)	0.060	0.052	0.054

(a)

	Training	Cross Val.	Testing
Number of Rows	480	101	94
MSE	0.005	0.004	0.004
Correlation (r)	0.993	0.994	0.995
Min Absolute Error	0.001	0.001	0.000
Max Absolute Error	0.225	0.125	0.169
Mean Absolute Error (MAE)	0.053	0.057	0.054

(b)

	Training	Cross Val.	Testing
Number of Rows	480	101	94
MSE	0.004	0.004	0.002
Correlation (r)	0.994	0.993	0.995
Min Absolute Error	0.000	0.000	0.000
Max Absolute Error	0.189	0.263	0.134
Mean Absolute Error (MAE)	0.047	0.052	0.035

(c)

	Training	Cross Val.	Testing
Number of Rows	480	101	94
MSE	0.003	0.005	0.002
Correlation (r)	0.995	0.995	0.997
Min Absolute Error	0.000	0.000	0.000
Max Absolute Error	0.163	0.170	0.173
Mean Absolute Error (MAE)	0.043	0.059	0.032

(d)

6.9 GA-ANN modelling of the proposed IHTP

Back propagation ANNs (BPN) are widely applied in a variety of engineering applications. Often, the resulting solutions are not robust and are highly sensitive to slight changes in the parameters. Hence, minor changes in the value of the key parameters may cause significant change in the ANN's performance.

In the absence of any accurate and defined theory to calculate parameter settings, the parameters such as the number of hidden layers must be determined heuristically and by trial and error methods. This fact makes the procedure for finding the structure of a simple conventional ANN very time consuming. In this study, a GA is used to determine the optimal values of the aforementioned parameters.

In order to find the optimized number of neurons in the hidden layer, the commercially available NeuroSolutions 6 software was employed. This software allows one to optimize the number of neurons in hidden and input columns.

The GA is an optimization method based on evolutionary principles. NeuroSolutions can be employed to use the GA as a learning algorithm for training multilayer perceptron ANNs. In this study, the optimized number of neurons in hidden layer was found by applying the GA.

When using the GA, the fitness of a chromosome can be quantified, as fitness is inversely related to Mean of Absolute Error (MAE) of the ANNs outputs. An initial population of chromosomes is determined in a random manner; the algorithm subsequently starts and continues in a 'survival of the fittest' mode to develop a better population. The commonly employed operators include selection, crossover and mutation (Table 6-2.).

Table 6-2 compares the performance of proposed GA-ANN and ANN by using four different sets of testing data

Table 6-2: comparing of the performance of four different testing data before and after GA optimization

(a)

Performance criterion	Trial-Error	GA
MSE	0.009	0.004
NMSE	0.033	0.016
MAE	0.070	0.054
Min Abs Error	0.0002	0.001
Max Abs Error	0.3248	0.198
R	0.983	0.993

(b)

Performance criterion	Trial-Error	GA
MSE	0.0046	0.0043
NMSE	0.0183	0.0170
MAE	0.048	0.054
Min Abs Error	0.0001	0.000
Max Abs Error	0.229	0.169
R	0.992	0.994

(c)

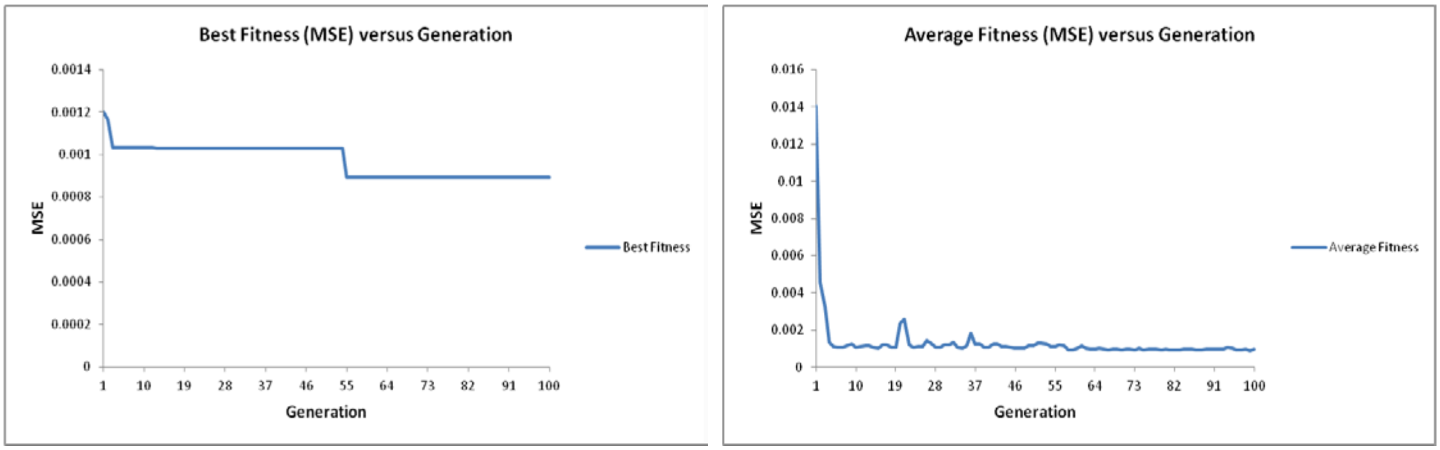
Performance criterion	Trial-Error	GA
MSE	0.004	0.001
NMSE	0.017	0.009
MAE	0.054	0.034
Min Abs Error	0.000	0.000
Max Abs Error	0.169	0.134
R	0.994	0.995

(d)

Performance criterion	Trial-Error	GA
MSE	0.0023	0.0021
NMSE	0.008	0.007
MAE	0.038	0.032
Min Abs Error	0.0008	0.0003
Max Abs Error	0.137	0.173
r	0.997	0.996

The results show that the GA-ANN produces more accurate solutions. In order to compare ANNs and GA-ANNs in terms of performance, the number of hidden layers in both methods should be compared. The number of hidden layers with ANNs is six (6) whilst with the GA-ANN only four (4) are required; hence the performance of GA-ANN is also superior.

(a)



(b)

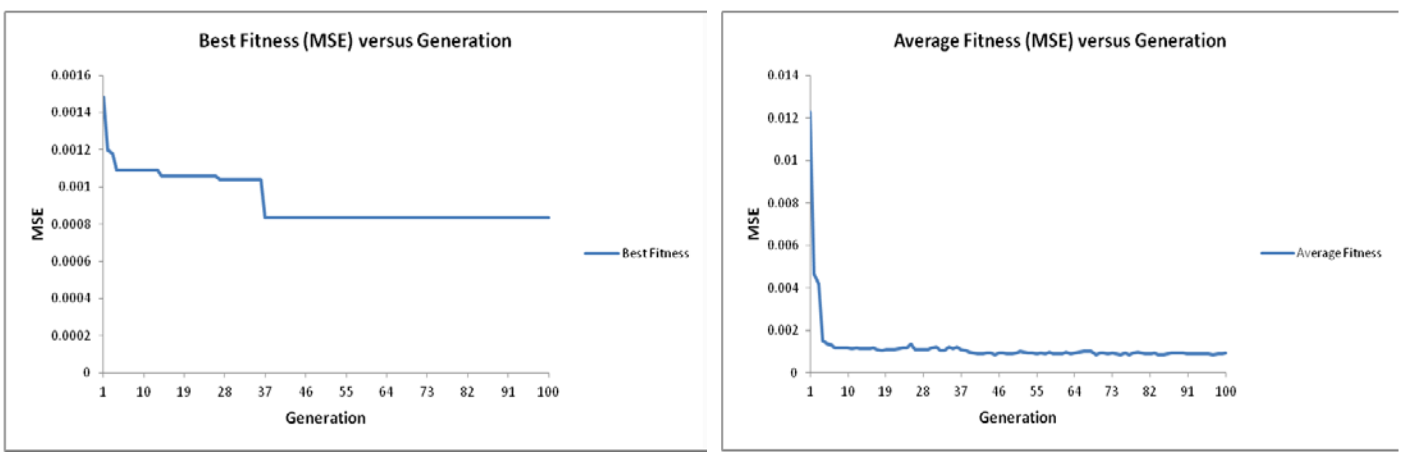
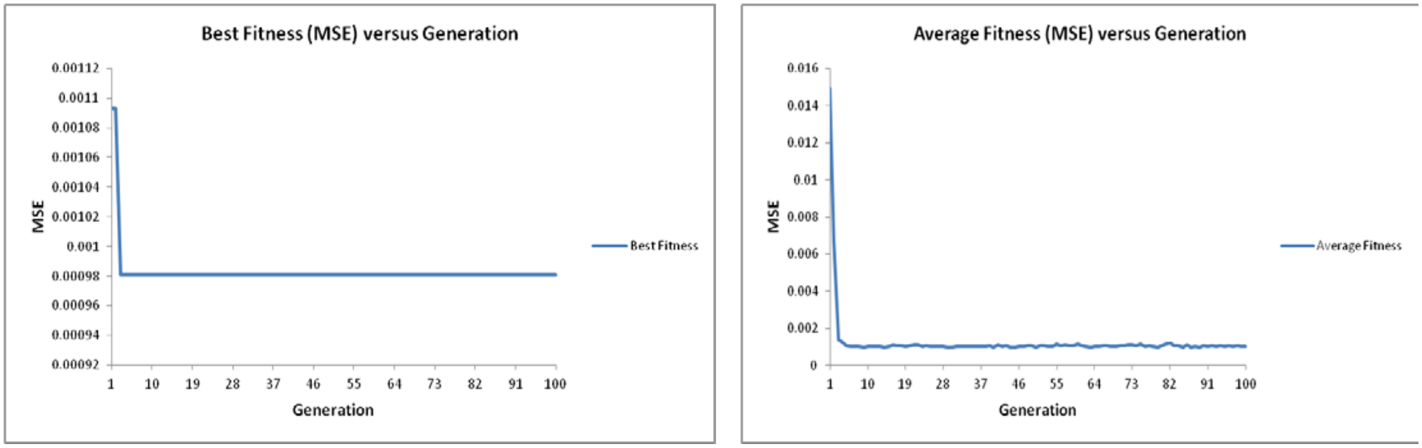


Figure 6-3-a : Average and best fitness in each generation after optimization the parameters by GA for four different checking data ((a) first set of checking data, (b) the second)

(c)



(d)

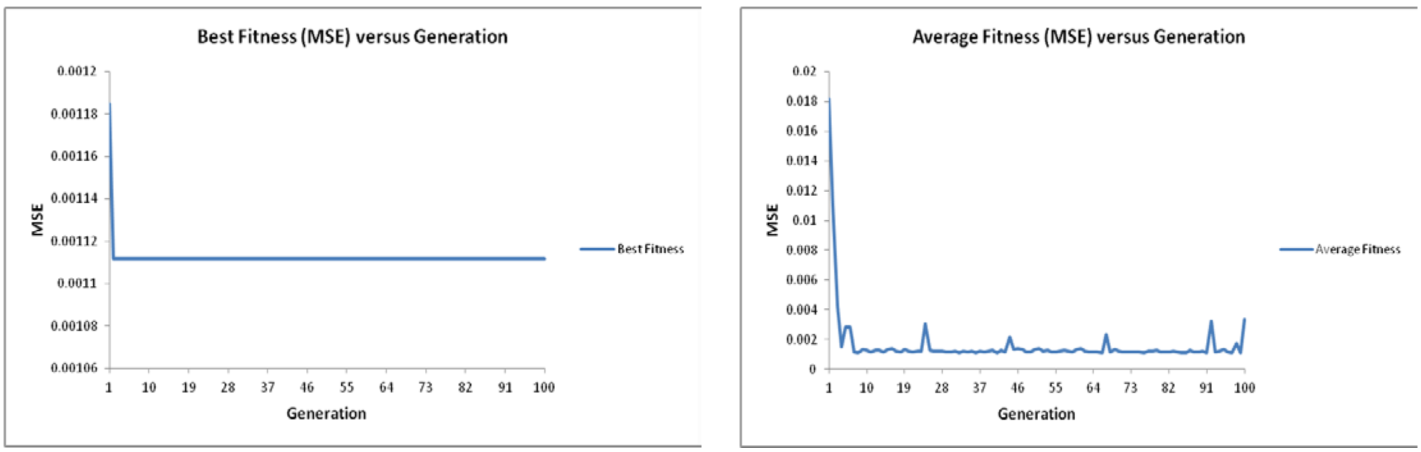


Figure 6-3-b : Average and best fitness in each generation after optimization the parameters by GA for four different checking data ((c) the third and (d) the fourth set of checking data)

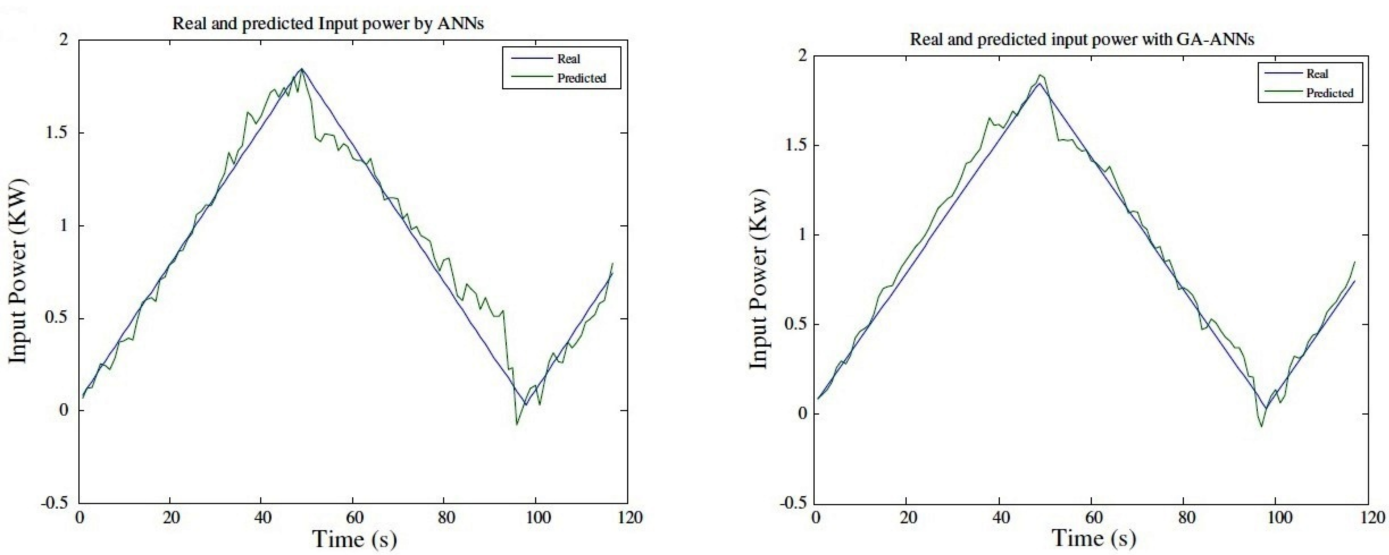
6.10 Experimental results

As shown in Appendix A, the proposed method by Mirsepahi *et al.* (MLP with one hidden and Levenberg-Marquadt in optimization part) exhibits the best fitness with experimental data among all the ANNs compared by NeuroSolutions (Figures 6-3).

