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A NEURAL NETWORK BASED METHOD FOR ESTIMATION OF HEAT GENERATION FROM A TEFLON CYLINDER

Sharath Kumar, Harsha Kumar, N. Gnanasekaran [*]

Department of Mechanical Engineering, National Institute of Technology, Karnataka, Mangalore, India

ABSTRACT

The paper reports the estimation of volumetric heat generation (q_v) from a Teflon cylinder. An aluminum heater, which acts as a heat source, is placed at the center of the Teflon cylinder. The problem under consideration is modeled as a three dimensional steady state conjugate heat transfer from the Teflon cylinder. The model is created and simulations are performed using ANSYS FLUENT to obtain temperature data for the known heat generation q_v. The numerical model developed using ANSYS acts as a forward model. The inverse model used in this work is Artificial Neural Network (ANN). Estimation of heat generation is carried out by minimizing the error between the simulated temperature and the experimental/surrogate temperature. The efficacy of the ANN method is explored for the estimation of unknown heat generation as both forward model and inverse model. The concept of Asymptotic Computational Fluid Dynamics (ACFD) is introduced as a fast forward model which is obtained by performing CFD simulations. The unknown heat generation is estimated for the surrogated data using ANN. In order to mimic experiments, noise is added to the surrogated data and estimation of heat generation is also carried out for the perturbed/noise added temperature data

KEYWORDS: heat generation, CFD, ACFD, Conjugate, ANN, fast forward

1. INTRODUCTION

Most of the major engineering applications utilize conduction and convection as their heat transfer phenomenon. Electronic cooling, heat exchangers are examples of its application. The ability to control the thermal process depends on how the designed mathematical model predicts the behavior of the thermal system. Mathematical design requires inputs such as boundary conditions, thermo physical properties and initial conditions. If any of the inputs is unknown, the only way to determine these parameters is by using the concept of parameter estimation. In heat transfer, we estimate the unknown properties using temperature data measured at one or several location at a domain. This type of estimation is called inverse problem. On contrary, if all the aforementioned properties are known then the defined model is well posed and this approach is referred to as direct problem. From past few years a lot of research is being carried out on inverse convection heat transfer due to its wide range of applicability and importance in engineering applications. (Yang, 1998) used the least-squares error method to determine the strength of the temporal dependent heat source when prior knowledge of the source functions is not available in a two-dimensional heat conduction problem. A comprehensive detail about inverse heat conduction problems has been given by (Ozisik and Orlande, 2000). (Chen and Yang, 2008) showed that the inverse convection problem is more complex than inverse conduction problem due to its parabolic nature. Energy and momentum equation coupling adds complexity to analysis. Adjoint and conjugate gradient methods were used for inverse convection analysis by (Yang and Chen, 2009; Zhao et al., 2009; Payan et al.2009). (Deng and Hwang, 2006) used non iterative methods are used to solve both forward and inverse conduction problem and showed advantages over iterative methods in terms of computational cost and accuracy. In inverse heat transfer problems deterministic and stochastic methods are used as the inverse methods. Conjugate gradient method and steepest descent method are the forms of

deterministic method, whereas Bayesian Inference which forms the stochastic method.

One among the non-iterative method is ANN, also being used for solving inverse convection and inverse conjugate heat transfer problems (Balaji and Kumar, 2010; 2011). ANN can be used as the forward model as well as the Inverse model in heat transfer and other applications. (Torre et al., 2015) used artificial neural network as a modeling tool to predict the strength of high performance concrete based on manufacturing parameters. (Wright et al., 2014) investigated the use of an artificial neural network to perform diagnostic classification of DMCA scans carried out in nuclear medicine to assess the level of functional renal tissue in patients. (Ligor et al., 2015) applied artificial neural network for selection of potential lung cancer biomarkers by obtaining volatile organic compounds (VOCs) in the exhaled breath samples of lung cancer patients. (Hamzaoui et al., 2015) developed an integrated approach using artificial neural network inverse (ANNi) coupling along with a Nelder Mead optimization method to estimate the resonance stress of the turbine blades. (Thibault and Grandjean, 1991) used ANN to correlate heat transfer data. (Zhao and Zhang, 2010) presented neural network approach to the evaluation of performance of the fin and tube air cooled condensers used in air-conditioning and refrigeration systems. (Basheer and Hajmeer, 2000) focused on the use of ANN in solving complex real-world problems. (Kumar et al., 2013) used artificial neural network as a design tool in the area of building services engineering. (Fannou et al., 2014) used ANN to model direct expansion geothermal heat pump. (Krishnan et al., 2003) used asymptotic computational fluid dynamics (ACFD) and obtained correlations for the average Nusselt number, for the mixed convection problem. (Premchandran and Balaji, 2006) developed a correlation for the non-dimensional maximum temperature using the method of asymptotic expansions.

