A NEURAL NETWORK APPROACH FOR EVALUATION OF SURFACE HEAT TRANSFER COEFFICIENT

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ABSTRACT

An artificial neural network (ANN) approach for tackling the inverse heat conduction problems was explored — specifically for the determination of surface heat transfer coefficient at the liquid-solid interface using the temperature profile information within the solid. Although the concept is quite generic, the specific cases considered have a particular relevance to food process engineering applications. The concept was tested with two geometric shapes: a sphere and a finite cylinder, the former representing the simplest geometry and the latter representing a cross product of an infinite cylinder and an infinite plate. In developing the ANN model, two approaches were used. In the first one, the ANN model was trained to predict the surface convective heat transfer function, Biot number (Bi) from the slope coefficient (m) of temperature ratio curve under varying boundary conditions. The associated mean relative prediction errors were as high as 5.5% with a standard deviation of 8%. In the second ANN approach, m was related to tan^{-1} *(Bi) which significantly improved the model's predictive performance. The second ANN model could be used with Biot numbers up to 100 with a mean error less than 1.5% for either of the two geometries. Heat transfer coefficients evaluated using the developed ANN model were in agreement (<3% error) with those calculated using conventional numerical/analytical techniques under a range of experimental conditions.*

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INTRODUCTION

Inverse heat conduction problems (IHCP) are encountered when the heat transfer coefficient, heat flux or temperature histories are to be determined at the surface based on the measured temperature history at one or more internal locations. In general, the direct problem determines the solution in the whole domain for known conditions at the boundary while the inverse problem deals with the opposite, i.e., the determination of boundary conditions based on known conditions within the domain. Experimentalists involved in estimating the heat flux histories at the surface of a heated body generally need to rely on IHCP. One of the main difficulties in solving the inverse heat conduction problems is their ill-posed nature. Hence, they are sensitive to measurement errors. Quite often, the heated surfaces are not suitable for fixing sensors or for making accurate measurements, and temperatures are measured at one or more internal locations. In such cases, temperature measurements suffer from damping and lagging effects also (Beck *et al.* 1985). One of the main tasks in developing an algorithm for the IHCP is to make the estimated surface quantities insensitive to the measurement errors. Several algorithms based on finite difference method (Beck and Wolf 1965 and Beck *et al.* 1981) and finite element method (Bass 1980) have been developed for solving the IHCP. An excellent treatment of the difficulties encountered in inverse heat conduction problems and the methods used to solve these problems can be found in Beck *et al.* (1985).

Inverse heat conduction problems are encountered in several applications. The problem considered is quite generic in terms of evaluation of convective surface heat transfer coefficients although this has been focussed on thermal processing conditions in this paper. Traditional thermal processing involves application of heat to foods, packaged in sealed containers, to destroy a designated population of microorganisms of public health concern at every location in the food (particles and liquid). Since liquids heat faster than solid particles, the central location of the largest solid particle is generally taken as the critical location. Under the heating conditions (retorting) designed to deliver the desired heat treatment to the critical particle, the bulk of the food at other locations in the container are obviously overcooked. Developments in thermal processing technology have centered around improving the product quality by minimizing the temperature gradients within the can. In one technique, cans containing liquid and solid foods are subjected to agitation while they are heated in a retort. The mixing of the contents improves the associated heat transfer. In continuous flow aseptic processing systems, particulate foods dispersed in a carrier liquid are heated in a scrapped surface heat exchanger (SSHE) and then made to pass through a set of holding tubes (where particles receive heat from the liquid through equilibration) subsequently cooled in another SSHE and finally packaged under aseptic conditions into presterilized containers. Modeling of time-temperature history in foods undergoing thermal processing requires data on the associated fluid-to-particle heat transfer coefficient. In aseptic processing, heat transfer is influenced by the fluid viscosity and flow rate as well as the tube flow conditions. In order to evaluate the heat transfer coefficient, the temperature history is measured inside a solid particle at a specified location and the heat transfer coefficient at the surface is estimated by solving an inverse heat conduction problem. This is done by computing the temperature history at a specified location based on an assumed heat transfer coefficient by solving the governing heat conduction equation (direct problem) and comparing it with the measured temperature history. The heat transfer coefficient is then altered sequentially in the appropriate direction until the computed and the experimental temperature histories match within the desired level of accuracy (Sablani 1996). This procedure is iterative and is subjected to some of the inherent disadvantages described earlier.

The objective of the present study was to devise a noniterative method, using ANN, to solve the IHCP for estimating the fluid-to-particle heat transfer coefficient from the temperature profile information gathered at an internal location in the solid body. As a first step, a spherical geometry was used. Subsequently, the procedure was extended to the more common cylindrical geometry of finite length which was a cross between an infinite plate and an infinite cylindrical configurations.

ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is a computational structure inspired by biological neural systems. An ANN consists of very simple and highly interconnected processors called neurons. These processors are analogous to biological neurons in the human brain. The neurons are connected to each other by weighted links over which signals can pass. Each neuron receives multiple inputs from other neurons in proportion to their connection weights and generates a single output which may be propagated to several other neurons. The function of the neuron is shown schematically in Fig. 1. The inputs (X_j) into a neuron are multiplied by their corresponding connection weights (W_j), summed together and a bias (b) is added to the sum. This sum is transformed through a transfer function (f) to produce a single output (P) which may be passed on to other neurons. Sigmoidal, hyperbolic tangent, linear threshold or Gaussian functions are the commonly used transfer functions. The function of a neuron can be mathematically expressed as:

$$P=f\left(\sum_{i=1}^{N} W_i X_i + b\right) \tag{1}$$

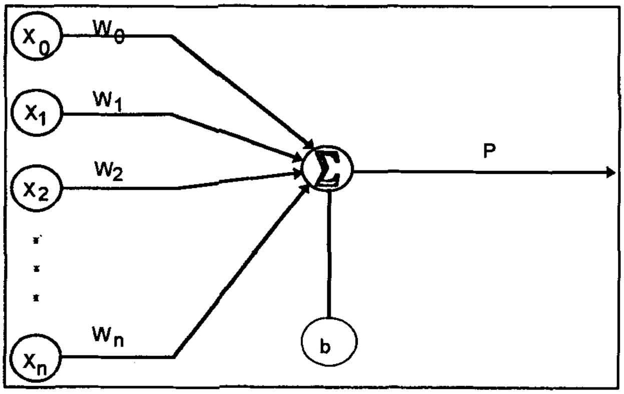

FIG. 1. SCHEMATICS OF A SINGLE NEURON

A multi-layer artificial neural network is shown in Fig. 2. Each layer will have several neurons. The layers are classified into input, hidden and output layers. The neurons in the input layer receive signal input from the user. These signals are carried to the first hidden layer through the connections. The signals are transmitted this way to the output layers which produce the network output. The number of neurons in the input and output layers correspond to the number of input and output variables. The number of hidden layers and the number of neurons in each hidden layer can be varied. Neural networks can have various structures depending on the way in which the neurons are interconnected and on the flow of information though the network. One of the commonly used ANN structures is the feed-forward structure. In this structure, the connections are linked from the input layer to the output layer. In their book on "Neural Network Computing", Bharath and Drosen (1994) have given a comprehensive description of the structure and function of ANN.

The development of ANN model involves a training phase. In this phase, the network parameters such as connection weights and bias are adjusted such that, for the given input dataset the neural network-predicted output dataset matches with the desired output dataset. At the beginning of the training phase, the network weights and bias are initialized arbitrarily. For the given set of inputs to the network, the response of each neuron in the output layer is then calculated and compared with the corresponding desired output response. The errors associated with the output response are computed and transmitted to the previous layers. The weights are adjusted so as to reduce these errors in each neuron from the output to the input layer. Such a method of adjusting the connection weights is called a back-propagation algorithm. This procedure is repeated over the entire training set for a specified number of times (training runs), usually several thousand times, chosen by the user.

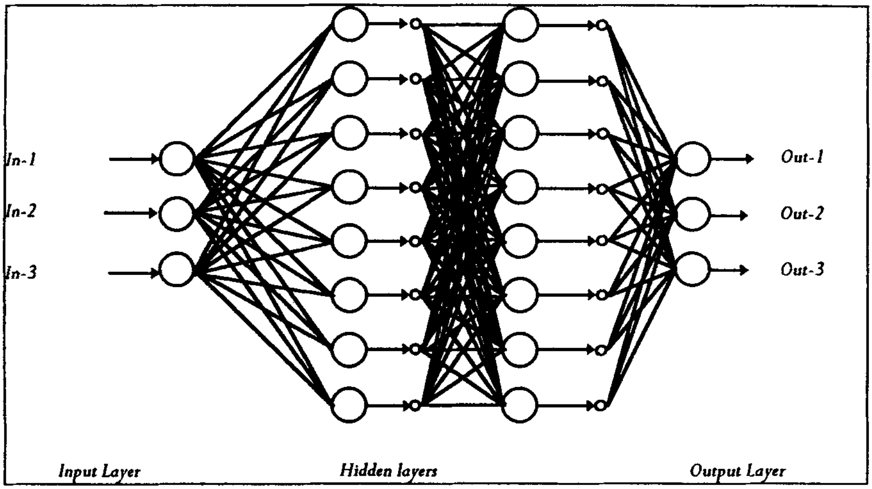

FIG. 2. SCHEMATICS OF A MULTILAYER ANN MODEL

In recent years, artificial neural network (ANN) models have attracted researchers in many engineering disciplines. ANNs, developed basically with the intention of mimicking the ability of the human brain in recognizing the pattern, distinguishing the shapes etc., have found useful applications in many areas. Schreck *et al.* (1995) used ANN models to predict the unsteady separated flow field on a wing. Dissanayake and Pan-Thien (1994) developed a method to solve the partial differential equations using neural network concept. Singh *et al.* (1994) used artificial neural network to model the entire flow field around an automobile.