As described in the previous parts, GA-ANNs perform better in comparison to ANNs in terms of accuracy and computing time.

Figures 6-4 illustrates the comparison of ANNs and GA-ANNs in terms of accuracy.

(a)



(b)

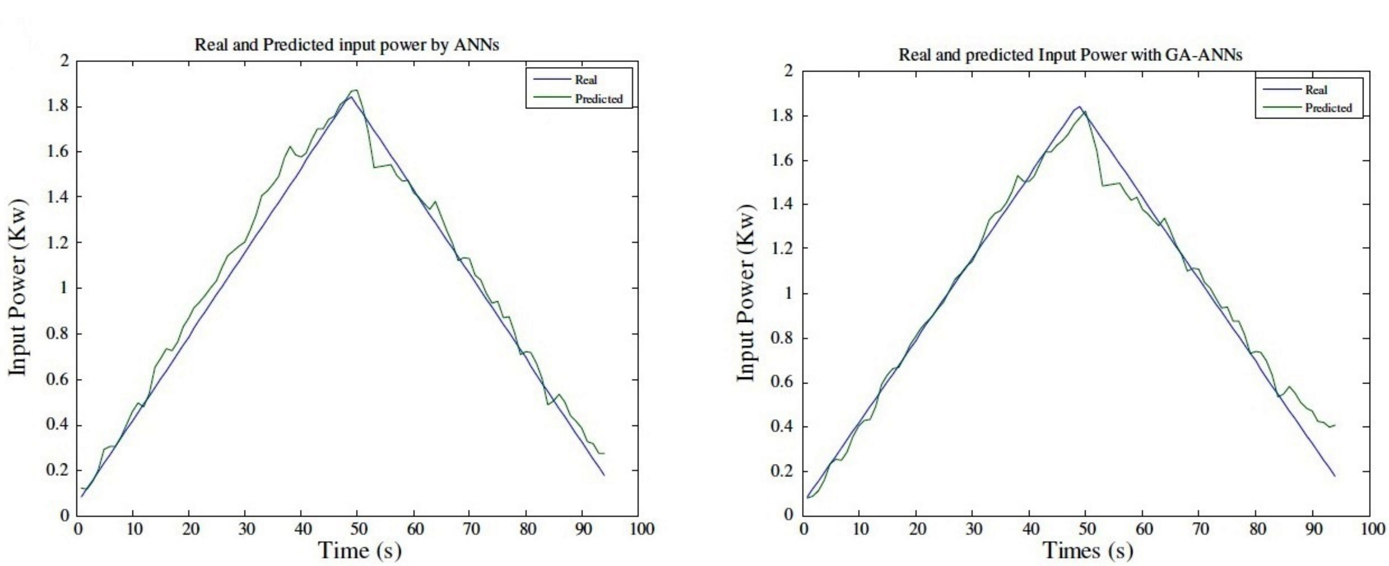
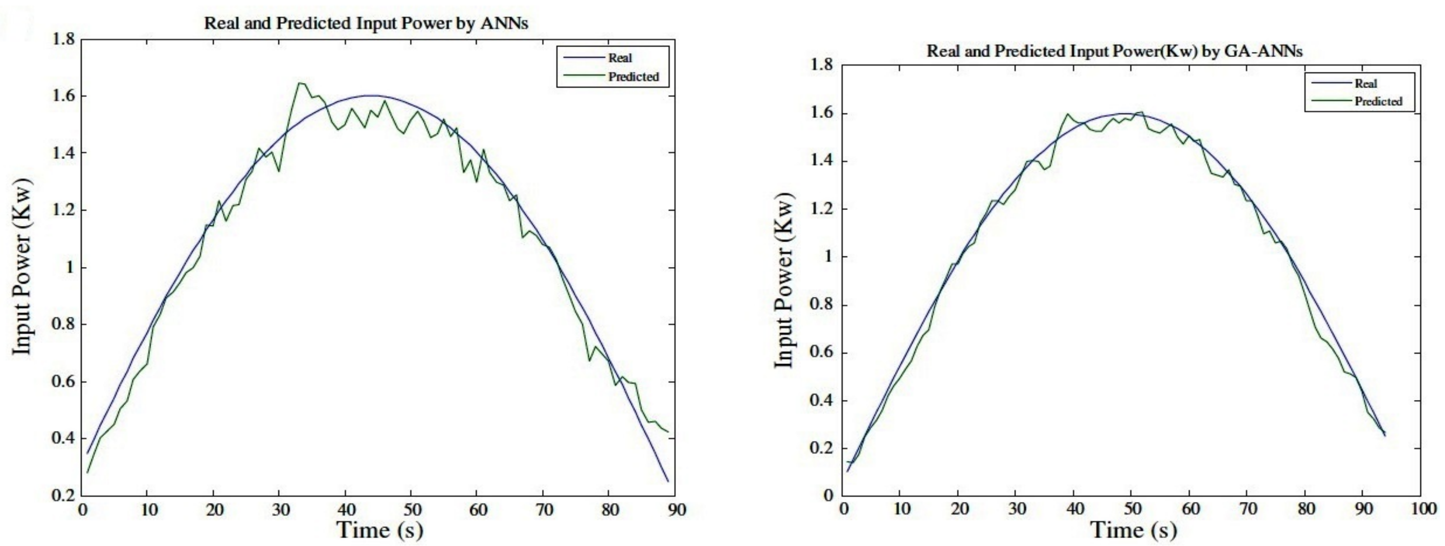


Figure 6-4-a: Real and predicted input power for four different series of checking data and comparison between ANNs and GA-ANNs method for each ((a) first set of checking data, (b) the second)

(c)



(d)

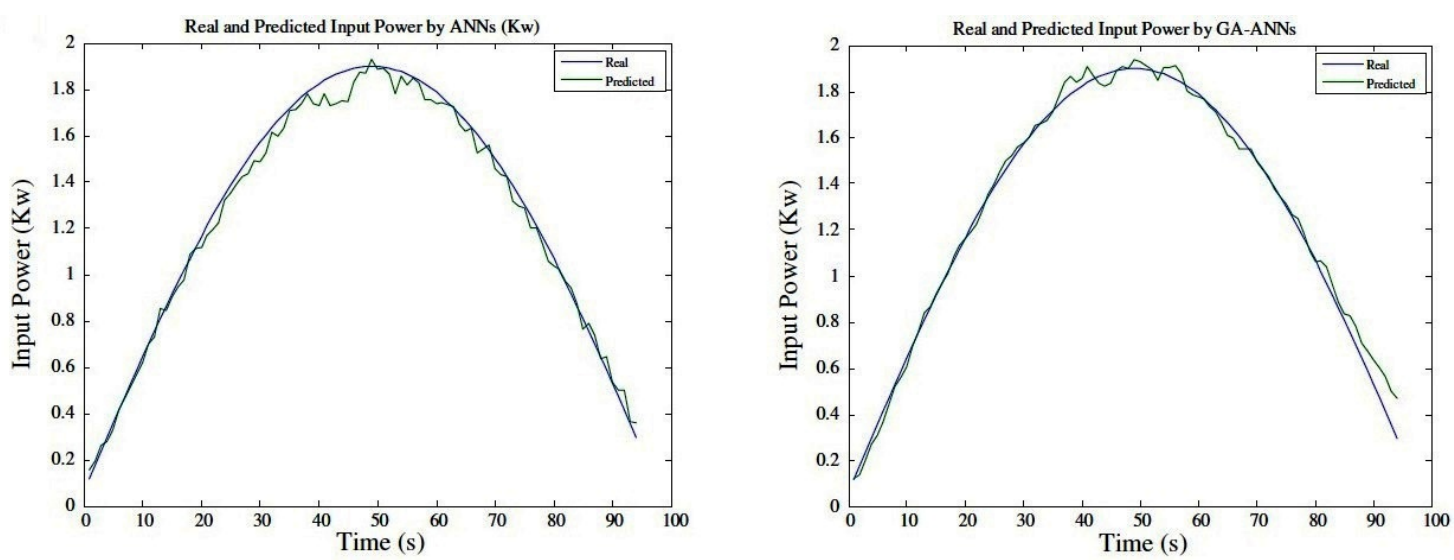


Figure 6-4-b: Real and predicted input power for four different series of checking data and comparison between ANNs and GA-ANNs method for each ((c) the third and (d) the fourth set of checking data)

The number of hidden layers decreased by one third (33%) when using the GA-ANNs, therefore the performance of GA-ANNs is superior when compared to the ANNs in terms of computing time as well. In the ANNs proposed by Mirsepahi et al. [30] the number of hidden layers was determined by trial and error but by using the GA-ANNs the number of layers was found by application of GA algorithms.

6.11 Summary

Here is a brief summary of the current chapter:

- The normal solution procedure for conventional inverse methods is based on trial-and-error. The probability of error is extremely high for such methods and they are normally very time-consuming [10, 20, 23, 36] but in the proposed method this restriction does not exist.

- Iterative methods inherent in other conventional inverse methods also incur a serious penalty of long convergence time [22, 31]. When ANNs are employed, the sole iterative part is in training which involves only simple mathematical relations; therefore the proposed method is much faster than conventional iterative methods.

- Detailed and accurate physical properties are required in many inverse methods. Their unavailability makes the solution difficult to achieve (impossible in some cases) and necessitate simplified (and often physically unrealistic) assumptions given the complexity of heat transfer systems [20, 22, 23, 29, 36-45]. The proposed method does not require detailed knowledge or estimation of the system's physical properties as it is solely based on input and output data.

- In order to use many conventional inverse methods, the direct problem must be solved first. Hence, the resulting inverse solution will be subject to serious computing errors and time-consuming calculations [20, 22, 23, 29, 36-45]. However, in the proposed method, there is no need to solve the direct model.

- With the aid of the NeuroSolutions software tool, it has been demonstrated that the MLP is the best ANN among many possible ones for inverse modelling of the studied irradiative furnace/dryer

- For the classical ANN methods employed in a previous study, the key parameters were found using a trial-and-error method. The use of evolutionary algorithms such as GA-ANN provides an optimized solution, consequently less effort is required.

- When using the GA-ANN, the training phase requires a slightly longer time, but this trade-off is acceptable as an optimal structure is defined. Furthermore, following training to produce an improved network, the solution time to determine the inverse is significantly reduced as the key parameters are optimized and the resulting structure is much simpler.

6.12 Conclusions

In this paper, several different ANNs has been designed, then successfully trained and utilized as an appropriate alternative to conventional methods for predicting the input power required by an irradiative batch dryer. In this study, for the first time, several ANNs have been compared to find the optimal neural net in terms of accuracy and computing time. In previous studies MLP were employed and introduced as the best solution method without any comparison with other possible ANNs. Models using intelligent techniques were developed by training using experimental data. For this purpose, input electrical power was applied to a halogen lamp attached to the dryer's top surface and the resulting temperature was measured by a thermocouple fixed to the bottom surface. Data was recorded, processed and employed to produce an inverse ANN model of the system. This model can then use the transient temperature history of a point and from this data estimate the input electrical power to the system. The results demonstrate that the power estimated by the MLP method was consistent with the real power applied during the experiment among several ANNs.

In the current study, a GA-ANN has employed to estimate key parameters by the aid of a GA optimizer. These parameters estimated by train-and-error in previous studies. A comparison of the results from the two methods prove that application of a GA-ANN simplifies the structure of ANNs by optimizing key parameters (the number of neurons in the hidden layers) and the resultant GA-ANN solves the problem faster than a simple MLP.

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Contribution to the Paper	Data gathering, Analyze the data, Data preparation, Data Training, Finding the direct ANN model, Finding the Inverse direct ANN model, make the comparison, writing the draft		
Overall percentage (%)			
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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Contribution to the Paper	Rewriting and representing the final draft		
Signature		Date	25/11/2015

Chapter 7

COMPARISON OF INVERSE MODELLING AND OPTIMISATION-BASED METHODS IN THE HEAT FLUX ESTIMATION PROBLEM OF AN IRRADIATIVE DRYER/FURNACE: A SINGLE-INPUT/SINGLE-OUTPUT STUDY

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7.1 Abstract

There are two major approaches in the sequential (real-time) heat flux estimation problems using measured temperatures: (i) development of inverse heat transfer models that directly estimate heat flux and (ii) use of a combination of a direct heat transfer model (which estimates temperature using heat flux information) and an optimisation algorithm. In physics-based solutions, using thermodynamics and heat transfer laws, the first approach is considered ill-posed and challenging, and the second approach is more popular. However, the use of artificial intelligence (AI) techniques has recently facilitated heat transfer inverse modelling, even for complex irradiative systems. Many of the claimed advantages of AI inverse models of irradiative systems result from the use of AI techniques rather than the inverse modelling approach. This research presents a rational comparison between the aforementioned approaches for an irradiative thermal system, both using AI techniques, for the first time. The results show that inverse models are superior because of their higher accuracy and shorter estimation delay time.