Based on the literature review, most of the research on inverse problems is devoted to the theoretical works and iterative methods are used as inverse method. The problem considered in the present work is conjugate heat transfer from Teflon cylinder which has not

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been discussed by other researchers. Navier stokes equation is solved for the conjugate heat transfer problem and temperature distribution is obtained. In view of this, the main contribution of this study is to develop a numerical model (Forward model) which would reduce the computational cost and to estimate the heat generation in the Teflon cylinder using a non-iterative method. In the ensuing sections, following a brief description about forward model and its validation, detailed evaluation of inverse model and ACFD as a forward model is discussed.

2. FORWARD MODEL

The problem deals with a cylindrical aluminum heater inside the Teflon cylinder that provides constant volumetric heat generation (q_v). The heater is placed at the center of the Teflon cylinder. The setup has an aluminum heater with dimensions of 30mm diameter and 30mm length. The Teflon cylinder with dimensions of 100mm diameter and 100mm length is considered for the present work. The velocity profiles and the convection effects are thus studied by modeling an extended air domain. The setup is modeled as a three dimensional steady state conjugate heat transfer problem. The geometrical model and the coordinate system considered in the present study are as shown in Fig.1
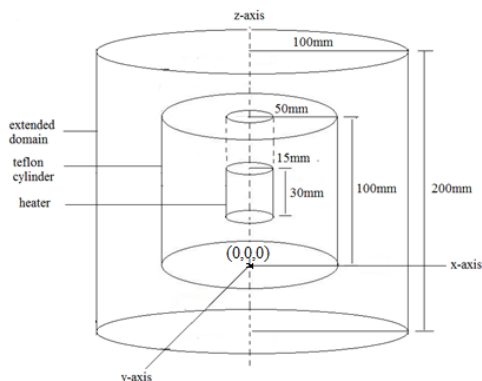
Fig. 1 Schematic representation of the Teflon cylinder along with aluminum heater

The governing equation contains both conduction and convection terms hence one cannot find the exact solution. So the governing equation along with the appropriate boundary conditions is solved using the commercially available CFD package ANSYS fluent 14. The fundamental equations of fluid flow are the continuity equation, momentum equations (Navier Stokes equation) and energy equation. Air is the medium under consideration with constant thermo-physical properties except for density. The assumption of constant density cannot be done in this case since the problem deals with convection and fluid motion in convection is driven by density change and gravity. Hence the density change is modeled using Boussinesq approximation for the buoyancy term in the momentum equation. This approach treats the density as constant in the continuity equation and allows it to change with temperature in gravity term.

The governing equations can be written as

Continuity:

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0 \qquad (1)$$

X-momentum equation:

$$u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} + w\frac{\partial u}{\partial z} = -\frac{1}{\rho}\frac{\partial p}{\partial x} + \vartheta\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2}\right) \qquad (2)$$

Y-momentum equation:

$$u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} + w\frac{\partial v}{\partial z} = -\frac{1}{\rho}\frac{\partial p}{\partial y} + \vartheta\left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} + \frac{\partial^2 v}{\partial z^2}\right) \qquad (3)$$

Z-momentum equation:

$$u\frac{\partial w}{\partial x} + v\frac{\partial w}{\partial y} + w\frac{\partial w}{\partial z} = -\frac{1}{\rho}\frac{\partial p}{\partial x} + \vartheta\left(\frac{\partial^2 w}{\partial x^2} + \frac{\partial^2 w}{\partial y^2} + \frac{\partial^2 w}{\partial z^2}\right) + g\beta(T - T_\infty) \qquad (4)$$

Energy equation:

$$u\frac{\partial T}{\partial x} + v\frac{\partial T}{\partial y} + w\frac{\partial T}{\partial z} = \alpha\left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2}\right) \qquad (5)$$

The governing equation for the conduction inside the Teflon cylinder is given by

$$k\left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2}\right) + q_v = 0 \qquad (6)$$

The following problem is effectively modeled by applying the boundary conditions as shown in Table 1.