There are several food processing areas in which ANN models have been used successfully. Examples include applications in sensory analyses and quality control (Park *et al.* 1994; Sayeed *et al.* 1995; Tomlins and Gay 1994), classifications (Ding and Gunashekaran 1994), drying applications (Balasubramanian *et al.* 1996), heat transfer (Sablani 1996; Sablani *et al.* 1996, 1997), psychrometry (Sreekanth *et al.* 1998) etc. The key feature of the ANN which has attracted researchers is its ability to learn and generalize the relationship between complex datasets.

METHODOLOGY

Development of an ANN model involves two basic steps, training and testing. Good quality data are needed for both purposes. Although the same data set can be used for both training and testing, it is preferable to have two different datasets. Data were generated using numerical simulation for both training and testing. Finally verification was done using data from published literature. The following general procedure was used for developing the ANN model:

(1) The first step was to assume/select a known value of heat transfer coefficient at the surface of the solid which together with assumed temperature of the fluid and thermo-physical properties of the solid defined the boundary conditions for the conduction heat transfer problem involving convection at the surface.

(2) The next step was to solve the governing equations for the appropriate geometry and obtain the temperature history at a specified location inside the body. Any appropriate method could be used for this purpose depending on the complexity of the model (i.e. analytical, numerical or experimental). The method used for this purpose has no specific bearing on the final result, as long as the data generated are accurate. In this paper, numerical simulations were used.

(3) This procedure was repeated for several values of the heat transfer coefficient, and thus, a set of data was developed consisting of several values of heat transfer coefficient (hence, Biot numbers, Bi) and the corresponding temperature profiles. The developed data were used for creating data subsets for both training and testing of the ANN model.

(4) ANN models were then trained and tested with the information about each temperature profile as input and the corresponding heat transfer coefficient (or Biot number) as the output.

(5) The trained ANN models could then be used to predict the heat transfer coefficient based on the measured temperature history for the solid particle.

Finite Difference Formulation

In order to generate the training and testing dataset, the heat conduction equation was solved using a finite difference method. Two geometries were considered in the present study: sphere and a finite cylinder, the former representing a simple case and the latter a more complicated one. Thermo-physical properties of the material were assumed to be constant. The heat conduction equation in non-dimensional form was written as,

$$\frac{\partial\theta}{\partial\tau} = j\frac{\partial^2\theta}{\partial X^2} + \frac{1}{R^m}\frac{\partial}{\partial R}\left(R^m\frac{\partial\theta}{\partial R}\right) \tag{2}$$

The equation for a sphere can be obtained by setting j = 0 and m = 2, and for a finite cylinder by setting j = 1 and m = 1. The initial and boundary conditions were:

$$\theta = 0 \text{ at } t = 1 \text{ for all R and X} \tag{3a}$$

$$\frac{\partial\theta}{\partial R} = 0 \text{ at } R = 0,\ t > 0 \text{ and for all X} \tag{3b}$$

$$\frac{\partial\theta}{\partial R} = Bi \cdot \theta \text{ at } R = 1,\ t > 0 \text{ and for all X} \tag{3c}$$

$$\frac{\partial\theta}{\partial X} = Bi \cdot \theta \text{ at } X = 0 \text{ and } X=L,\ t > 0 \text{ and for all R} \tag{3d}$$

$$\frac{\partial\theta}{\partial X} = 0 \text{ at } X=L/2 \text{ for all R} \tag{3e}$$

Circumferential variations in the temperature were ignored; hence, the problem was essentially one-dimensional in the case of sphere and two-dimensional in the case of finite cylinder. The above equations were solved using Crank-Nicholson scheme. The spatial derivatives were evaluated using a second order accurate difference scheme. Details of the numerical algorithm are given in Sablani (1996) and Sablani and Ramaswamy (1995). Solutions were generated using uniformly spaced grids in the radial and axial directions (for the finite cylinder). Grid refinement study was made to determine the sensitivity of the results to the number of grid points. The final results were generated using the grid with 20 nodal points in both directions, since no significant differences in the center point temperature responses were noted beyond this level.

Training / Testing Dataset

Data used for training and testing the ANN model were generated using the finite difference program. The Biot numbers were varied from 0.005 to 100. The increments to Bi increased with increasing Bi. The finite difference program was run for each of these Bi and the center point temperature profile was obtained. Since the nondimensionalized temperature varied linearly with the Fourier number when plotted in the semi-log scale, the temperature profile could be characterized by two parameters: slope and the intercept values of this curve. The slope was denoted by m and the intercept by C. The above two parameters were obtained from the calculated temperature profiles for each Bi and used for training and testing.

The optimal ANN configuration was selected from amongst various ANN configurations based on their predictive performance. Several error parameters (MAE — mean absolute error; STD_A — standard deviation in absolute errors; MRE — mean relative error; STD_R — standard deviation in relative errors) were used in order to compare performances of the various ANN configurations:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |(Y_i - D_i)| \tag{4a}$$

$$STD_A = \text{Standard deviation of } |(Y_i - D_i)| \tag{4b}$$

$$MRE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(Y_i - D_i)}{D_i} \right| \tag{4c}$$

$$STD_R = \left| \frac{(Y_i - D_i)}{D_i} \right| \tag{4d}$$

In the above equations Y_i is the neural network output for a given input and D_i is the desired output for the same input. In addition to this, the R^2 value of the regression between the neural network output and the desired output was also used for comparison.