7.2 Introduction

All thermal modelling problems can be characterised into the following two classes: direct and inverse problems. For a known geometry, direct problems deal with temperature estimation, provided that the (i) boundary conditions (i.e., heat flux), (ii) thermo-physical parameters and (iii) initial conditions are known. If the temperature distribution is known and any factor in the aforementioned three groups is missing, the problem is called an inverse heat transfer problem (IHTP) [1, 2]. In general, IHTPs are considered to be ill-posed problems [3]. This research focuses on a heat flux estimation case. This problem is tackled through two major approaches: whole domain and sequential. The whole domain method estimates the heat flux and requires temperature data for the entire operating time; therefore, it cannot be used in real time. A sample algorithm widely used in whole domain heat flux estimation is the Tikhonov regularisation [3]. In contrast, if the heat flux estimation is meant to be assessed in real-time, the problem is considered sequential [4]. This study focuses on sequential heat flux estimation.

Two main approaches have been employed for sequential heat flux estimation: inverse modelling and optimisation-based heat flux estimation. In the first approach, a model is developed to estimate heat flux based on a sequence of measured temperatures. Examples include the linear filters (models) suggested in [1, 4, 5] for flux estimation in inverse conduction problems. Development of these so-called 'inverse' models using heat equations is a challenge, particularly if radiation is present as it adds nonlinearity to the system [6]. In contrast, optimisation-based heat flux estimation approaches consider a guessed heat flux as the input to the direct model of the system for a number of instants and then the heat flux is tuned such that the output temperature of the direct model matches the real temperature [5, 7]. As direct modelling is well-posed, the difficulties of inverse modelling do not appear in the optimisation-based heat function estimation. In short, in inverse modelling, a model which can estimate heat flux in real time is identified, whereas in an optimisation-based approach, a heat flux value is estimated for each instant with the use of an optimisation algorithm.

In this study, irradiative thermal systems in which the dominant heat transfer mode is radiation are specifically addressed due to their complexity and importance in various engineering applications. In solutions based on heat transfer and thermodynamics laws, optimisation-based algorithms with a variety of methods (e.g. conjugate-gradient [8-10], Levenberg–Marquardt [9] and genetic algorithm (GA) [11]) are the prominent approaches for real-time heat flux estimation of irradiative thermal systems, whereas inverse models based on thermal equations [12] are less common. However, in recent years, artificial intelligence (AI) techniques have been used to provide solutions to both direct [13] and inverse [14] heat transfer problems with minimal use of thermal equations. AI techniques have specifically created a breakthrough in developing inverse models for real-time heat flux estimation in thermal systems [4, 15], including complicated irradiative ones [16]. AI inverse models have been claimed to outperform optimisation-based heat flux estimation, mainly based on two relative advantages: (a) AI inverse models do not require knowledge of the thermo-physical properties of the system and (b) they are not limited by the time-consuming numerical solutions of direct models. However, with the use of appropriate AI techniques, optimisation-based algorithms can also be improved so as to possess the aforementioned advantages. No rational comparisons between the two approaches of heat flux estimation, inverse models and optimisation-based algorithms have been reported in the literature so far, particularly for irradiative thermal systems. This article presents such a comparison experimentally, although both approaches benefit from AI techniques.

7.3 Inverse modelling vs. optimization-based estimation

For a system with a heat source and one temperature sensor, with emitted heat flux and measured temperature of q and T, respectively, an inverse model for heat flux estimation is

$$\hat{q}(k) = F_I\left(T(k+r_d), T(k+r_d+1), \ldots, T(k+r_d+r_I)\right), \qquad (7\text{-}1)$$

where $r_d = t_d/t_s$, t_d and t_s are the delay and sampling times, respectively. Delay time is the time needed for the heat source to influence the temperature of the sensor. r_I, the order of the inverse model, is the number of temperature samples used in real-time heat flux estimation. Variables with hats are the estimated ones. Obviously, real-time estimation includes a reasonable estimation delay $(= t_d + r_I . t_s)$. The problem is to identify F_I.

A direct model is presented as

$$\hat{T}(k) = F_D\left(T(k-1), \ldots, T(k-r_T), q(k-r_d), \ldots, q(k-r_d-r_q)\right), \qquad (7\text{-}2)$$

where r_q and r_d are the heat flux and temperature orders, respectively. To formulate optimisation-based heat flux estimation algorithms F_D and a sequence of temperatures at $r_T . t_s$ seconds ahead of estimation as well as the past values of heat flux are assumed to be known.

As a result, with a guessed heat flux $\widehat{q}$, the temperature can be estimated by

$$\hat{T}(k+r_d) = F_D\left(T(k-1+r_d), \ldots, T(k-r_T+r_d), \widehat{q}(k), \ldots, \widehat{q}(k-r_q)\right), \qquad (7\text{-}3)$$

where the measured value of $T(k+r_d)$ is readily available. The solution of the heat flux estimation problem is

$$\hat{q}(k) = \widehat{q}(k) \mid f_E\left(\hat{T}(k+r_d) - T(k+r_d)\right) \text{ is minimum}, \qquad (7\text{-}4)$$

where f_E is a function used to represent the error, such as squared or absolute. An optimisation algorithm needs to be employed to solve the problem presented in Equation 7-4.

In short, Equation 7-1 defines an inverse model and Equations 7-3 and 7-5 define the optimisation-based approach for a single-input/single-output thermal system.

7.4 Experimental setup

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

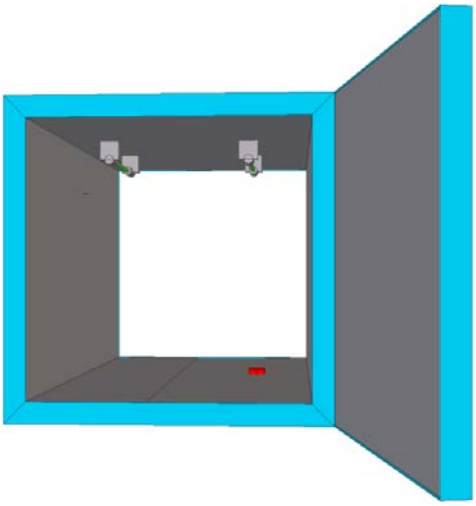
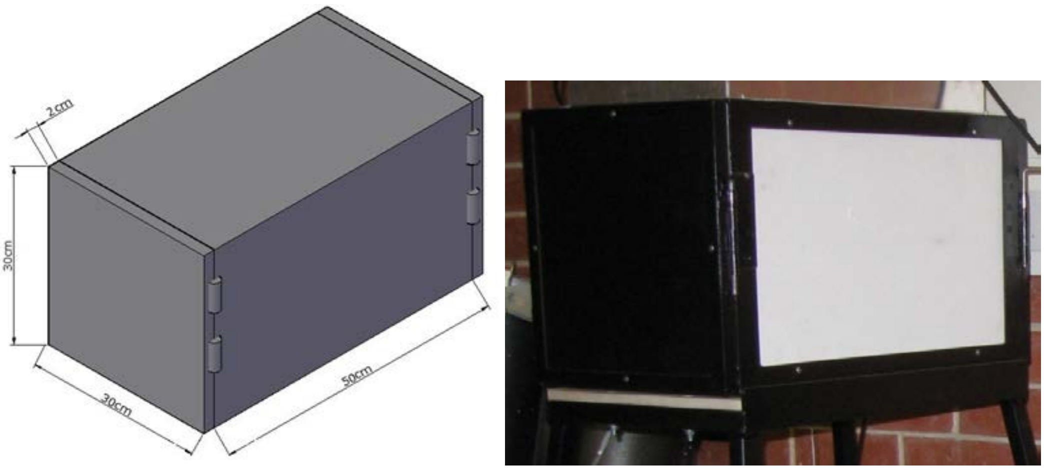


Figure 7-1: Arrangement of lamps and thermocouples in the dryer/furnace.

In the current study (Figure 7-1), only one of the heat sources (on the right) is working and an attached thermocouple is used as its sensor (coloured red in Figure 7-1).



(a) (b)

Figure 7-2: (a) Dryer body dimensions and (b) dryer walls made from insulation boards and steel frame

The dryer body was constructed using insulation boards (thickness = 20^{mm}) and a steel frame (Figure 7-2). An amplifier was employed to increase the output voltage of the thermocouples and to direct this signal to a digital input–output card connected to a computer. The control command was sent to the power amplifier unit from the MATLAB program. The power controller (amplifier) varied the input voltage to the lamp, based on the magnitude of the signal received from the personal computer (PC) (Figure 7-4).

In the MATLAB environment of the PC, the real-time windows target (RTWT), a prototyping toolbox was employed to connect the furnace/dryer to a computer to facilitate data gathering. RTWT employs a single computer as both the host and target PC (Figure 7-3).

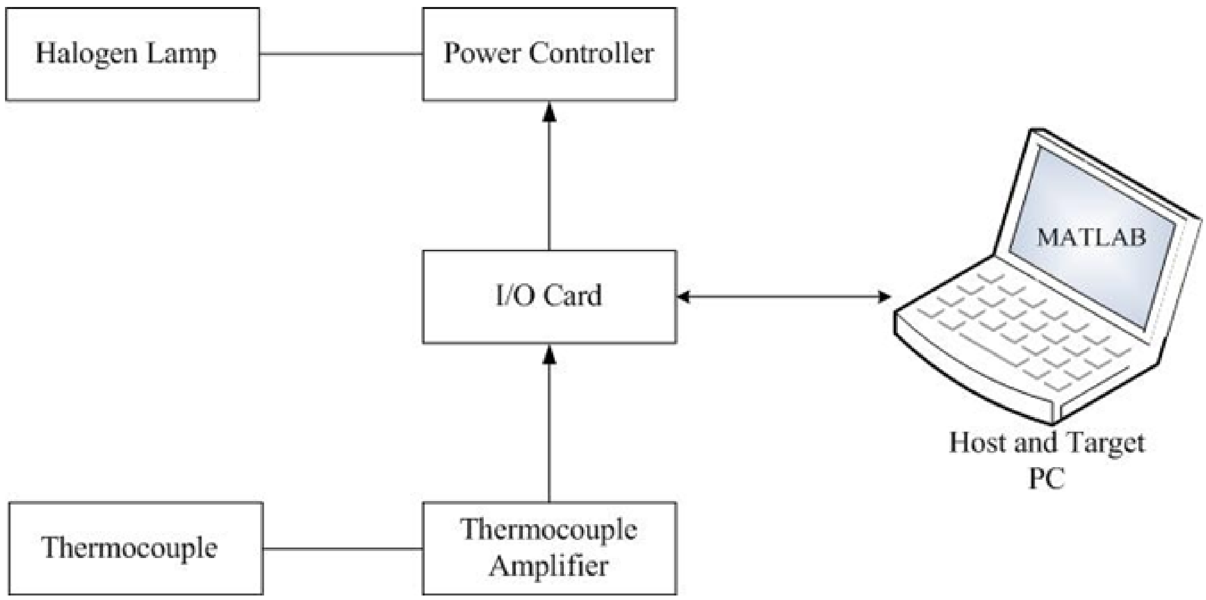


Figure 7-3: Connecting signals in the experimental setup.

In the calibration stage, both the lamp and sensors were calibrated, two lookup tables were prepared to convert the relevant voltages and currents to temperature and power values, respectively, for the lamp and thermocouple.

Using the employed Simulink program, the power function applied to the system comes from the workspace to the lamp lookup table and then the relevant power is sent to the output card to the power controller and finally to the lamp.

On the other hand, the current coming from the thermocouple amplifier to the I/O card is sent to the sensor lookup table, where it is converted to a degrees Kelvin value. The resultant data is not noise-free, so a low-pass filter is used for noise removal. The data are then saved as the temperature history (Figure 7-4).

In the data gathering stage, four different sets of data were obtained: the first set was used for training both artificial neural networks (ANNs) (an ANN was utilised as the inverse model and the other ANN was employed in the direct modelling part of the optimization-based method), and the other three sets were used to test the accuracy of both. The sampling time for all sets of data was 200 seconds.

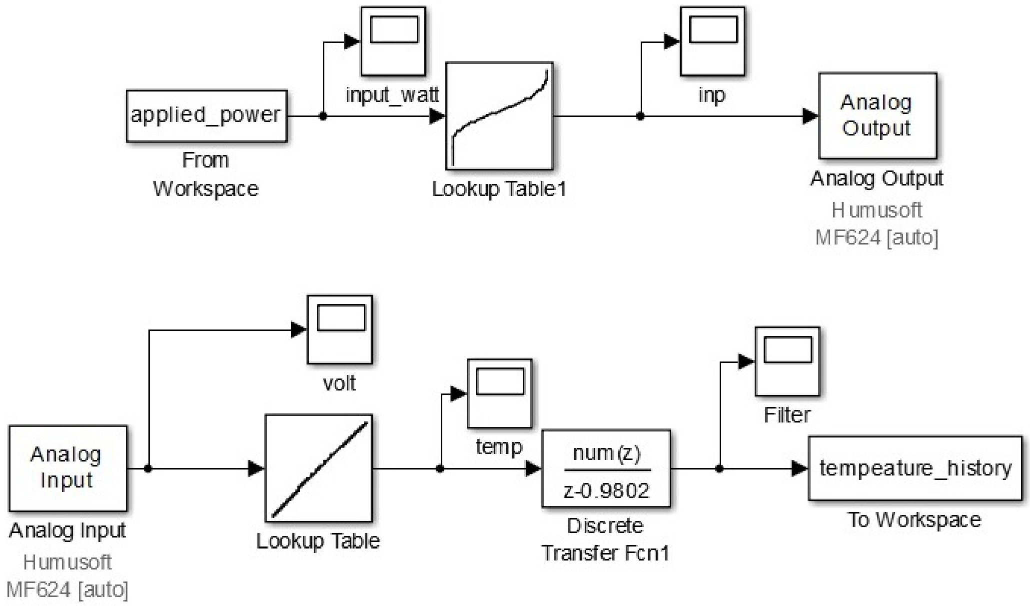


Figure 7-4: Simulink data gathering model.