Table 1 Boundary conditions

Boundary	Condition
Inner cylinder top	Coupled wall
Inner cylinder bottom	Coupled wall
Inner cylinder lateral	Coupled wall
Inner cylinder	Constant heat generation (Aluminum)
Outer cylinder top	Coupled wall
Outer cylinder bottom	Coupled wall
Outer cylinder lateral	Coupled wall
Outer cylinder	k =0.25W/mK (Teflon)
Extended domain top	pressure-outlet
Extended domain bottom	pressure-outlet
Extended domain lateral	pressure-outlet

The meshed portion of the geometry considered is shown in Fig. 2.
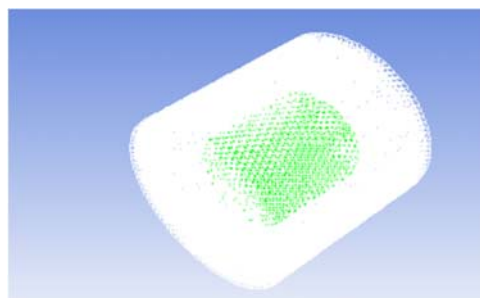
Fig. 2 Schematic of the meshed Teflon cylinder

2.1 Grid Independence study

Grid Independence study is performed to fix the optimum grid size for meshing with a balance in computational time and accuracy. The domain is meshed with a coarse mesh and the simulation is performed for fixed convergence criteria until the solution is converged. The grid size is then refined and simulations are studied until solution is not varied. The proper meshing has been selected after carrying out many case studies. Table 2 represents the details

of grid independence study carried at location $(x,y,z) = (50,0,50)$ mm.

**Table 2** Grid independence study for $q_v = 5\times10^5$ W/m^3

Sl No.	No. of grids	T (K)
1	50000	341.95
2	75000	342.69
3	90000	342.56
4	110000	339.83
5	120000	339.56

From the grid independence study, the total number of cells considered throughout the entire analysis is fixed to be 110000. The deviation observed is very less and results can be considered to be reasonably accurate. The forward model is executed with the fixed grid for the heat generation of 300000 W/m^3 and 400000 W/m^3 to obtain temperature distribution of the Teflon cylinder. Fig. 3 shows the temperature distribution on the surface of the Teflon cylinder for the heat flux mentioned previously.
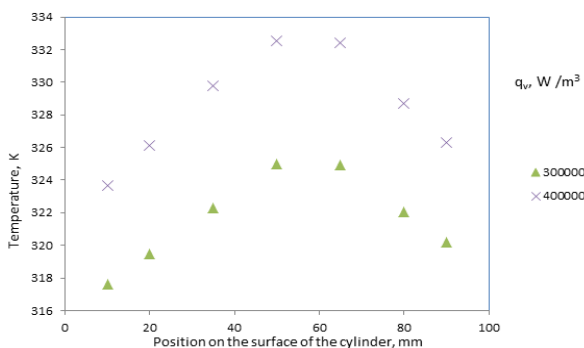
**Fig. 3** Temperature distribution along with the surface of the cylinder

CFD Simulations are carried out for different heat generation value as input and the temperature and velocity plot for each of the heat generation value is obtained. One such simulation result is shown in Fig. 4 in which temperature distribution along the surface of the Teflon cylinder is shown and Fig.5 shows the velocity distribution for heat generation value of q_v=400000W/m^3.
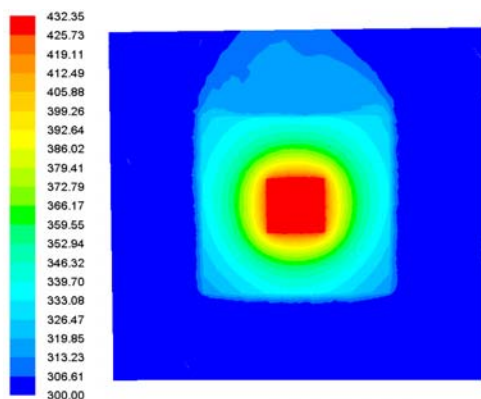
**Fig. 4** Temperature(K) distribution in the Teflon cylinder for $q_v = 4\times10^5$ W/m^3