RESULTS AND DISCUSSION

In the present work, a finite difference program was used for the purpose of generating data. Alternatively, depending on the specific cases considered, one could generate data using analytical solutions in the form of infinite series (Carslaw and Jaeger 1959). The present work represents the first stage of a more comprehensive work involving situations where no analytical solutions are available. To have a common platform covering all these situations, a finite difference simulation was preferred to the analytical solution. The numerical algorithm was first validated against analytical solutions. The temperature profiles generated at the center of the particle for Bi = 0.5 and 5 using the finite difference code are shown in Fig. 3 along with those calculated from the analytical solutions (Carslaw and Jaeger 1959). The figure shows excellent comparison between the two. The calculated time (Fourier number) required to cool the particle center to a temperature ratio of 0.1 at different values of Bi obtained from the finite difference program was within 1% of the value from the analytical solution which validates the performance of finite difference program.

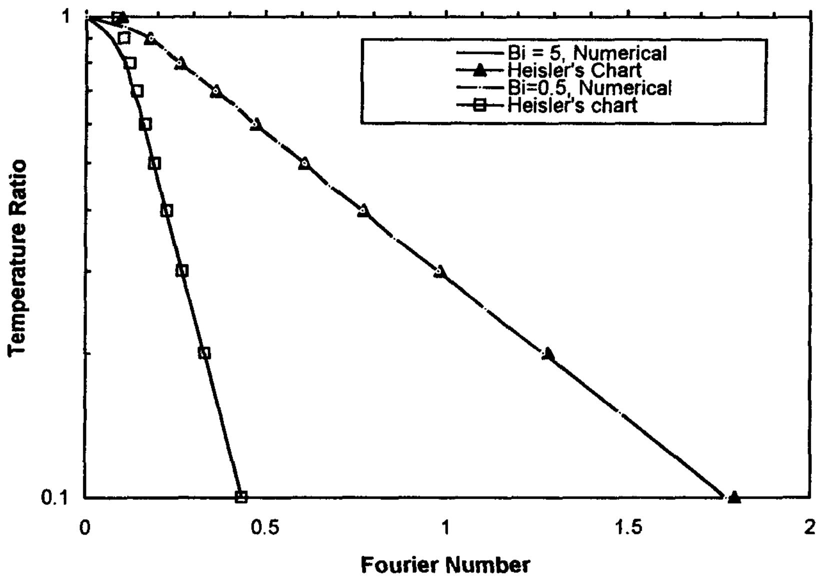

FIG. 3. TEMPERATURE PROFILE FOR Bi = 0.5 AND 5

Spherical Geometry

The slope m and the intercept constant C of the temperature profile are functions of only Biot number, when the fluid temperature remains constant. Hence Bi can be expressed as a function of either the slope or the intercept. In order to determine Bi, one of the two parameters was sufficient. In the present work, slope of the temperature profile was used for developing the ANN model because it is independent of location. In the ANN configurations considered, the input layer had one neuron corresponding to the slope of the temperature profile, the output layer had one neuron representing the Biot number in some form. A hyperbolic tangent function (default) was used as the transfer function in all the cases. Several configurations were tried to optimize the number of training cycles, the number of hidden layers and the number of neurons in each hidden layer.

Two different approaches were used in developing the ANN models. In the first approach (ANN model 1), the input neuron represented the slope (m) and the output neuron represented the Biot number (Bi). When the entire Biot number range was used for developing a single model, the performance of the model was not very satisfactory. Figure 4 shows a plot of the desired and predicted Biot numbers. Especially the prediction of higher Bi was not very good. The relative errors for the best ANN model (6 neurons in 2 hidden layers) was 5.4% and the standard deviation of the relative error was 8% which is quite high. The maximum relative error was 41.8% which was far from satisfactory. However, when the Biot numbers were split into two different ranges (1 to 25 and 25 to 100) and two independent models were developed, a marked improvement in the results was observed. Figure 5a and Fig. 5b show the results of the developed models. Clearly, Fig. 5a and Fig. 5b show a large improvement over Fig. 4. For the best ANN configurations in these two cases, the maximum relative errors were 7.7% and 2.9%, respectively, and the mean relative errors were 1.61% and 0.84%. Although, the neural network model predicted the Biot number reasonably well when the two models covering smaller Biot number ranges were independently considered, the results are not fully useful, particularly for inverse heat conduction problems. In IHCP, Biot number is the parameter to be determined and hence is not previously known.

Generally, ANN models do not require any prior knowledge of the relationship between the input and the output which they are trying to relate. However, if some knowledge about the relationship is available, it could be used in the ANN model to get better performances. Some idea about the relationship between the Biot number and the slope can be obtained from the plot of Bi vs m (Fig. 6). In this figure m is scaled between 0 to $\pi/2$. Also shown in the figure is the plot of tan (m) which indicates that Bi varies in a crude manner similar to tan (m). In the second approach, this information was fed while developing the second ANN model. In this ANN model 2, the input neuron represented the slope m and the output neuron represented $\tan^{-1}$ (Bi).