7.5 Solutions to a real problem using Artificial Intelligence

The problem was the estimation of heat flux in an infrared dryer, shown in Figure 7-1, using the measured temperatures at a point on the bottom surface. The delay time for this problem was1.4 seconds. To solve this problem using an inverse modelling with an optimisation-based approach, F_I and F_D in Equations 7-1 and 7-2 needed to be identified, respectively, and the optimisation problem presented in Equation 7-4 had to be solved. The accomplishment of these three aforementioned tasks is described in the following subsections.

7.5.1 Identifying the inverse model, F_I

The orders, r_d, and inverse model, r_I (in Equation 7-1), were 2 and 5, respectively. An ANN model was used to identify F_I. A three-layer, fully connected, multi-layer perceptron (MLP) with five neurons in its hidden layer was employed in this research to approximate F_I. The Levenberg–Marquardt batch error back-propagation algorithm was employed to train the model. Linear mapping of variables in to the range of [-1, 1] and the Nguyen–Widrow methods were used as normalisation and initialisation algorithms [17]. Amongst all series data used for training and validation, 30% were used for training and the remainder went to validation (to avoid overfitting) on a random basis. A detailed explanation of the MLP used in this research, as well as the role of training and validation data, is presented in Appendix B, and a detailed explanation of the data preparation stage is presented in Appendix C.

7.5.2 Identifying the direct model, F_D

In F_D, presented in Equation 7-2, $r_T = 2$, and r_Q=5 an MLP (further detailed in Appendix B) with seven neurons in the hidden layers was employed to approximate F_D. The following matrix outlines the training data set of the MLP.

$$\begin{matrix} \overbrace{\begin{matrix} \hat{q}_r & \cdots & \hat{q}_{r-r_Q+1} & \hat{T}_r & \cdots & \hat{T}_{r-r_t+1} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \hat{q}_n & \cdots & \hat{q}_{n-r_Q+1} & \hat{T}_n & \cdots & \hat{T}_{n-r_Q+1} \end{matrix}}^{\text{Input}} & \overbrace{\begin{matrix} \hat{T}_{r+1} \\ \vdots \\ \hat{T}_{n+1} \end{matrix}}^{\text{Output}} \end{matrix} \qquad (7\text{-}5)$$

Details about Equation 7-5 can be found in Appendix C. F_D is a dynamic model,that is, its outputs (temperature) at each instant were fed back to the model to estimate the output for the next instant, for example,

$$\hat{T}(k+1) = F_D\left(\hat{T}(k),\ldots,T(k+1-r_T),q(k+1-r_d),\ldots,q(k+1-r_d-r_q)\right) \qquad (7\text{-}6)$$

After $r_T \times t_s$ seconds have elapsed, all temperature inputs to the model are estimated

$$\hat{T}(k+i) = F_D\left(\hat{T}(k+i-1),\ldots,\hat{T}(k+i-r_T),q(k+i-r_d),\ldots,q(k+i-r_d-r_q)\right) \qquad (7\text{-}7)$$

As a result, the inevitable estimation error at each iteration is returned to the estimation process, and the error accumulation phenomenon occurs [18, 19]. To ensure the reliability of dynamic models, error accumulation was taken into account by applying Equation 7-6 in testing (cross-validating) the model. This approach is called simulation. On the other hand, if all inputs to the model were assumed to be known or if:

$$\hat{T}(k+i) = F_D\left(T(k+i-1),\ldots,T(k+i-r_T), q(k+i-r_d),\ldots,q(k+i-r_d-r_q)\right) \tag{7-8}$$

A one-step prediction approach would be used, which would cause misleading results with very small values of testing error [20].

7.5.3 Optimization algorithm

To minimise f_E in Equation 7-4, we employed a metaheuristic algorithm, known as the harmony search (HS). Three sets of data, employed as checking data in the inverse model, were chosen. The results were then compared with those of our inverse model method.

7.5.3.1. Harmony Search

The HS, first developed in 2001, belongs to a breed of optimization algorithms referred to as metaheuristics [21]. Metaheuristics seek the optimal solution of a problem through two major operations: diversification and intensification [22]. During diversification, also known as exploration, random searches are attempted over a broad range of the search space. This avoids falling into a local optimum. On the other hand, intensification, also known as exploitation, is used to select potentially good solutions through the use of memory and/or elitism [23-25]. HS has been applied to a wide range of applications and results have confirmed that it is a viable alternative to other complex optimisation algorithms such as GA and simulated annealing [23, 26-29].

To find the solution vector to a multivariate problem, HS first generates a number of initial solution vectors called harmony memories (HM), either randomly or by educated guess. Next, through multiple iterations, each variable in the solution vector is either generated randomly (diversification) or chosen from the memory repository (HM) using an acceptance rate (typically $0.7 \leq r_{\mathrm{a}} \leq 0.95$) and then slightly changed (intensification).

Pitch adjustment is often performed through a linear adjustment expression given by:

$$x_{new} = x_{old} + b, \tag{7-9}$$

where x_{new} is the adjusted value of a variable x_{old}, which is the existing value in the memory, b is the pitch bandwidth and ε is a random number chosen from the uniform distribution between [-1, 1]. The careful choice of HS parameters is an important factor in acquiring a good balance between the seemingly opposite components of intensification and diversification and the quality of results [30].

To obtain the optimised input parameters (input heat), the direct model (designed ANN) described in the previous section was implemented in MATLAB and then used to generate the corresponding output (i.e. the temperature function). The root mean square (RMS) value of the error between the estimated output from HS and the desired output (i.e. the measured temperature) was used as the HS fitness criterion. The objective was to find the optimal values of all input parameters (heat flux), such that the RMS error was minimised. The values of all input parameters ranged from 0 to 2 to avoid unrealistic results.

Due to the large number of input variables and the small range of values, a number of different combinations of HS parameters were explored [22]. Then, according to the best results obtained, the parameter values in Table 7-1 were used in our HS implementation.

The HS algorithm was implemented in C++, and all the simulations were run on a Dell Precision workstation with 20 GB SDRAM. The HS is first initialised by generating 30 random solution vectors (HM), each containing the same number of input variables representing the desired inputs. Through iterations, HS then attempts to improve the quality of solutions through the previously outlined optimization processes. The process stops when either the difference between the fitness of the two best solution vectors is lower than the termination threshold (T_{t}) or when the maximum number of iterations (IT) is reached. Our results indicate no significant difference (less than 0.2%) between the average RMS error values using either an educated guess or randomly generated input as the initial condition of the problem set.

Table 7-1: Selected HS parameters

Parameter	Notation	Value
Number of Iterations	IT	15,000
Number of Harmonies Memories	HM	30
Harmony Memory Consideration Rate	r_{a}	0.95
Pitch Adjustment Rate	r_{pa}	0.6
Pitch Adjustment Bandwidth	b	0.1
Termination Threshold	T_{t}	10^{-6}

7.6 Experimental results

7.6.1 Direct model results

Figure 7-5 shows the accuracy of the estimated inputs (heat flux) using our model for three different temperature profiles. As a criterion for the predictive accuracy (PA) of the ANN, we employed the PAN definition used in [31]:

$$\mathrm{PAN} = \sum_{i=1}^{N} \left| \widehat{C_b}(i) - C_b(i) \right| \tag{7-10}$$

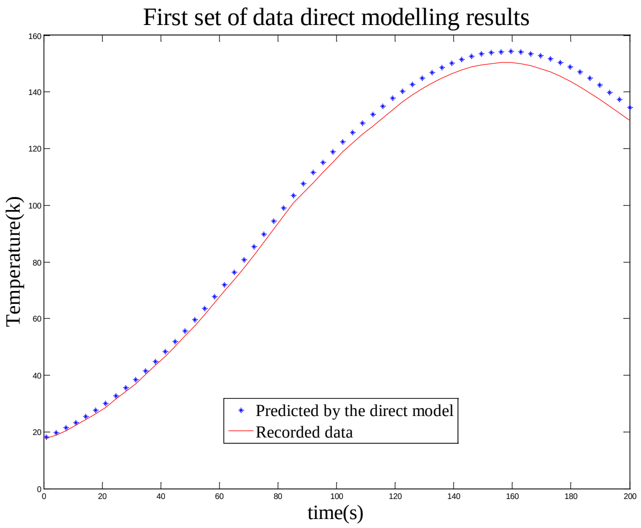
where $C_b(i)$ is the measured quantity gathered from experimental data, and $\widehat{C}_b(i)$ is the value estimated by the ANNs. *N* is the number of instances of prediction.

Table 7-2 presents PA50, PA100 and PA150 (the sums of absolute error of prediction for 50, 100 and 150 future instants) for the three data series in Figure 7-6.

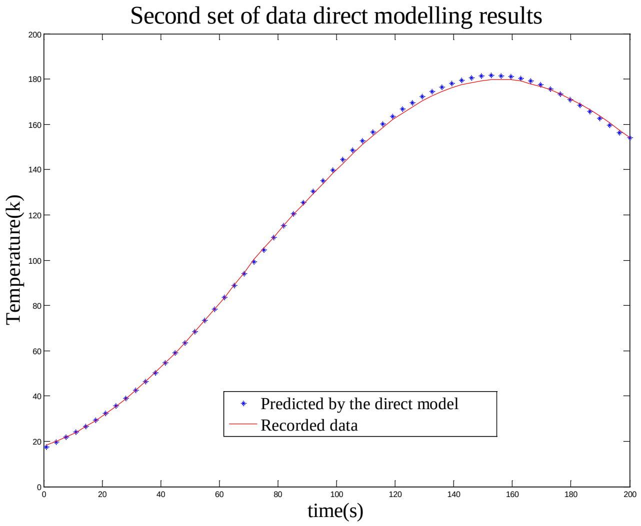
A well-known use of ANN models is for neuro-predictive control solutions. In this mode, a few future intervals are employed (usually seven or less). The extremely high accuracies achieved are shown in Table 7-2 and these confirm that the designed ANN fits for the purposes of a neuro-predictive model. Note that both training and checking were performed with noisy data received from a thermocouple with an error of ±1°C. Figure 7-6 indicates that the ANN can return accurate predictions even after a rather long period of time. A significant advantage of this method is that it does not require knowledge of the mechanical properties of the system (e.g. thermal conductivity or the system's emissivity). In summary, three prominent error sources are eliminated with the proposed methodology when compared against the classical heat transfer methods:

1. Inevitable errors in the value of mechanical properties and dimensions.
2. Inevitable simplifications in heat transfer modelling (e.g. considering adiabatic boundary conditions and homogenous properties on surfaces).
3. Numerical errors incurred by the large number of computations needed in numerical heat transfer. As a consequence, the furnished neural network model should produce high-fidelity predictions.

(a)



(b)



(c)

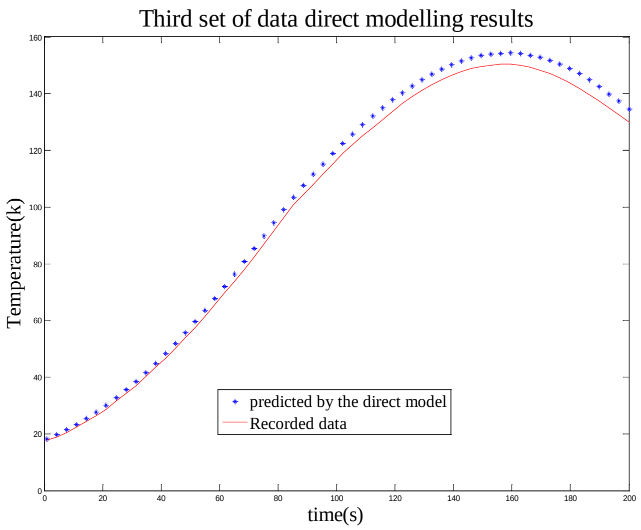


Figure 7-5: Direct modelling results for three sets of data (predicted by ANN vs. experimental recorded data).

Table 7-2: PA for different trained models

Criterion	PA50(°C)			PA100(°C)			PA150(°C)		
Data Series	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
Error(°C)	1.98	13.90	3.08	4.05	42.86	6.61	9.59	85.92	21.49

7.6.2 Optimisation-based results

To check the applicability of the optimisation-based method and compare the results with those of the inverse method, three different data sets were employed as benchmarks (Figure 7-6). The results from the optimization method were then compared with those acquired from the same data sets using our proposed inverse model. Note: the benchmark datasets in the following sections are different from data sets used to train the ANN employed in the inverse model.

Estimated inputs obtained from the optimization method result in a mean absolute error of 153.5 W over the three chosen benchmarks:

$$E_{mean} = \frac{\sum_{i=1}^{N} |\hat{Q}(i) - Q(i)|}{N} \tag{7-11}$$

In Equation 7-11, E_{mean} is mean of absolute error, N is the number of data points after the data preparation process and Q is the input heat. The accuracy of the estimate is completely acceptable, with a temperature sensing error of ±1°C. Figure 7-6 and Table 7-3 illustrate the accuracy of the optimisation-based method.

