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Comparison of inverse modelling and optimization-based methods in the heat flux estimation problem of an irradiative dryer/furnace

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ABSTRACT

There are two major approaches in 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 optimization 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.

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 optimization-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, optimization-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 optimization-based heat function estimation. In short, in inverse modelling, a model which can estimate heat flux in real time is identified, whereas in an optimization-based approach, a heat flux value is estimated for each instant with the use of an optimization algorithm.

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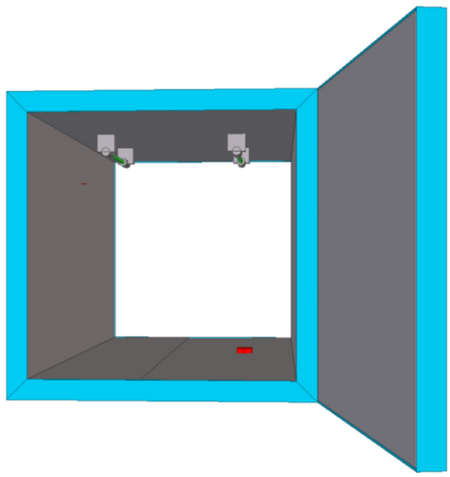

Fig. 1. Arrangement of lamps and thermocouples in the dryer/furnace.

In this study, irradiative thermal systems wherein the dominant mode of heat transfer is radiation are specifically addressed due to their complexity and importance in various engineering applications. In solutions based on heat transfer and thermodynamics laws, optimization-based algorithms with a variety of methods (e.g. conjugate-gradient[8–10], Levenberg–Marquardt [9] and genetic algorithm(GA) [11]) are the prominent solution 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 [16–18]. AI inverse models have been claimed to outperform optimization-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, optimization-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 optimization-based algorithms have been reported in the literature so far, particularly for irradiative thermal systems. This article presents such a comparison experimentally while demonstrating the benefit of use of AI techniques in both approaches.

2. 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

$$\hat{q}(k) = F_I(T(k+r_d), T(k+r_d+1), \ldots, T(k+r_d+r_I)) \tag{1}$$

where $r_d = t_d/t_s$, and 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. Delay time is composed of the time needed for radiation to reach the sensor (almost zero) and the time needed for the received energy to affect temperature. 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. Indeed, 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

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

where r_q and r_d are the heat flux and temperature orders, respectively. To formulate optimization-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 $\hat{q}$, the temperature can be estimated by

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

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

$$\hat{q}(k) = \hat{q}(k) | f_E\left(\hat{T}(k+r_d) - T(k+r_d)\right) \quad \text{isminimum}, \tag{4}$$

where f_E is a function used to represent the error, such as squared or absolute. An optimization algorithm needs to be employed to solve the problem presented in Eq. (4).

In short, Eq. (1) defines an inverse model and Eqs (3)–(5) define the optimization-based approach for a single-input/single-output thermal system.

3. Experimental setup

The irradiative dryer/furnace contains two radiation heat sources (lamps) and several temperature sensors can be attached on the surfaces. Both the lamps and thermocouples are arranged

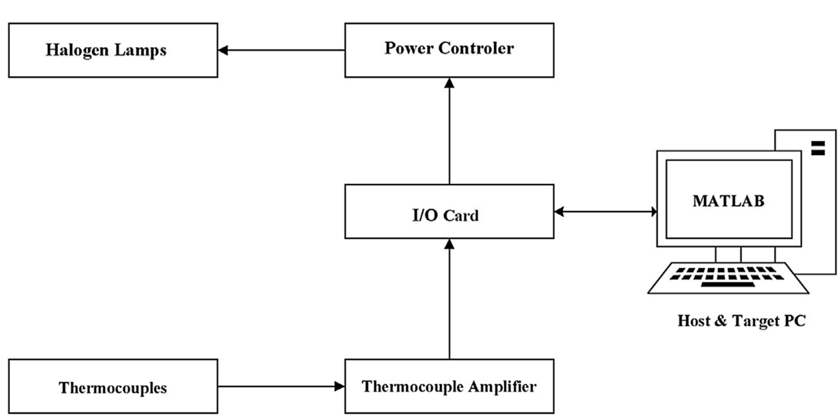

Fig. 2. Signal flow in the experimental setup.