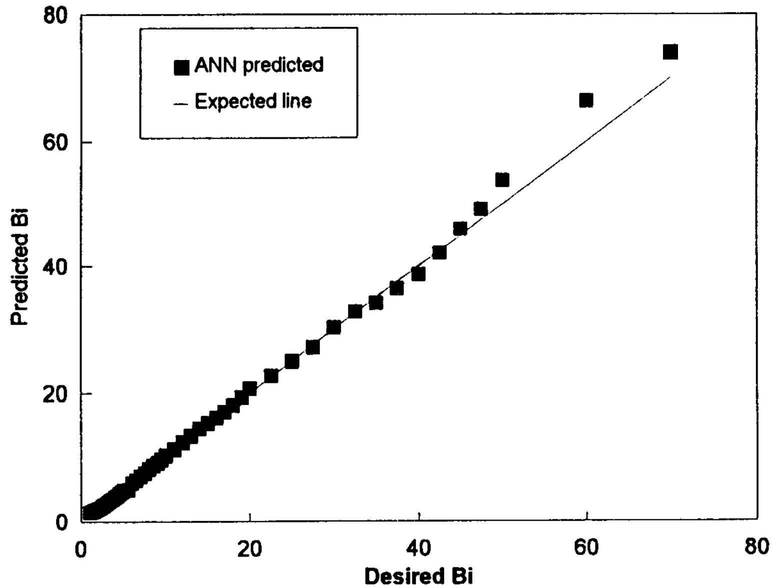

FIG. 4. PREDICTED VERSUS DESIRED Bi FOR ANN MODEL 1

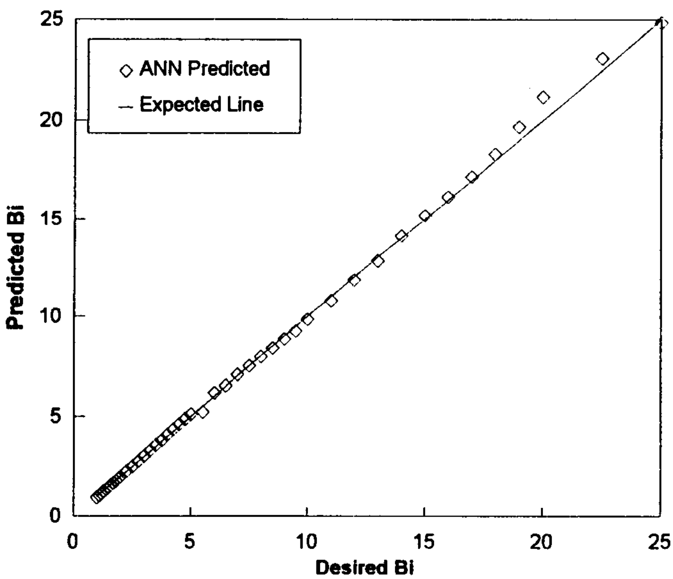

FIG. 5a. PREDICTED VERSUS DESIRED Bi WITH ANN MODEL 1
($1 < Bi < 25$)

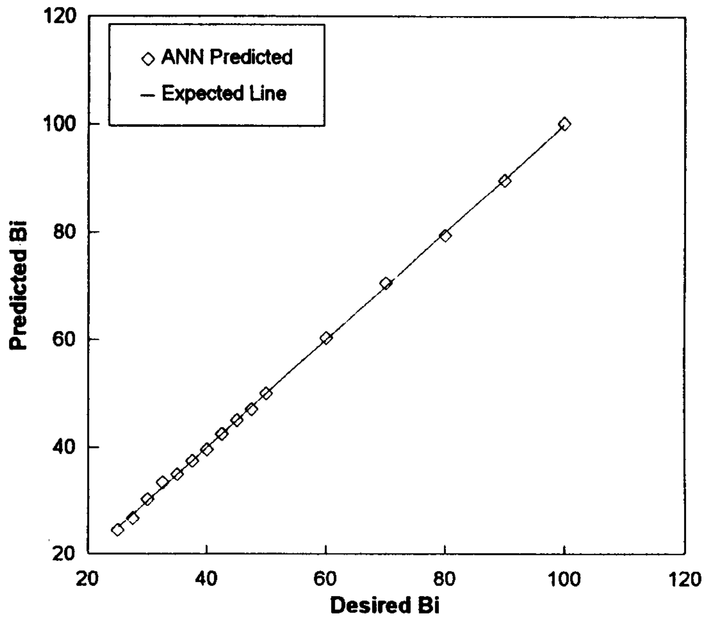

FIG. 5b. PREDICTED VERSUS DESIRED Bi WITH ANN MODEL 1
(25 < Bi < 100)