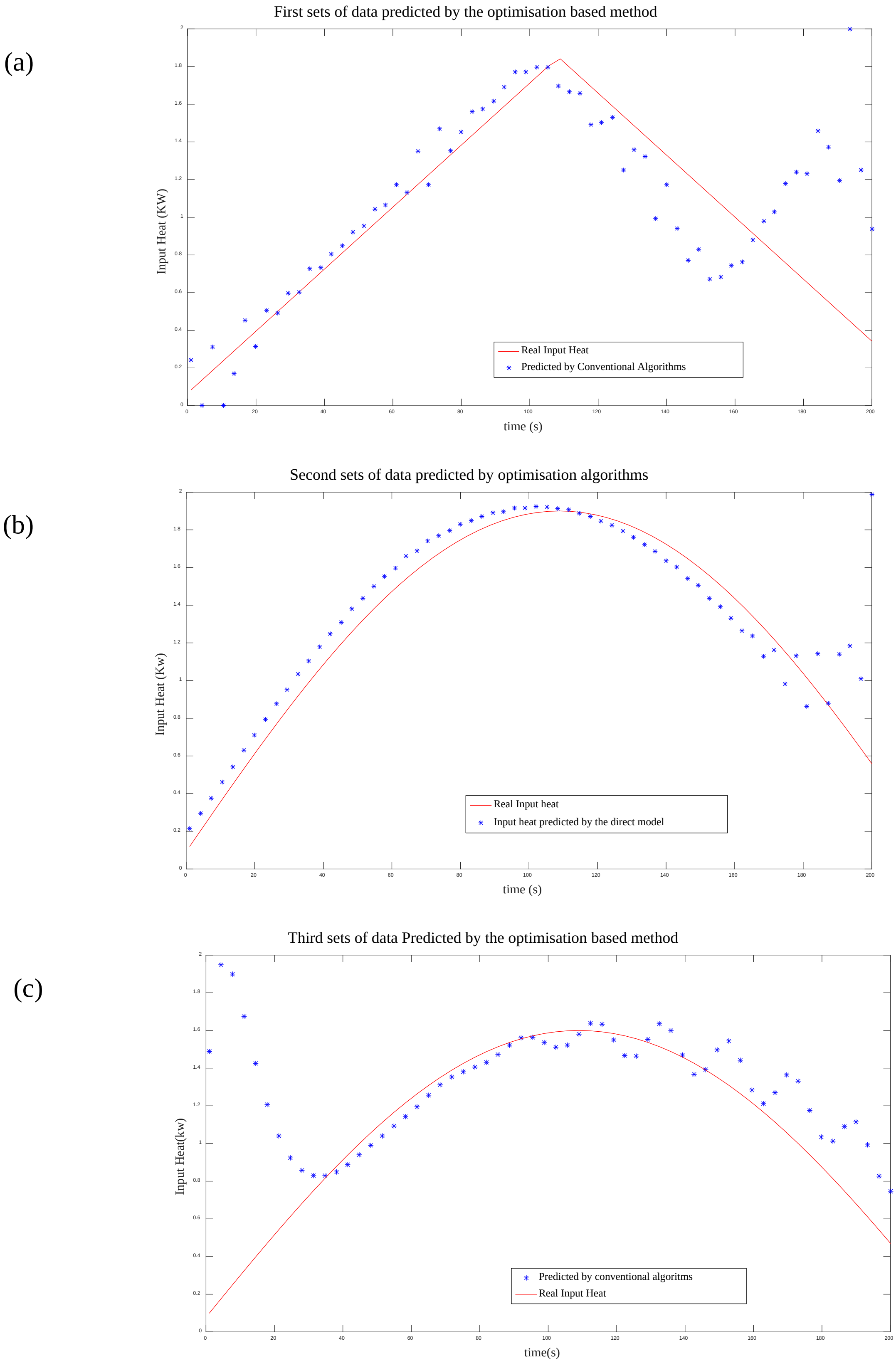


Figure 7-6: Comparison between the actual and estimated input heat data using the optimisation-based method.

The dots represent the estimated data, whereas the red line signifies the actual input to the system. (a) , (b) and (c) represents three different sets of data

Table 7-3: PA of the optimisation-based method

Criterion	E_{mean} (w)			E_{max}(w)		
Data Series	1st	2nd	3rd	1st	2nd	3rd
Error (w)	149.0	241.4	70.1	286.1	246	380.4

7.7 Comparison and Discussion

Table 7-4 summaries the prediction accuracy of the inverse model (direct heat flux estimation) vs. optimisation-based method. The results show that the inverse model can predict the input power in a much better way from the viewpoint of accuracy (Table 7-4 and Figure 7-7)

Table 7-4: PA of the designed ANN

Technique	Criterion	E_{mean} (w)			Maximum Error (w)		
	Data Series	1st	2nd	3rd	1st	2nd	3rd
AIs	Error (W)	49.74	37.38	39.9	192.82	136.8	192.94
Optimisation based		149.0	241.4	70.1	286.1	246	340.4

The designed ANN for the inverse modelling estimation method requires only simple mathematical calculation, where as the training section simply uses a fraction of input and output measured data. By comparison, the optimisation-based algorithms are dependent on an initial guess of their iterative nature. In conclusion, the inverse model method is significantly quicker than the optimisation-based method.

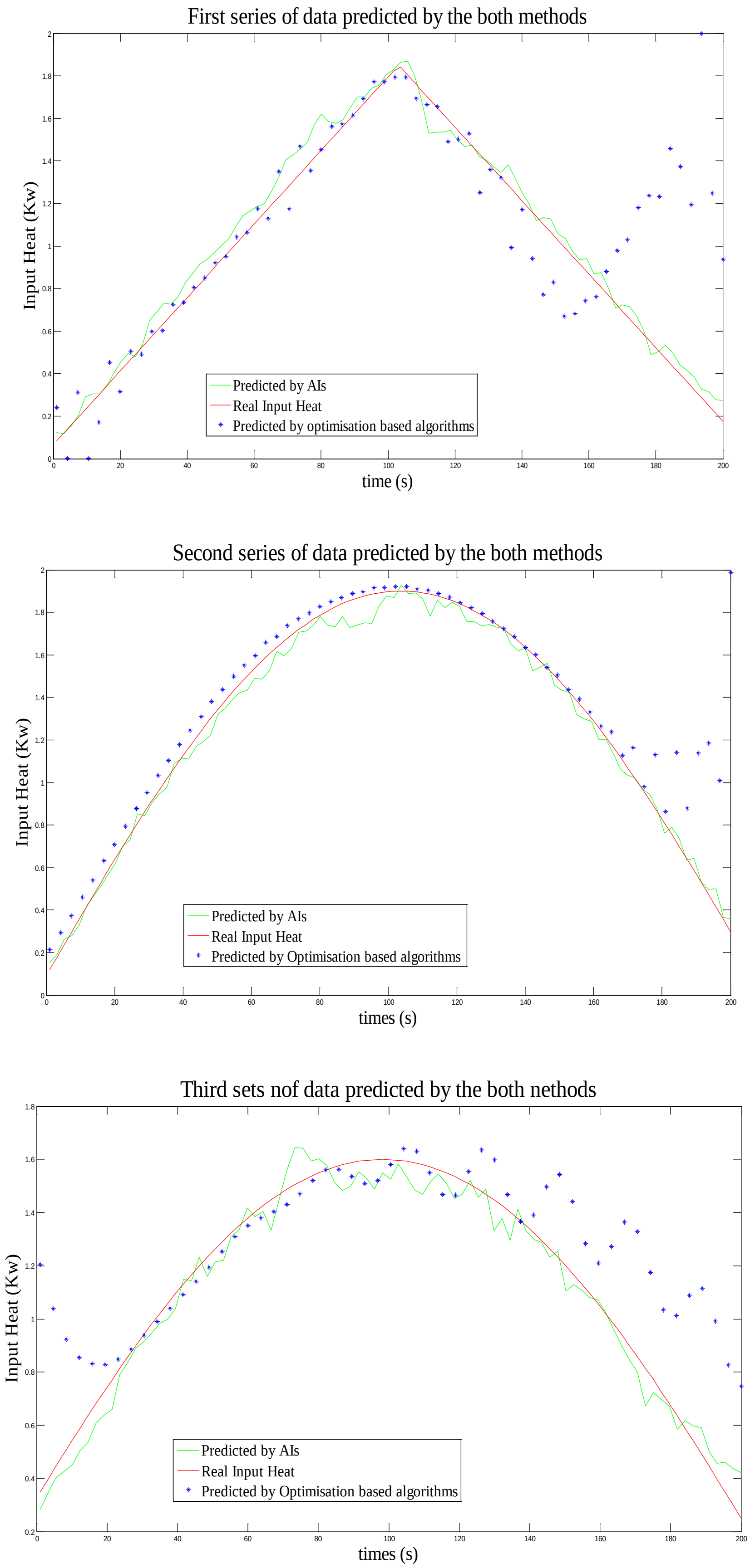


Figure 7-7: Accuracy of AIs (inverse method) vs. optimisation-based-methods

7.8 Conclusion

In this chapter, when using an irradiative batch dryer, two major approaches in real-time heat flux estimation problems are compared. Therefore, heat was applied through a halogen lamp hung from the top surface of the dryer, and the temperature was measured by a thermocouple at the bottom surface. An ANN was designed and trained to check the applicability of AI techniques for estimating the heat flux directly. Subsequently, a direct heat transfer model was developed by an ANN linked to optimisation algorithms to check the capabilities of optimisation-based methods and compare the efficacy of these two methods.

The results demonstrate that the power estimated using the AI technique closely followed the actual heat response applied during the experiment. The results from the optimisation-based algorithms consumed more computing time and resulted in higher errors when compared against those using the AIs.

From a practical point of view, in accordance with the results obtained in this research, the dimensions and thermo-physical properties of the dryer are not required to solve the problem. Another significant advantage is that the first method requires only a small number of simple calculations, without any recursive computation, implying that this method is very fast and accurate, compared to the optimisation-based methods under similar circumstances.

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Overall percentage (%)	
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature	Date 01/10/2015

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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Chapter 8

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

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8.1 Abstract

In order to check the applicability of Artificial Intelligent (AI) techniques as reliable inverse models to solve the multi-input/multi-output (MIMO) 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.

8.2 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 [1-5]. In general, inverse heat transfer problems (IHTPs) are considered ill-posed problems [6]. 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 [5]. 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 [7], 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 [5]. 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 [8], Levenberg–Marquardt [9] and genetic algorithm [10]) 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 [5, 11-15].

In recent years, artificial intelligence (AI) techniques have been used to solve both direct [16] and inverse [17] 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 [18], including complex irradiative models [4]. 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 [2]. In their subsequent study, some different AIs were compared to find the best AI [4] and then several ANNs were compared in terms of accuracy and computational time [3]. 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 a 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.

8.3 TITO inverse modelling problem

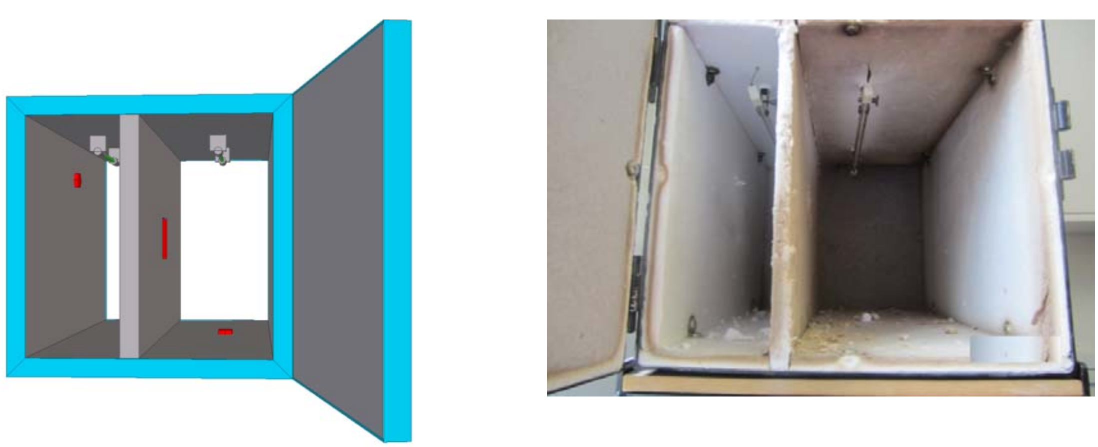
For a system of two heat sources and two temperature sensors with input powers q_1 and q_2 and measured temperatures of T_1 and T_2, respectively, an inverse model for heat flux (input power) estimation is defined as follows:

$$(\hat{q}1\left(k-\frac{\tau_{d1}}{\tau_s}\right),\hat{q}2\left(k-\frac{\tau_{d2}}{\tau_s}\right)) = F_I[\,T_1(k),T_1(k+1),\dots,\ T_1(k+r_1),T_2(k),T_2(k+1),\dots,T_2(k+r_2)], \quad (8\text{-}1)$$

In Equation 8-1 τ_{d1} and $\tau_{d\,2}$ 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.

8.4 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.



(a) (b)

Figure 8-1: The experimental setup (a) The arrangement of lamps and thermocouples in the studied dryer/furnace (b) Two halogen lamps with their clamps

In this study (Figure 8-1.a), 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 (20 milimeter thick) and a steel frame (Figure 8-1.b). 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 (Figure 8-2).

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 (Figure 8-2).

