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Evaluating convective heat transfer coefficients using neural networks

K. JAMBUNATHAN, S. L. HARTLE, S. ASHFORTH-FROST and V. N. FONTAMA
Department of Mechanical Engineering, The Nottingham Trent University, Burton Street, Nottingham NG1 4BU, U.K.

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Abstract—Liquid crystal thermography combined with transient conduction analysis is often used to deduce local values of convective heat transfer coefficients. Neural networks based on the backpropagation algorithm have been successfully applied to predict heat transfer coefficients from a given set of experimentally obtained conditions. Performance characteristics studied on numerous network configurations relevant to this application indicate that a 3–6–3–1 arrangement yields the least errors with convergence improving directly with both the global learning rates and those of individual layers. Copyright © 1996 Elsevier Science Ltd.

1. INTRODUCTION AND BACKGROUND

Transient heat transfer analysis is of significant practical interest because of the large number of heating and cooling processes associated with industrial applications. Components such as heat exchangers and boilers in power generation plants necessitate the knowledge of surface temperature distribution with respect to time. Recent experimental techniques such as liquid crystal thermography, used to establish the full-field distribution of convective heat transfer coefficients, require the solution of the one-dimensional transient conduction equation. Experimental work using this technique has been carried out for the determination of heat transfer coefficients in various geometries [1–3]. Despite advances in image processing [4], the large quantities of data which are necessary to obtain detailed distributions of heat transfer coefficients in complex geometries, still render analysis time-consuming. The aim of the present work is to eventually interface artificial neural networks with image processing techniques to provide an automated and efficient stand-alone system.

The recent development of powerful learning algorithms for Artificial Neural Networks (ANNs) has led to their use in many engineering thermo-fluid applications. The capability of perception type multilayer networks to approximate any continuous function has been established, as in Kurkova [5] and Ito [6]. Kavaklioglu and Upadhyaya [7] have used ANNs to predict feedwater flowrates and the thermal efficiency of key components of a Pressurized Water Reactor (PWR). Thibault and Grandjean [8] employed them to model three problems in heat transfer ranging from the thermocouple to correlations in natural convection. Further, they have also been utilized by Singh *et al.* [9] to model the response of a vibratory system and by Kudav *et al.* [10] to simulate steady and unsteady-state heat conduction. The latter is limited by the fact that the neural nets are trained to predict the temperature changes based on just one initial temperature.

This paper reports the results of using ANNs to model one-dimensional transient heat conduction, for liquid crystal thermography (LCT). Neural networks were trained to predict the convective heat transfer coefficients at a point in a duct which is heated by the flow of hot air. The neural networks were trained on a broad range of initial temperatures and other parameters to cover reasonable ranges of real-life transient experiments.

2. APPLICATION OF ANNs TO LIQUID CRYSTAL THERMOGRAPHY

Transient wall heating involves raising the surface temperature of a wall from a known value to a predetermined value, during some measurable period of time. Liquid crystals reflect colour as a function of temperature through the complete visible spectrum within the temperature range for which they are prepared, and can therefore be used to monitor the surface temperature of the test specimen. Deduction of convective heat transfer coefficients due to a fluid flowing over a surface involves the solution of the one dimensional transient heat conduction equation (without generation) together with the respective boundary conditions namely

$$\frac{\partial^2 T}{\partial x^2} = \frac{1}{\alpha}\frac{\partial T}{\partial t} \quad \text{with}$$

$$T(\infty, t) = T_0$$

$$q = h[T_\infty - T(0, t)] = -k\left(\frac{\partial T}{\partial x}\right)_{x=0}. \tag{1}$$

NOMENCLATURE

c	specific heat capacity of the specimen	Greek symbols	
h	convective heat transfer coefficient	α	thermal diffusivity $= k/\rho c$
k	thermal conductivity of the specimen	θ	dimensionless temperature
q	heat flux	Ω	intermediate parameter in equation (3).
T	temperature	Subscripts	
t	time	lc	pertains to liquid crystal
x	distance from the surface of the specimen.	0	initial conditions
		∞	property of the fluid.

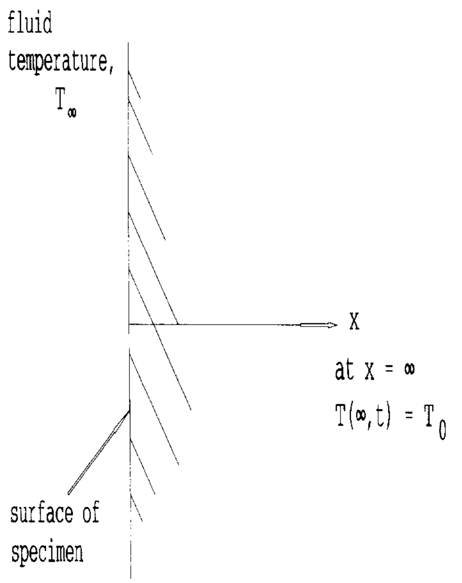

Fig. 1. A diagram to illustrate the transient heating of a semi-infinite wall.

Figure 1 illustrates the above situation where the specimen is assumed to be sufficiently thick for the temperature to stay constant at infinite depth. The exact solution of equation (1) at the surface of the specimen is given by equation (2), [11].

$$\theta = \frac{T_{lc} - T_0}{T_\infty - T_0} = 1 - e^{\Omega}(1 - \mathrm{erf}\sqrt{\Omega}) \qquad (2)$$

where erf(x) is the Gaussian error function and

$$\Omega = \frac{h^2 \alpha t}{k^2}. \qquad (3)$$

The convective heat transfer coefficient, h, can be obtained by an iterative process which uses an estimate of h to obtain the surface temperature. The advantage of using neural networks for this case is that once trained, their prediction of the surface heat transfer coefficient (as a function of θ, α and t) is very fast.