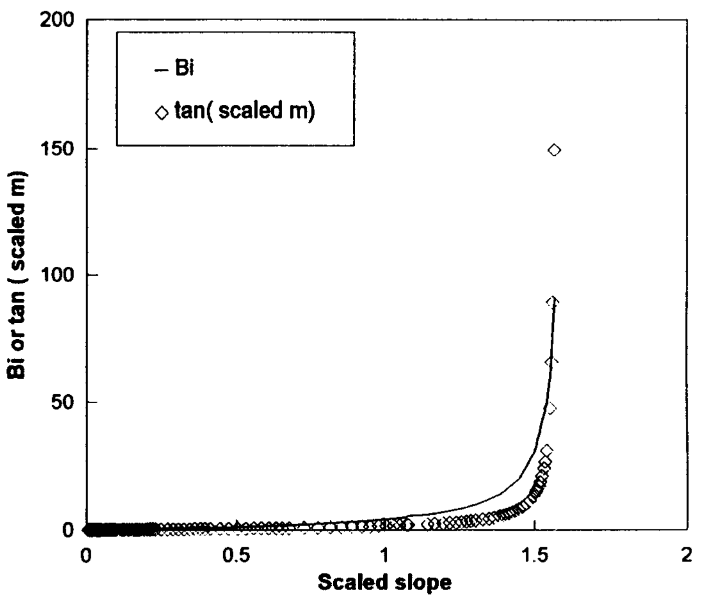

FIG. 6. VARIATION OF Bi WITH THE SLOPE m

Errors associated with different configurations for the ANN model 2 are shown in Table 1. The best ANN configuration was that of a single hidden layer with 4 neurons. The mean relative errors were less than 1.5%. It should be noted that, in this case, the complete range of Biot numbers (0.005 to 100) was used for training and testing. For this configuration, Fig. 7 shows the plot of predicted vs desired Biot numbers demonstrating an excellent agreement between the two. In addition to providing an ANN model which works over a broad range of Bi, these results demonstrate that the choice of input or output parameters has a major impact on the performance of the ANN model and a prior knowledge of the relationship (even if it is crude) can be utilized to improve the performance of the ANN models.

TABLE 1.
PREDICTION ERRORS ASSOCIATED WITH DIFFERENT ANN CONFIGURATIONS

Layers	Neurons	MRE	STD_R	MAE	STD_A	R^2
1	2	4.22	7.89	1.39	4.88	0.978
1	**4**	**1.12**	**1.11**	**0.17**	**0.38**	**0.999**
1	6	1.53	1.37	0.23	0.52	0.999
1	8	1.32	1.62	0.28	0.83	0.999
1	10	1.07	1.64	0.25	0.90	0.998
2	2	1.79	1.35	0.24	0.47	0.999
2	4	2.89	2.40	0.49	0.90	0.999
2	6	1.73	1.26	0.27	0.69	0.998
2	8	1.90	2.63	0.52	1.56	0.995
2	10	1.46	1.48	0.30	0.801	0.998

Comparison with Literature Data. Once the slope coefficient of logarithmic temperature ratio versus time is known, the developed ANN model can be used to predict the Biot number. In the determination of the heat transfer coefficient, the solid temperature history is measured at some specific location during the experiment as a function of time from which the slope m can be obtained. Using m as the input, the ANN model can be used to predict $\tan^{-1}$ (Bi), and since Bi = (ha/k), the associated heat transfer coefficient can easily be calculated. Zareifard and Ramaswamy (1997) investigated the effect of various system and product parameters on heat transfer coefficient to the spherical Nylon particles in continuous flow situations. The ANN model 2 developed in this study was used to predict the h value and compared against the

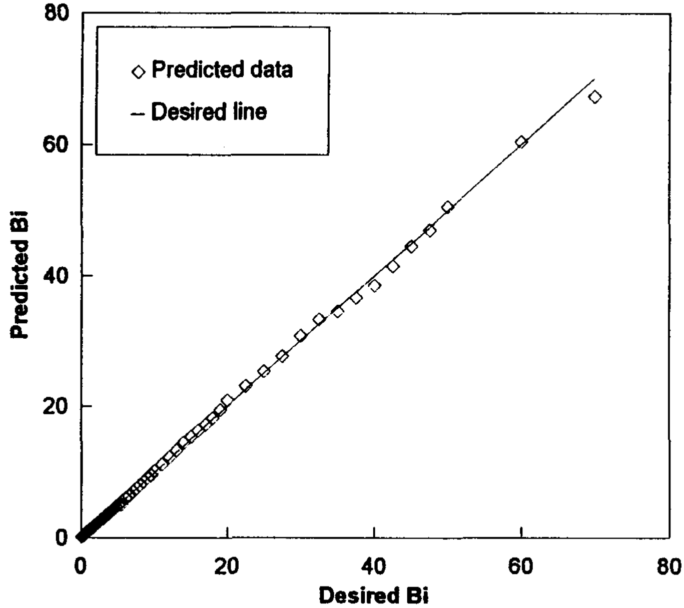

FIG. 7. DESIRED VERSUS PREDICTED Bi WITH ANN MODEL 2

reported experimental values. Table 2 shows the radius, experimental Bi and the estimated heat transfer coefficient (h) of the spherical particles reported in Zareifard and Ramaswamy (1997) along with the Biot numbers and h predicted from the ANN model. For all the cases, the predicted values were very close to the reported experimental values (error $< 3\%$). The experimental range covered Biot numbers from about 10-30 and heat transfer coefficient from 450-1350 W/m^2C. Additional data from Ramaswamy *et al.* (1996) covered even a lower range of Biot numbers (8-15) with h varying from 250-500 W/m^2C in which, again, the estimated errors were less than 3%.