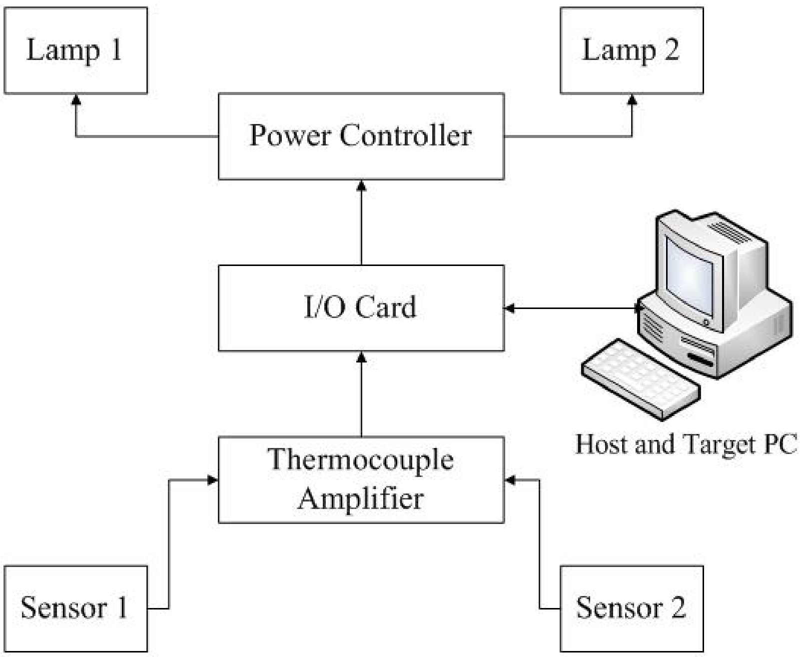


Figure 8-2: Connected signals in the experimental setup

8.5 Solutions to a real problem using Artificial Intelligence

The problem is the heat flux estimation of an infrared dryer (Figure 8-1) using the measured temperatures of two points at two shown surfaces. To identify FI in Equation 8-1, 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.

8.5.1 Identifying the inverse model, FI

The orders r_1 and r_2 (Equation 8-1) 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 8-5) 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 $(= 2 \times 8 + 1)$ [19]. 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.

8.5.1.1 Data preparation

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

$$A=\begin{bmatrix} q_{11} & q_{21} & \cdots & T_{11} & T_{21} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ q_{1n} & q_{2n} & \cdots & T_{1n} & T_{2n} \end{bmatrix}, \tag{8-2}$$

Where 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 0.8 seconds for the first and second thermocouples, respectively. The sampling time (2 seconds 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 [2]:

$$B=\begin{bmatrix} q_{1(1)} & q_{2(1)} & T_{1(d)} & T_{2(D)} \\ \vdots & \vdots & \vdots & \vdots \\ q_{1(n\text{-}D+1)} & q_{2(n\text{-}D+1)} & T_{1(n\text{-}D+d)} & T_{2(n)} \end{bmatrix}, \tag{8-3}$$

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:

$$C=\begin{bmatrix} \overbrace{T_{1(d+1)} & \cdots & T_{1(d+R)} & T_{2(d+1)} & \cdots & T_{2(d+r)}}^{Input} & \overbrace{q_{1(1)} & q_{2(1)}}^{Output} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{1(n\text{-}R+1)} & \cdots & T_{1(n)} & T_{2(n\text{-}r\text{-}R+1)} & \cdots & T_{2(n\text{-}R)} & q_{1(n\text{-}d\text{-}r\text{-}R+1)} & q_{2(n\text{-}d\text{-}r\text{-}R+1)} \end{bmatrix}, \tag{8-4}$$

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 (Equation 8-5):

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

8.6 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 (Figures 8-3 & 8-4).

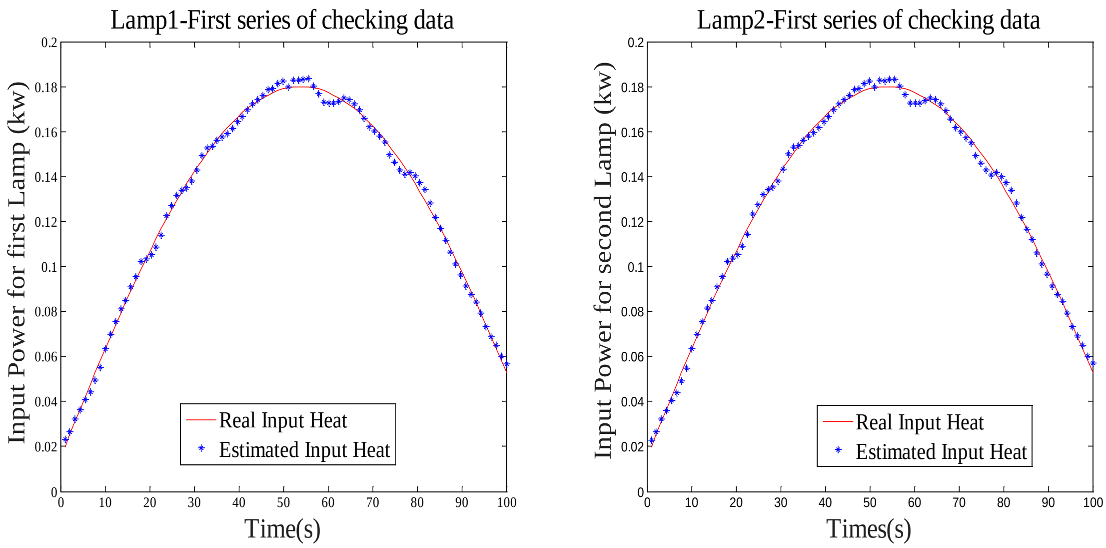
By employing Equation 8-6 , estimated inputs obtained from the optimisation method resulted in a mean absolute error of 6.045 W over the four chosen benchmarks.

$$E_{mean} = \frac{\sum_{i=1}^{N} |\hat{Q}(i) - Q(i)|}{N} \tag{8-6}$$

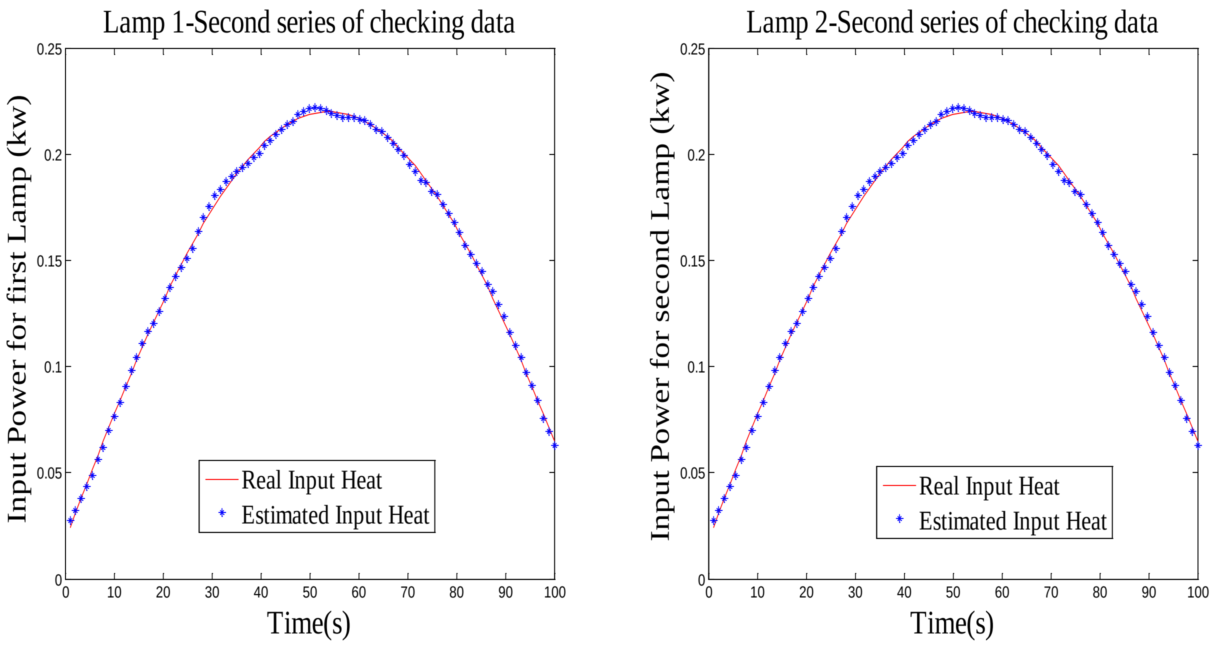
In Equation 8-6, E_{mean} is mean of absolute error , N is the number of data points after the data preparation process and Q is the amount of heat input. The accuracy of the estimation is considered to be acceptable with a temperature sensing error of ±1°C. Figures 8-3 and 8-4 and Table 8-1 show the 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 [11, 12, 20, 21], 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 [11, 13, 20-31]. 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[13, 21, 32, 33]. Conversely, in introduced method, there is no need to solve the direct problem.

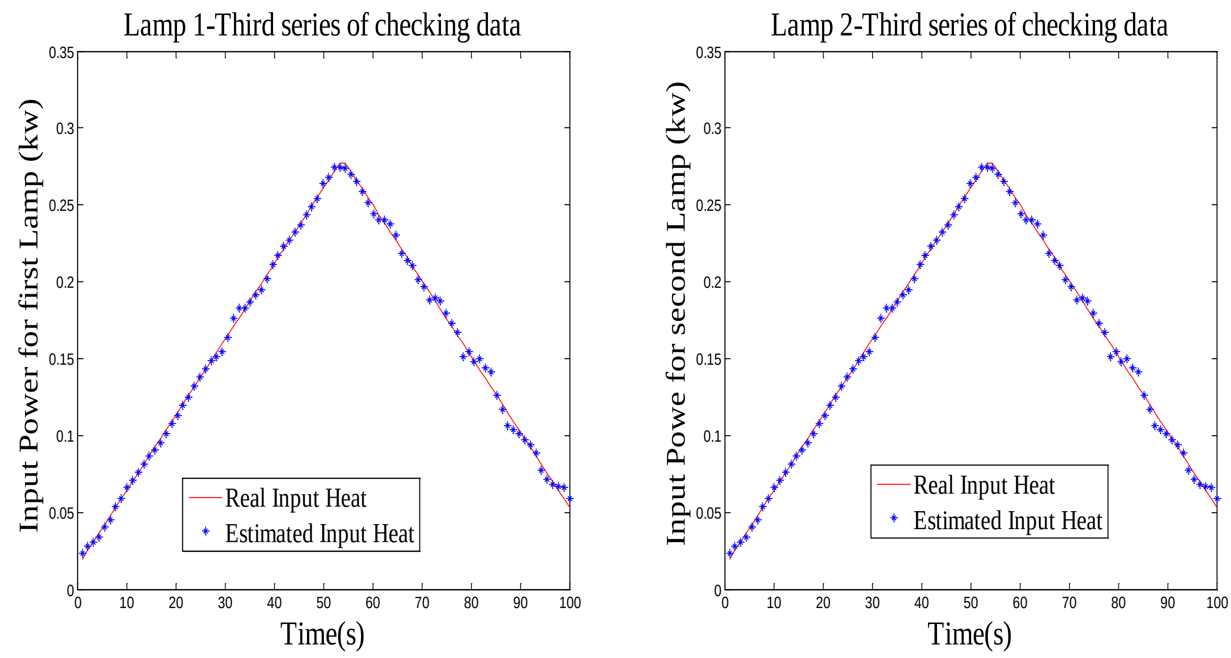


(a)

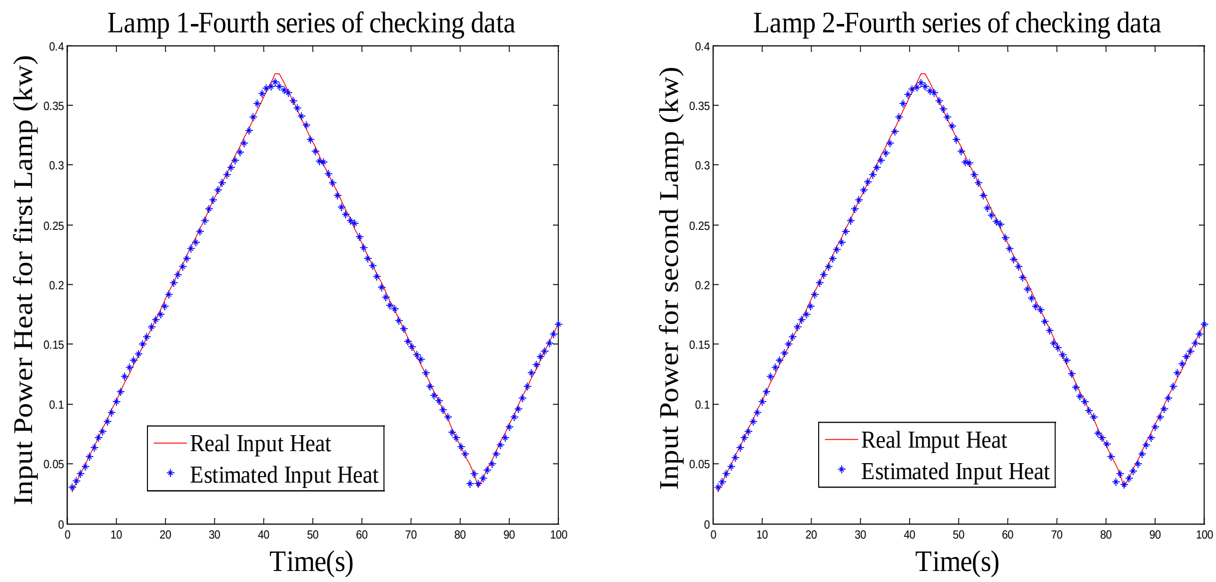


(b)

Figure 8- 3: The accuracy of proposed AI (inverse) model (the first two sets of checking data)



(a)



(b)

Figure 8- 4: The accuracy of proposed AI (inverse) model (the second two sets of checking data)

Table 8- 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

8.7 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 is capable of receiving the temperature function histories of the points used to estimate the input heat/power functions applied to the system. It is 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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Chapter 9

Conclusion

The major contribution of this thesis is that it introduces new methodological solutions for solving sequential (real-time) heat flux estimation problems. These solutions use measured temperatures where the radiation provides the governing mode for thermal energy transport. In the methodologies proposed, with the assistance of intelligent techniques (ITs), inverse models are developed to directly solve sequential (real-time) heat flux estimation problems. To this end, a simple laboratory drying furnace was constructed that was capable of employing both SISO and MIMO studies.