The backpropagation model used in this work is a learning algorithm which applies to multi-layered networks. This model involves supervised learning; hence each input pattern is presented with its corresponding output pattern. Learning involves minimizing the error between the expected and the actual network outputs. This is carried out using the Gradient Descent method. When the complete training set is presented the root mean squared (r.m.s.) error is calculated. Training continues until the global minimum of this r.m.s. error is attained. More details of the backpropagation model are available in [8–10].

3. RESULTS AND DISCUSSION

The approach adopted in this investigation was to model the heat transfer coefficient, h, as a function of three variables namely, (i) θ, the non-dimensional temperature, (ii) α, the thermal diffusivity and (iii) t, the time. These three input networks were developed on NeuralWorks Professional II Plus™, a commercial neural networks package developed by NeuralWare, Inc. [12]. Figure 2 shows a typical three-input network used in this application. All these nets were trained to model real-life transient experiments and their training sets were generated by an iterative solution to equation (2).

From experimental results, a plot of h against time shows a curve which represents the fall in h with time (see Fig. 3). For each value of θ there is one such curve which depicts the change in h with time. The training set comprised data taken for many different values of θ, in the range: $0.25 \leqslant \theta \leqslant 0.68$. This range for θ represents the limits of typical experimental tests. The maximum elapsed time for the experiment was set as 60 s which, again, represents a typical experimental test. For each network the test set comprised 20 examples which did not appear in the training set, but which were carefully selected to span the full range of the training set. Figure 3 compares the actual values of h with the predictions of the 3–6–3–1 network. Average errors of up to 2.7% were obtained using this network, while the worst-case average error of 6.5% was obtained from the 3–4–3–1 net.

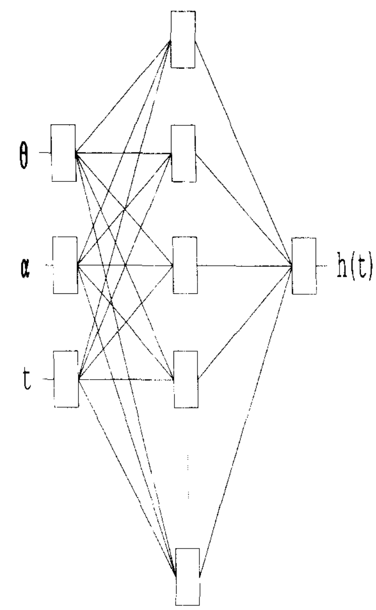

Fig. 2. A typical three-input backpropagation network used in this study.

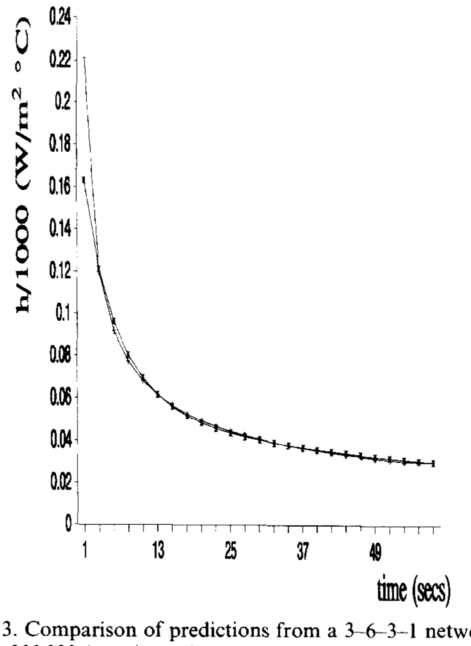

Fig. 3. Comparison of predictions from a 3–6–3–1 network after 200 000 iterations. * network's predictions; + actual values of h (derived from simulation).

The speed of learning was improved by investigating three different approaches: firstly, the effect of the number of hidden nodes was studied; secondly, the global learning coefficient and momentum term of the whole network, as well as the learning coefficient of the individual layers were varied. Finally, the configuration of networks was changed.

The tests confirmed that the networks converged faster with increasing number of nodes in the first hidden layer. However, the performance of networks with greater than 20 nodes in the first hidden layer was generally worse. This arises from the fact that too many nodes result in overfitting of the data and hence, poor generalization. It was also found that the speed of convergence of the networks increased with the global learning rates and with the learning rate of each individual layer.

An alternative configuration of networks was also studied. Each node was connected directly to all others in the layers below. This has the effect of adding an extra bias term to each node. For networks with less than six nodes in the first hidden layer, the speed of convergence was improved by the adoption of this alternative configuration. However, for networks with seven or more nodes in the first hidden layer, this alternative structure did not necessarily improve convergence.

4. CONCLUSIONS

Artificial neural network methodology has been successfully applied to deduce convective heat transfer coefficients from experimental data using liquid crystal thermography. The technique involved the modelling of the one dimensional transient conduction equation together with its boundary conditions. Accuracies of up to 2.7% have been obtained using the 3–6–3–1 network. The speed of learning increases directly with the number of units in the first hidden layer. It is also improved by increasing the global learning coefficients or the learning coefficients of individual layers. It has also been shown that, for this problem, networks with less than seven units in the first hidden layer learn faster when they are connected such that each node is directly linked to all others below this layer.

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