Finite Cylinder

For the spherical geometry considered in the above case, it may be argued that there is no distinct advantage of using ANN model. Analytical solutions for the temperature history could easily be obtained using the first term of the infinite series (Carslaw and Jaeger 1959). Using these solutions, one can easily solve the inverse problem in a straight forward manner i.e. the Bi can be readily calculated once the slope of the temperature profile is known (provided the Fo is greater than 0.2). The case of spherical geometry was considered, only as a first step because of its simplicity, to demonstrate the concept. The ANN modeling can be really advantageous for more complicated problems in which either the inverse problem is iterative or there is no closed form solution available for the temperature history. One such example is the case of a finite cylinder. Although, in this case closed form solutions could be obtained as a product of solutions in the infinite cylinder and infinite slab, the inverse problem is not straight forward as in the case of sphere. This case was chosen as the next step.

TABLE 2.
VERIFICATION OF THE ANN MODEL WITH EXPERIMENTAL RESULTS

Product Description and Heating Conditions		Experimental Biot No.	h W/m^{2}C	ANN predicted Biot No.	h W/m^{2}C
Zareifard and Ramaswamy (1997)					
Spherical Nylon particles	a (mm) 9.5	31.9	1240	33.5	1300
heated in water and sucrose	9.5	35.3	1370	36.7	1420
solutions	9.5	21.9	850	21.2	833
	9.5	27.3	1069	27.0	1050
	9.5	21.6	840	21.2	822
	9.5	24.5	950	24.7	958
	9.5	17.0	660	16.2	630
	9.5	14.9	560	14.6	548
	9.5	13.6	530	13.3	525
	9.5	11.8	460	11.7	455
Ramaswamy et al. (1996)					
Spherical Teflon particles	a (mm) 9.5	15.6	475	16.0	487
	9.5	12.9	395	12.5	383
	9.5	9.83	300	9.80	299
	9.5	8.20	249	8.53	259
Teflon cylinders heated	a/L = 0.48	8.78	268	9.21	281
in CMC sol. at different	0.37	8.58	262	8.75	267
temperatures and	0.49	5.57	129	5.51	127
flow rates	0.63	4.53	105	4.60	107
	0.37	16.3	496	15.8	480
	0.37	12.0	365	11.8	359
	0.31	24.4	893	25.1	918
Awuah et al. (1993)					
Potato cylinders	a/L = 0.29	8.00	456	8.21	468
heated in CMC	0.29	3.48	199	3.32	190
solution	0.29	2.50	143	2.50	143
Carrot cylinders	a/L = 0.29	9.75	556	9.85	560
Heated in CMC	0.29	4.08	233	4.07	232
solution	0.29	3.01	172	3.00	171

The training data were generated using the finite difference code for several a/L ratios (0.1 < a/L < 1.0) of the cylinder and for several Biot numbers in the range of 0 to 100. The two ANN models tried for the spherical geometry were also tried in this case. Figure 8 shows the result for an a/L ratio of unity from the ANN model 1 to which the input was the slope and the output was Biot number. As with the case of sphere, the results were not good. In fact, in this case the performance was bad almost in the entire Bi range. The mean relative error and the standard deviation of the errors were 20% and 32%. Figure 9 shows similar results from the ANN model 2 trained for predicting $\tan^{-1}$(Bi) rather than Bi. There is a marked improvement in the results with the mean relative error and their standard deviations of 1.35% and 1.37%, respectively, substantially lower as compared to the ANN model 1. The above results were obtained with 2 neurons and one hidden layer. As a next step, the a/L ratios of the cylinder was also considered as an input so that it can be extended to different can sizes used in thermal processing of foods. An ANN model was trained with the slope of the temperature profile and a/L ratio as the inputs and $\tan^{-1}$(Bi) as the output. This model is very general in nature in the sense that it accounts for any finite cylinder with an a/L ratio of unity or lesser. Up to Bi of 40, the results were very good with the mean relative error and the standard deviation being 3.6% and 2.57%, respectively.