In Chapter 4, an ANN was employed to model SISO, and promising results were achieved. In Chapter 5, several ITs, including ANNs, GA-ANNs and ANFIS, were compared to find the best intelligent methodology in terms of accuracy and time consumption. ANNs were found to be the most appropriate method. In Chapter 6, several ANNs were compared to find the one that best reflected the inverse model of the employed irradiative furnace. In Chapter 7, a comparison study was conducted between optimisation-based methods and ITs, with the results showing that ITs are faster and more accurate than classical optimisation-based methods. In Chapter 8, an ANN was employed as an inverse model of a TITO problem in the studied furnace.

9.1 Inverse modelling of ANNs: SISO study

For the aforementioned irradiative batch dryer/furnace, an ANN was designed, successfully trained and utilised to reveal the capability of ANNs as an alternative method to classical methods for heat flux estimation problems in real-time mode (chapter 4). This ANN model was trained using experimental data. Heat was applied using a halogen lamp that was hung from the top surface of the dryer, and the temperature was measured using a thermocouple that was placed on the bottom surface. All data were recorded, processed and employed to construct an inverse ANN model of the system. This model received temperature history of a point and estimates of the input heat into the system. This provided promising results, and it was demonstrated that the heat function estimated by the designed neural network was consistent with the real input heat applied during the experiment.

From a practical perspective, the only requirement for constructing a highly accurate neural network model for a heat estimation problem is a series of temperature-input heat data for a few minutes of operation. The dimensions and thermophysical properties are not needed. Representing another significant advantage, the estimation stage for the trained neural networks only included a small number of simple calculations, excluding any recursive computation; this indicates that this method is faster than the classical techniques of numerical heat transfer for similar problems. In short, an accurate method for the inverse heat transfer problem was proposed and successfully tested using experimental data.

This chapter introduces a new vision for evaluating ANNs as the alternative methodology for solving IHTPs. To this end, further studies were conducted to find the best possible intelligent methodologies.

9.2 ANNs, GA-ANNs and the ANFIS approach of IHTPs: SISO study

In chapter 5, a variety of new approaches were developed, and the results were compared for solving sequential (real-time) heat flux estimation problems where radiation is the dominant mode of thermal energy transport. The ANNs, two hybrid methods of GA-ANNs and an ANFIS were designed. A comparison of the results showed that the most accurate method is the ANFIS because it has more parameters than the ANNs. Consequently, applying the ANFIS solution is too time-consuming. For the studied ANNs, the hybrid method of GA-ANN using the LM optimisation algorithm during back propagation (BP) is optimal in terms of accuracy and the network's performance.

Without GA-ANN optimisation, the neural net's parameters must be discovered through trial and error. The use of the GA allows the designer to determine the optimal parameters for the net, thus producing a more accurate solution and a simplified network structure (providing, for instance, fewer hidden layers). This simplification resulted in a faster response for the network.

In general, as the number of parameters increases, so does the training time. The training times for the ANFIS method exceeded those for the ANN structure. This may be due to the standard ANFIS structure, which is not very flexible.

When using GA-ANN, the training phase requires a slightly longer time frame, but this trade-off is acceptable because an optimal structure is defined. Further, following training to produce an improved network, the solution time required to determine the inverse is significantly reduced because the key parameters are optimised and the resulting structure is much simpler.

For the BP phase of the MLPs, the LM method provided a more accurate solution than the Momentum Algorithms solution. This observation is reasonable because the LM method uses a quadratic method to update the weights and thus would be expected to outperform linear methods.

The comparison study in the chapter 5 proves that ITs are superior alternatives to classical the methods and introduces ANNs (optimised by GA) as the best ITs for their aforementioned application.

9.3 Different approach by ANNs to inverse modelling of the studied furnace: SISO study

Chapter 6 focused on comparing commonly employed ANNs in engineering applications to identify the most efficient ANN for inverse modelling of an irradiating furnace/dryer in terms of accuracy and computing time. To this end, several ANNs were designed, trained and employed to estimate the heat emitted during the irradiative batch drying process with the aid of NeuroSolution®.

This study involves designing and training different ANNs to play the role of the inverse heat transfer model. The reasons for exploiting these ANNs were derived from various studies in which they were employed for engineering modelling purposes. The results showed that the MLP with the LM in the BP was the best ANN among the methods evaluated for solving inverse heat estimation problems arising from the irradiative batch drying processes. An important advantage of the ANN method over classical inverse heat transfer modelling approaches was that detailed knowledge of the geometrical and thermal properties of the system (such as wall conductivity and emissivity) was not required. Such properties are difficult to measure and may undergo significant changes during the temperature transient mode.

In Chapter 6, a GA was employed to determine the key parameters of the applied ANNs. These parameters are usually identified heuristically or through a trial-and-error brute-force process. The results demonstrated that the key parameters may be estimated more accurately and rapidly by a GA. Further, the performance of the networks was improved and the number of required hidden layers was discovered using a non-trial-and-error method, which also eliminated time-consuming re-testing procedures and produced more accurate results.

The main purpose of Chapter 6 was to prove that MLP is the best ANN for solving IHTPs. This was achieved by conducting a comparison study and displaying the results in figures and tables.

9.4 Comparison between intelligent methodologies and classical methods: SISO study

Chapter 7 compared two major approaches to sequential (real-time) heat flux estimation problems using measured temperatures: (i) development of inverse heat transfer models that directly estimate heat flux; and (ii) use of a combination of a direct heat transfer model (which estimates temperature using heat flux information) and an optimisation algorithm. The first method was called the ‘inverse approach’ in this study, and the second optimisation-based method was called ‘classical’. Chapter 7 presented a rational comparison between these two approaches for an irradiative thermal system—both using AI techniques—for the first time. The results showed that inverse models are superior because of their higher accuracy and shorter estimation delay time. An ANN was designed and trained to check the applicability of AI techniques indirectly estimating the heat flux. Subsequently, a direct heat transfer model was developed by an ANN linked to optimisation algorithms to check the capabilities of optimisation-based methods, and the efficacy of these two methods was compared.

The results demonstrate that the power estimated using the AI technique closely follows the actual heat response applied during the experiment. The optimisation-based algorithms consume more computing time and result in higher errors than those using AI.

Chapter 7, the most significant section of this thesis, compared classical methods and the intelligent technique, which were developed through the models, to find the best methodology in terms of accuracy and computing time. The results confirmed that intelligent methodologies are more reliable.

9.5 ANN inverse modelling: TITO study

As noted earlier in this study, inverse models are routinely used to develop a controller to generate the input power profile that produces a desired temperature distribution. Further, real-world industrial applications of heat flux control areas suggest that the majority of industrial problems (especially those relating to inverse radiative solutions) are usually non-linear and multivariable with a MIMO nature. Consequently, Chapter 8 focuses on the applicability of AI to address MIMO heat flux estimation problems (particularly those involving radiation). To achieve this, the structure of the previous experimental set-up employed to solve SISO problems was modified, and a new TITO problem in real-time heat flux estimation problems is defined. An ANN was designed and trained to directly check the applicability of AI techniques in estimating heat fluxes. 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. The energy input functions estimated by the proposed ANN matched the real heat/power functions applied during the experiment.

Thus, Chapter 8 showed that ITs can be employed to develop controllers to generate an input power profile that produces the desired temperature distribution.

9.6 Future work

This study revealed that ITs can be employed to develop inverse heat transfer models as appropriate alternatives to classical methods. However, some identified problems need to be solved in future studies:

1. As mentioned earlier, inverse models are routinely used to develop controllers to generate the input power profile that produces the desired temperature distribution. The black-box nature of the ANN solution is often cited as a weakness because some control problems require human expertise or linguistic knowledge. The ANFIS can address this deficiency; accordingly, a new comparison of various ITs should be conducted for TITO problems in future studies.
2. One of the most important applications of IHTPs is to control the temperature in inaccessible areas in order to check the capability of the proposed method; the associated controller can be designed for both SISO and TITO studies.
3. The necessity of checking the applicability of ITs in solving IHTPs raised complications in mathematical modelling (especially where radiation was the dominant mode of heat transfer). Therefore, a review study could play an important role in identifying more opportunities to investigate heat transfer areas in the application of intelligent methodologies.

Appendix A

Chapter 6 appendix

Table A-1: Summary of all Networks to find the best ANN with the first series of testing data

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**
MLP-1-O-M (Multilayer Perceptron)	0.023	0.966	0.117	0.022	0.975	0.128	0.022	0.974	0.117
LR-0-B-M (Linear Regression)	0.165	0.644	0.347	0.186	0.559	0.337	0.214	0.642	0.393
LR-0-B-L (Linear Regression)	0.164	0.647	0.347	0.185	0.563	0.337	0.213	0.644	0.393
MLP-1-B-L (Multilayer Perceptron)	0.006	0.990	0.056	0.008	0.989	0.065	0.006	0.992	0.058
PNN-0-N-N (Probabilistic Neural Network)	0.052	0.907	0.161	0.208	0.728	0.297	0.148	0.810	0.215
RBF-1-B-L (Radial Basis Function)	0.061	0.896	0.213	0.040	0.929	0.176	0.051	0.926	0.204
GFF-1-B-L (Generalized Feedforward)	0.005	0.990	0.057	0.008	0.989	0.069	0.007	0.992	0.066
MLPPCA-1-B-L (MLP with PCA)	0.005	0.994	0.058	0.004	0.990	0.048	0.006	0.993	0.057
SVM-0-N-N (Classification SVM)	0.190	0.910	0.378	0.425	0.719	0.577	0.441	0.802	0.587
MLP-2-B-L (Multilayer Perceptron)	0.003	0.994	0.046	0.005	0.994	0.057	0.004	0.995	0.053
MLP-1-B-M (Multilayer Perceptron)	0.008	0.987	0.065	0.010	0.984	0.078	0.009	0.986	0.075
MLP-2-O-M (Multilayer Perceptron)	0.022	0.970	0.112	0.029	0.962	0.133	0.034	0.961	0.143
MLP-2-B-M (Multilayer Perceptron)	0.109	0.792	0.238	0.191	0.708	0.291	0.155	0.787	0.263
MLPPCA-1-O-M (MLP with PCA)	0.255	0.738	0.270	0.023	0.975	0.134	0.021	0.979	0.121
MLPPCA-1-B-M (MLP with PCA)	0.138	0.728	0.270	0.214	0.650	0.307	0.186	0.737	0.289
GFF-1-O-M (Generalized Feedforward)	0.045	0.923	0.163	0.020	0.974	0.112	0.018	0.976	0.100
GFF-1-B-M (Generalized Feedforward)	0.054	0.907	0.172	0.103	0.844	0.223	0.087	0.879	0.199
RBF-1-O-M (Radial Basis Function)	0.185	0.705	0.306	0.119	0.764	0.197	0.099	0.828	0.200
RBF-1-B-M (Radial Basis Function)	0.176	0.716	0.346	0.228	0.553	0.346	0.232	0.687	0.395
MLP-1-H-L	0.006	0.992	0.060	0.004	0.994	0.052	0.004	0.994	0.054

	Training	Cross Val.	Testing
Number of Rows	477	105	118
MSE	0.006	0.004	0.004
Correlation (r)	0.992	0.994	0.994
Min Absolute Error	0.000	0.002	0.001
Max Absolute Error	0.227	0.126	0.199
Mean Absolute Error (MAE)	0.060	0.052	0.054

Table A-2: Summary of all Networks to find the best ANN with the second series of testing data

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**
MLP-1-O-M (Multilayer Perceptron)	0.014	0.977	0.095	0.023	0.977	0.123	0.017	0.984	0.101
LR-0-B-M (Linear Regression)	0.168	0.640	0.351	0.167	0.577	0.318	0.216	0.586	0.386
LR-0-B-L (Linear Regression)	0.167	0.642	0.350	0.167	0.581	0.319	0.213	0.608	0.383
MLP-1-B-L (Multilayer Perceptron)	0.004	0.993	0.049	0.005	0.992	0.059	0.005	0.994	0.054
PNN-0-N-N (Probabilistic Neural Network)	0.054	0.904	0.164	0.161	0.778	0.259	0.177	0.733	0.241
RBF-1-B-L (Radial Basis Function)	0.040	0.936	0.165	0.029	0.954	0.130	0.032	0.944	0.153
GFF-1-B-L (Generalized Feedforward)	0.004	0.994	0.049	0.004	0.993	0.049	0.005	0.993	0.052
MLPPCA-1-B-L (MLP with PCA)	0.021	0.969	0.121	0.019	0.959	0.107	0.016	0.969	0.092
SVM-0-N-N (Classification SVM)	0.186	0.910	0.368	0.351	0.743	0.514	0.344	0.815	0.511
MLP-2-B-L (Multilayer Perceptron)	0.006	0.993	0.064	0.004	0.992	0.044	0.006	0.992	0.051
MLP-1-B-M (Multilayer Perceptron)	0.012	0.979	0.083	0.012	0.981	0.091	0.013	0.988	0.094
MLP-2-O-M (Multilayer Perceptron)	0.037	0.961	0.144	0.015	0.977	0.093	0.026	0.969	0.120
MLP-2-B-M (Multilayer Perceptron)	0.082	0.852	0.207	0.134	0.798	0.250	0.153	0.773	0.260
MLPPCA-1-O-M (MLP with PCA)	0.015	0.973	0.093	0.021	0.975	0.118	0.022	0.989	0.113
MLPPCA-1-B-M (MLP with PCA)	0.128	0.747	0.257	0.187	0.701	0.290	0.161	0.752	0.259
GFF-1-O-M (Generalized Feedforward)	0.025	0.958	0.122	0.022	0.964	0.122	0.018	0.980	0.097
GFF-1-B-M (Generalized Feedforward)	0.043	0.925	0.158	0.092	0.875	0.228	0.100	0.874	0.200
RBF-1-O-M (Radial Basis Function)	0.202	0.702	0.333	0.087	0.793	0.174	0.114	0.760	0.213
RBF-1-B-M (Radial Basis Function)	0.183	0.679	0.357	0.201	0.576	0.304	0.233	0.540	0.368
MLP-1-H-L	0.005	0.993	0.053	0.004	0.994	0.057	0.004	0.995	0.054