2.2 Forward model – Neural Network

The temperature data obtained fhom the forward model (CFD) with heat generation q_v as input is used to train the artificial neural network. By doing so, the computational cost involved in executing
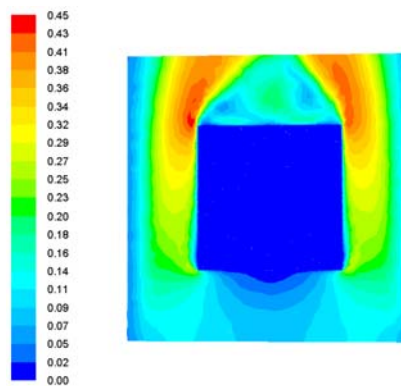
Fig. 5 Velocity (m/s) contour plot for $q_v = 4\times10^5$ W/m^3

the forward model simulations is reduced. Commercially available MATLAB neural network tool box is used to train the neural network. A network is created between heat generation q_v as input and temperature distribution as output.Similar to grid independence study one should perform neuron independence study in order to obtain better correlation and accuracy. A three layer Neural Network is shown in Fig. 6 and for the present case network input is heat generation q_v and the network output is temperature. Each layer consists of more neurons that are represented by circular nodes. The first layer input which is called as input layer recieves the information from the user and the output of the particular neuron is passed as the input to the next layer.
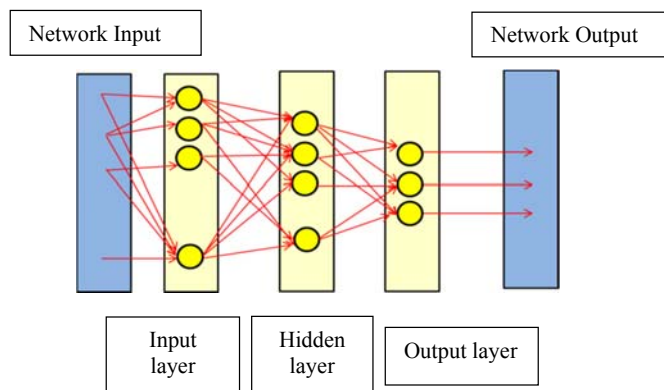

Fig. 6 Schematic of three layer Neural Network

2.3 Neuron independence study

The neuron independence study is carried out to fix the optimum number of neurons in the hidden layer. Once the input is specified, the next step is to create a network. The study is started with one neuron and the network is trained with the help of specified input and output data. In order to fix the number of neurons in the hidden layer, a neuron independency study is carried out by increasing the number of neurons from 5 to 15 in the interval of 5 till the satisfactory results are obtained. The feed forward model is trained by Levenberg-Marquardt algorithm. The selection of the network is based on the error on the network training, validation and testing the data. The performance of the network can be expressed in terms of mean relative errors (MRE), mean square errors (MSE) and the coefficient of determination R^2. The number of neuron is selected in such a way that the mean square error is less and the regression value approaches one.

Table 3 represents the data tabulated for the trained neural network.The regression coefficient for three different neuron studies is shown in Fig. 7-9. We can observe that 10 neurons are sufficient to train the neural network.
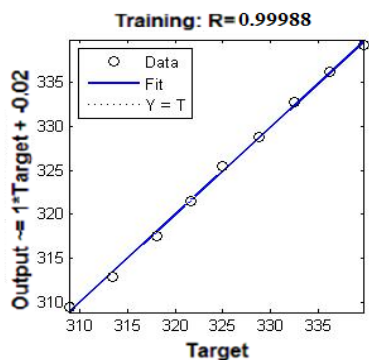
Table 3 Neuron Independence Study

Sl. No	No. of neurons in the hidden layer	MRE (%)	R^2	R_{test}
1	5	0.010137	0.99974	0.932661
2	10	0.0000175	0.99999	0.997319
3	15	0.0019204	0.99988	0.877846
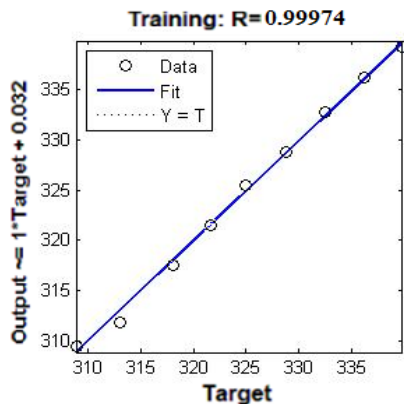
Fig. 7 Regression for 5 neurons in the hidden layer
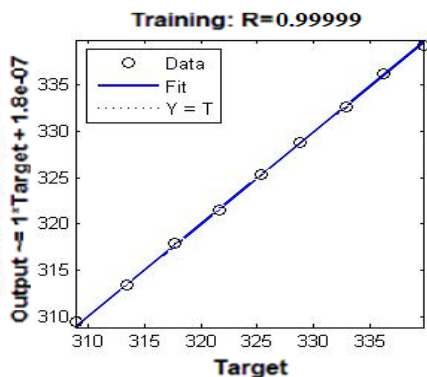
Fig. 8 Regression for 10 neurons in the hidden layer