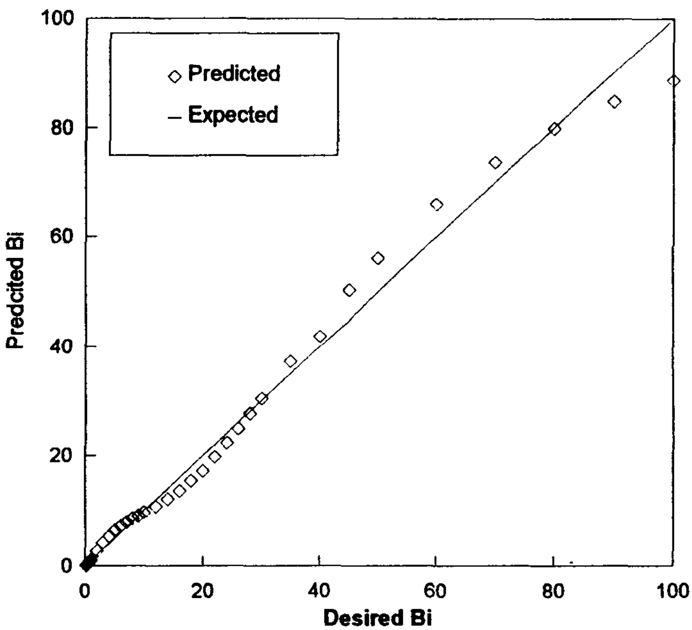

FIG. 8. DESIRED VERSUS PREDICTED Bi FOR CYLINDER (ANN MODEL 1)

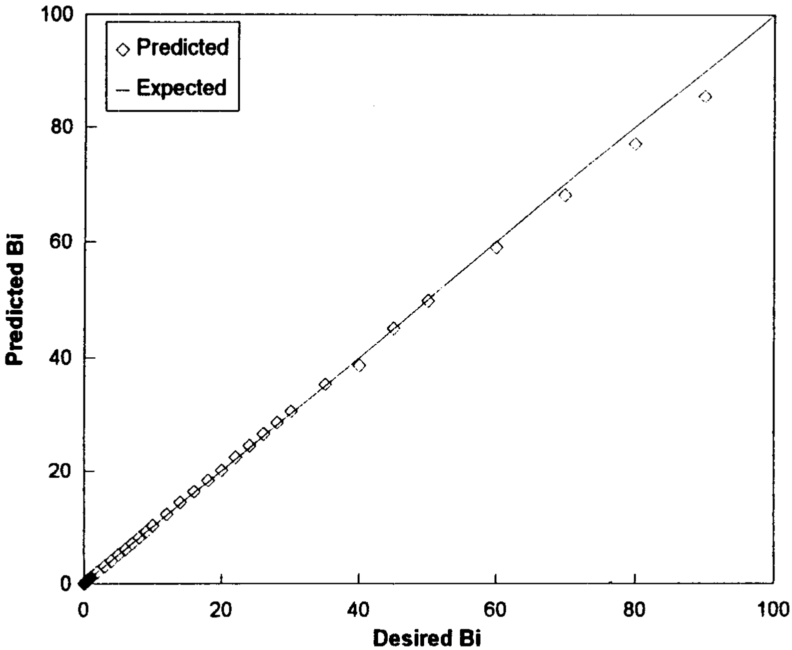

FIG. 9. DESIRED VERSUS PREDICTED Bi FOR A FINITE CYLINDER USING ANN MODEL 2

Comparison with Literature Data. Literature data were again used to compare the model performance. Data were obtained from two sources (Ramaswamy *et al.* 1996, and Awuah *et al.* 1993) which involved heating of cylindrical particles of Teflon and food (potato and carrots), of different length to diameter ratios, in water and viscous carboxymethyl cellulose (CMC) solutions under tube flow conditions. As before the experimental a/L ratio, Bi, h are listed along with the ANN predicted values of Bi and h values. Once again, in all these cases, the predicted value was within 3% of the experimental value. These results demonstrate that the developed ANN model provides an excellent alternative to conventional computation methods for inverse heat conduction problems like the one involved with the determination of convective surface heat transfer coefficient associated with regularly shaped solids.

CONCLUSIONS

ANN models were developed for the determination of heat transfer coefficient at the surface of spherical and cylindrical solids using measured temperature profile inside the solid particle. Although emphasized and tested with literature data to be applicable for situations involving fluid to particle heat transfer as found in food processing applications, the concept is quite generic and can work well for most situations involving inverse conduction heat transfer and boundary conditions of third kind (convective heat transfer at the surface).

It should also be noted that the concept of using neural networks for inverse problem has been demonstrated using one and two dimensional examples. On similar lines it can easily be extended to other geometries. As the complexity of the problem increases (when for example, the fluid temperature is not constant or thermo-physical properties are functions of temperature etc.) different strategies may have to be evolved in defining the input to the ANN model. In summary, ANN models could be efficiently used to tackle the IHCP. One has to consider the characteristics of the specific case to decide on how to implement the ANN model.

NOMENCLATURE

a	=	radius of the sphere or cylinder (m)
Bi	=	h a/k = Biot number
Fo	=	α t/a^2 = Fourier number
h	=	heat transfer coefficient (W/m^2-K)
k	=	thermal conductivity (W/m-K)
R	=	r/a = nondimensional radial coordinate
t	=	time (s)
T	=	temperature of the solid at any location and time (K)
T_i	=	initial temperature of the sphere (K)
T_a	=	temperature of the fluid (K)
X	=	x/a = nondimensional axial coordinate
L	=	nondimensional length of the cylinder
α	=	thermal diffusivity (m^2/s)
θ	=	$(T-T_a)/(T_i-T_a)$ = nondimensional temperature

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