	Training	Cross Val.	Testing
Number of Rows	480	101	94
MSE	0.005	0.004	0.004
Correlation (r)	0.993	0.994	0.995
Min Absolute Error	0.001	0.001	0.000
Max Absolute Error	0.225	0.125	0.169
Mean Absolute Error (MAE)	0.053	0.057	0.054

Table A-3. Summary of all Networks to find the best ANN with the third series of testing data

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**
MLP-1-O-M (Multilayer Perceptron)	0.012	0.980	0.088	0.024	0.976	0.124	0.013	0.983	0.088
LR-0-B-M (Linear Regression)	0.168	0.640	0.351	0.167	0.577	0.318	0.149	0.604	0.313
LR-0-B-L (Linear Regression)	0.167	0.642	0.350	0.167	0.581	0.319	0.147	0.620	0.310
MLP-1-B-L (Multilayer Perceptron)	0.007	0.990	0.062	0.007	0.987	0.059	0.004	0.992	0.048
PNN-0-N-N (Probabilistic Neural Network)	0.054	0.904	0.164	0.161	0.778	0.259	0.077	0.848	0.164
RBF-1-B-L (Radial Basis Function)	0.041	0.934	0.168	0.029	0.954	0.129	0.029	0.943	0.132
GFF-1-B-L (Generalized Feedforward)	0.004	0.994	0.049	0.004	0.992	0.052	0.003	0.993	0.045
MLPPCA-1-B-L (MLP with PCA)	0.042	0.946	0.165	0.023	0.946	0.122	0.022	0.952	0.116
SVM-0-N-N (Classification SVM)	0.186	0.910	0.368	0.351	0.743	0.514	0.243	0.866	0.431
MLP-2-B-L (Multilayer Perceptron)	0.006	0.993	0.063	0.004	0.991	0.049	0.005	0.992	0.055
MLP-1-B-M (Multilayer Perceptron)	0.007	0.988	0.064	0.009	0.985	0.075	0.004	0.992	0.049
MLP-2-O-M (Multilayer Perceptron)	0.026	0.970	0.123	0.018	0.974	0.100	0.006	0.986	0.064
MLP-2-B-M (Multilayer Perceptron)	0.090	0.837	0.215	0.146	0.776	0.256	0.099	0.797	0.188
MLPPCA-1-O-M (MLP with PCA)	0.610	0.353	0.570	0.224	0.577	0.408	0.274	0.528	0.424
MLPPCA-1-B-M (MLP with PCA)	0.128	0.745	0.258	0.194	0.697	0.300	0.097	0.796	0.199
GFF-1-O-M (Generalized Feedforward)	0.021	0.976	0.115	0.020	0.971	0.120	0.006	0.985	0.072
GFF-1-B-M (Generalized Feedforward)	0.079	0.853	0.204	0.130	0.804	0.246	0.086	0.826	0.180
RBF-1-O-M (Radial Basis Function)	0.199	0.693	0.328	0.101	0.772	0.176	0.076	0.787	0.177
RBF-1-B-M (Radial Basis Function)	0.172	0.688	0.335	0.197	0.603	0.293	0.133	0.666	0.254
MLP-1-H-L	0.004	0.994	0.047	0.004	0.993	0.052	0.002	0.995	0.035

	Training	Cross Val.	Testing
# of Rows	480	101	94
MSE	0.004	0.004	0.002
Correlation (r)	0.994	0.993	0.995
Min Absolute Error	1E-04	2E-04	6E-04
Max Absolute Error	0.189	0.263	0.134
Mean Absolute Error (MAE)	0.047	0.052	0.035

Table A-4 Summary of all Networks to find the best ANN with the fourth series of testing data

	Training			Cross Validation			Testing		
Model Name	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**	**MSE**	**r**	**MAE**
MLP-1-O-M (Multilayer Perceptron)	0.014	0.978	0.093	0.024	0.975	0.127	0.012	0.984	0.089
LR-0-B-M (Linear Regression)	0.207	0.563	0.399	0.165	0.483	0.340	0.240	0.458	0.433
LR-0-B-L (Linear Regression)	0.167	0.642	0.350	0.167	0.581	0.319	0.184	0.636	0.370
MLP-1-B-L (Multilayer Perceptron)	0.004	0.993	0.051	0.004	0.992	0.047	0.004	0.995	0.044
PNN-0-N-N (Probabilistic Neural Network)	0.054	0.904	0.164	0.161	0.778	0.259	0.074	0.872	0.199
RBF-1-B-L (Radial Basis Function)	0.100	0.807	0.253	0.084	0.850	0.221	0.136	0.722	0.296
GFF-1-B-L (Generalized Feedforward)	0.004	0.994	0.051	0.003	0.992	0.047	0.002	0.997	0.034
MLPPCA-1-B-L (MLP with PCA)	0.004	0.993	0.052	0.004	0.991	0.053	0.003	0.997	0.038
SVM-0-N-N (Classification SVM)	0.186	0.910	0.368	0.351	0.743	0.514	0.166	0.861	0.324
MLP-2-B-L (Multilayer Perceptron)	0.004	0.993	0.048	0.005	0.992	0.057	0.004	0.995	0.048
MLP-1-B-M (Multilayer Perceptron)	0.007	0.988	0.062	0.009	0.986	0.076	0.003	0.996	0.047
MLP-2-O-M (Multilayer Perceptron)	0.018	0.979	0.106	0.018	0.976	0.103	0.017	0.996	0.121
MLP-2-B-M (Multilayer Perceptron)	0.057	0.900	0.175	0.108	0.850	0.235	0.068	0.895	0.198
MLPPCA-1-O-M (MLP with PCA)	0.305	0.689	0.309	0.023	0.968	0.123	0.583	0.607	0.483
MLPPCA-1-B-M (MLP with PCA)	0.131	0.738	0.259	0.187	0.694	0.285	0.126	0.786	0.278
GFF-1-O-M (Generalized Feedforward)	0.031	0.945	0.144	0.024	0.956	0.116	0.044	0.930	0.185
GFF-1-B-M (Generalized Feedforward)	0.068	0.879	0.191	0.111	0.825	0.224	0.075	0.891	0.213
RBF-1-O-M (Radial Basis Function)	0.212	0.683	0.337	0.089	0.792	0.164	0.332	0.626	0.452
RBF-1-B-M (Radial Basis Function)	0.184	0.675	0.345	0.171	0.660	0.300	0.191	0.659	0.362
MLP-1-H-L	0.003	0.995	0.043	0.005	0.995	0.059	0.002	0.997	0.032

	Training	Cross Val.	Testing
Number of Rows	480	101	94
MSE	0.003	0.005	0.002
Correlation (r)	0.995	0.995	0.997
Min Absolute Error	0.000	0.000	0.000
Max Absolute Error	0.163	0.170	0.173
Mean Absolute Error (MAE)	0.043	0.059	0.032

Appendix B

Chapter 7 first appendix

Before training ANNs, the input and output data columns are often normalised to remove the effect of magnitude difference between variables [32]. A common way of normalization employed in this research is to map the data from their real range into the range of [−1, 1]. The input(s) to an ANN, trained by the normalised data, should be normalised, and the output(s) should be de-normalised (de-mapped) into the real range. The normalization and de-normalization stages can be embedded into the final presentation of the ANN to remove the need for normalization/de-normalization of input(s)/output(s).

After normalization, the first stage in training an ANN is to define an error function that well represents the discrepancy between the ANN output and the real system. A popular error function, and the one used in this research, is mean of squared errors, which is presented as Equation B-1 or B-2:

$$E=(y_{ANN}-y_{system})^2 \tag{B-1}$$

$$E = \sum_{i=1}^{n_d}(y_{ANN} - y_{system})^2 \tag{B-2}$$

where y represents the output(s) of the system or the ANN, and n_d is the number of training data sets. Equation B-1 is used when a single set of input–output data is utilised for error calculation, i.e. single-pattern training. If the error is calculated using all of the training data (n_d sets), i.e. bath training, Equation B-2 is employed, which is the case in this research.

y_{ANN} and consequently the error functions are influenced by the weights and biases. Thus, E is presented as $E(\theta)$, whereas θ is a vector of all ANN parameters. Training is the process of tuning θ components so as to minimise (optimise) $E(\theta)$. An approach for tackling this optimisation problem is to approximate the error function using the Taylor series up to the second-order derivatives:

$$E(\theta+\Delta\theta)\cong E(\theta)+\frac{\partial E(\theta)}{\partial\theta}(\Delta\theta)+\frac{1}{2}\frac{\partial^2 E(\theta)}{\partial\theta^2}(\Delta\theta)^2 \tag{B-3}$$

The goal is to find $\Delta\theta$ so that the error converges towards its minimum value. Since θ is a vector rather than a scalar, the derivatives are in the following form:

$$\frac{\partial E(\theta)}{\partial\theta}=g=\left[\frac{\partial E(\theta)}{\partial\theta_1},\cdots,\frac{\partial E(\theta)}{\partial\theta_{n_p}}\right]^T$$

$$\frac{\partial^2 E(\theta)}{\partial\theta^2}=H=\begin{bmatrix} \frac{\partial^2 E(\theta)}{\partial\theta_1^2} & \frac{\partial^2 E(\theta)}{\partial\theta_1\partial\theta_2} & \cdots & \frac{\partial^2 E(\theta)}{\partial\theta_1\partial\theta_{n_{p-1}}} & \frac{\partial^2 E(\theta)}{\partial\theta_1\partial\theta_{n_p}} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \frac{\partial^2 E(\theta)}{\partial\theta_{n_{np}}\partial\theta_1} & \frac{\partial^2 E(\theta)}{\partial\theta_{n_{np}}\partial\theta_2} & \cdots & \frac{\partial^2 E(\theta)}{\partial\theta_{n_{np}}\partial\theta_{n_{p-1}}} & \frac{\partial^2 E(\theta)}{\partial\theta_{n_p}^2} \end{bmatrix}$$

where n_p is the number of parameters. A solution to this optimisation problem is presented in (B-4), namely the Newton direction [33]:

$$\Delta\theta = -H^{-1}g \tag{B-4}$$

However, Equation B-4 is applicable only if H is invertible. Levenberg and Marquardt[33] presented an alternative to improve and generalise (B-4):

$$\Delta\theta = -\eta(H + \lambda I)^{-1}g \tag{B-5}$$

where I is the unit matrix with size n_p, and λ is the smallest number that can make the matrix within the parenthesis invertible; η is calculated through a linear search. Algorithms for finding η and λ have been detailed in[33, 34]. As a prerequisite to calculating $H$and$g$, E and its derivatives are analytically presented as functions of θ, namely error back-propagation.

However, as a drawback of all derivative-based optimisation algorithms including Levenberg–Marquardt, the algorithm may be trapped in a local minimum. That is, training results in ANN parameters that do not lead to the minimum error function. If training is restarted from the same initial values of parameters, the algorithm moves in to the same trap again. As a result, an initialization algorithm is essential for assigning the appropriate initial values to the ANN parameters at the beginning or after each unsuccessful training. Such an algorithm should have two features: (i) The assigned initial values must not be very far from the best values of parameters, to reduce both computational effort and the chance of being trapped in local minima; this demands the use of training data. (ii) Randomness should be included to make sure that the initial conditions leading to the local minima are not repeated. Nguyen and Widrow presented such an algorithm in 1990, which is still widely used [17].

Appendix C

Chapter 7 second appendix

Experimental data for the transient are stored as a two-column matrix containing the input power (Q) and temperature (T).

$$A = \begin{bmatrix} Q_1 & T_1 \\ \vdots & \vdots \\ Q_n & T_n \end{bmatrix} \quad \text{(C-1)}$$

where n is the number of collected data values and A is the matrix of raw recorded data. It was found experimentally that the delay or dead time of the system is 1.4 s. The sampling time (0.2^s in the current job) and order (5 in this research) should be guessed [35](0.2^s and 5, respectively, in this research).

B is the matrix of raw data and prepared data:

$$B = \begin{bmatrix} Q_1 & Q_2 & \cdots & Q_{n-d} \\ \vdots & \vdots & \vdots & \vdots \\ T_{d+1} & T_{d+2} & \cdots & T_n \end{bmatrix} \quad \text{(C-2)}$$

where B is the matrix of data after considering dead time, and $d = \frac{\tau_d}{\tau_s}$

For an inverse model of order r, the data should be arranged as

$$C = \left[\begin{array}{cccc} \multicolumn{3}{c}{\overbrace{\hphantom{T_{d+1} \quad \cdots \quad T_{d+r}}}^{\text{Input}}} & \overbrace{\hphantom{Q_{n-d-r+1}}}^{\text{Output}} \\ T_{d+1} & \cdots & T_{d+r} & Q_1 \\ \vdots & \vdots & \vdots & \vdots \\ T_{n-r+1} & \cdots & T_n & Q_{n-d-r+1} \end{array} \right] \quad \text{(C-3)}$$

where C is the matrix of the prepared data.