Fig. 9 Regression for 15 neurons in the hidden layer

The numerical model created using CFD is used to obtain temperature distribution on the surface of the Teflon cylinder. The full numerical simulation provides information about temperature for various heat generation q_v. The network is trained between heat generation q_v and surface temperatures as mentioned earlier. The temperature obtained from full numerical simulation and ANN is compared for different values of q_v at a particular location say (50, 0, 50)mm on the Teflon cylinder. Such a comparison is shown in Table 4. A maximum error of 0.39 % further corroborates that the numerical model can be replaced with ANN model which now becomes a fast forward model to provide temperature information on the surface of the Teflon cylinder.

Table 4 Comparison between full numerical solution and ANN

S. No	q_v, W/m³	Temperature, K (full numerical solution)	Temperature, K (ANN)	Error (%)
1	100000	308.85	307.89	0.31
2	200000	317.14	316.28	0.27
3	300000	324.99	323.72	0.39
4	400000	332.54	331.44	0.33

2.4 Forward solution using ACFD

Thus far, the numerical model based on ANN has been used as the forward model. In this section, the concept of Asymptotic Computation Fluid Dynamics (ACFD) is introduced as a forward model. The key point for the problem under consideration is the concept of Asymptotic Computation Fluid Dynamics (ACFD) which acts as a further fast forward model to obtain the temperature distribution. An Asymptotic analysis is the study of behavior of algorithms when the size of the data being processed grows very large. Asymptotic Computational Fluid Dynamics (ACFD) is the combination of asymptotic analysis with Computational Fluid Dynamics (CFD).The ACFD forward model provides the information about temperature for the given input q_v. The asymptotic expansion approach is the expansion of the solution to the problem from the particular solution taken as reference solution.
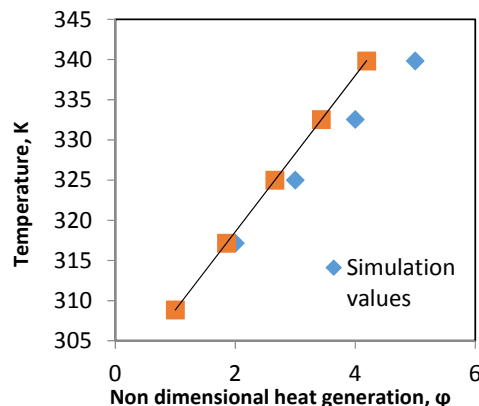
Fig. 10 Variation of temperature with variable qv

The ACFD correlation for the model is given as

$$T = T_o + \frac{\Delta T}{\Delta \phi}(\phi - \phi_0) \tag{6}$$

$$T = 308.85 + 9.72\left[(q_v/q_{v,ref})^{0.89} - 1\right] \tag{7}$$

where $\phi = (q_v/q_{v,ref})^{0.89}$

$\frac{\Delta T}{\Delta \phi}$ = slope obtained from the linearized plot

T_o = Reference temperature value,K

q_v = Given heat generation value, (W/m³)

$q_{v,ref}$ = Reference heat generation value, 100000(W/m³)

Fig.10 shows the linearized temperature values obtained from simulated temperatures. CFD simulations are carried out for various input values of heat generation and the temperature plotted with respect to the heat generation ratio $(q_v/q_{v,ref})$, now this plot is linearized by subjecting it to a power law relation which is termed

as linearized plot in Fig.10. Based on the plot obtained Eq. (7) is obtained which forms the ACFD correlation.

Eq. (7) is the temperature correlation obtained using ACFD with respect to heat generation q_v. Eq. (8) gives the value of temperature for any given value of heat generation. The ACFD correlation thus obtained reduces the computational time and hence used as the forward model in the present work. Table 5 shows a comparison between CFD and ACFD temperature values at (50, 0, 50) mm.

Table 5 Comparison between temperatures obtained from CFD and ACFD

S. No	Volumetric heat generation(q_v), W/m^3	Simulation temperature, K (CFD)	Forward model temperature, K (ACFD)	Error (%)
1	150000	311.91	313.07	0.37
2	250000	320.26	321.09	0.26
3	350000	327.38	328.76	0.42
4	450000	335.04	336.19	0.34

From Table 5, it is observed that a maximum error of 0.42% is obtained, which indicates that the correlation obtained from ACFD as a forward model predicts the temperature very close to the simulated temperature. Therefore, it has been safely concluded that the ACFD model as a forward model that can accurately predict the temperature in estimating the unknown heat generation inside the Teflon cylinder.

3. RESULTS AND DISCUSSION

3.1 Inverse problem – Neural network

In the inverse problem, estimation of heat generation is done for the known temperture distribution from the Teflon cylinder. The inverse method adopted is also Artificial Neural Network. The temperature data obtained through CFD analysis is given as input and heat flux is obtained as output. It should be noted that the Neural Network inverse model also requires neuron independence study and such an exercise is reported in the next section.

3.2 Neuron independence study– ANN as the forward model

A neuron independence study was carried out to determine the optimum number of neurons in the hidden layer.

Table 6 Neuron independence study for the inverse model

Sl. No	No. of neurons in the hidden layer	MSE (%)	$R_{training}$	R_{test}
1	**5**	0.0335651	0.99995	0.99923
2	8	0.00101929	0.99999	0.99972
3	10	0.160204	0.99980	0.99839

Table 6 represents the data tabulated for inverse model neural network. From Table 6 we can observe that 8 neurons are sufficient to train the neural network.

### 3.3 Neuron independence study- ACFD as the forward model

A neuron independence study was carried out to determine the optimum number of neurons in the hidden layer for ACFD model. Table 7 represents the data tabulated for inverse model neural network. From the table we can observe that 8 neurons are sufficient to train the neural network in order to obtain the target data.

Table 7 Neuron independence study for inverse model

Sl. No	No. of neurons in the hidden layer	MSE (%)	$R_{training}$	R_{test}
1	5	0.025874	0.9994	0.99949
2	8	0.0010027	1.0000	0.99983
3	10	0.24869	0.9973	0.99745

3.4 Retrieval of heat generation q_v, W/m^3

Single parameter estimation is attempted in this section for the known temperature distribution. It must be noted that to estimate the unknown heat generation q_v, W/m^3 experimental/surrogated temperature is required. In other words, the surrogated temperature is obtained by the procedure given in Fig. 11.

(INPUT)   (OUTPUT)
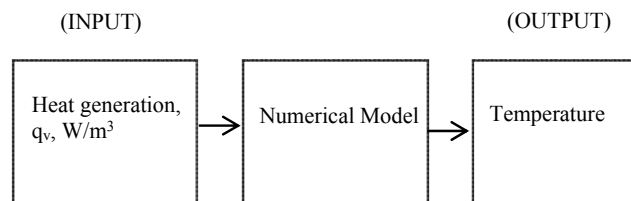
Fig. 11 Schematic representation of surrogated temperature

The surrogated temperature obtained from CFD simulation and ACFD is fed into the neural network which also acts as an inverse model to obtain q_v. Table 8 shows the retrieved q_v from the surrogated temperature data obtained at (50,0,50)mm on the surface of the Teflon cylinder. For example, from Table 9 when a temperature of 317.14 K is specified as input to the inverse model, the estimated heat generation turns out to be 196912 W/m^3. This in turn, compared with the heat generation reported in Table 9 for the same temperature. More precisely, the error between the actual and estimated heat generation is 1.5 % for ANN model and 2.08% for ACFD model which is within the acceptable limit.

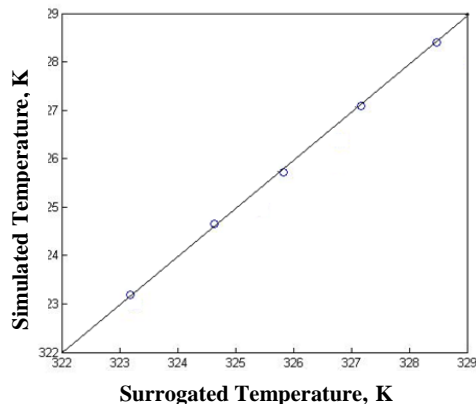**Table 8** Retrieval of heat generation

S. No	Temperature (K) at (50,0,50)mm	q_v retrieved from ANN (W/m^3)	q_v retrieved from ACFD (W/m^3)
1	317.14	196912	195840
2	324.99	295569	294987
3	332.54	396582	396038

The retrieved value of internal heat generation q_v, W/m^3 is now given as input to the forward model to obtain the simulated temperature distribution. The simulated and experimental temperature are compared and shown in a parity plot Fig 12. Surprisingly, the simulated temperatures using forward model and the surrogated temperatures agree very well.

3.5 Retrieval of heat generation for perturbed temperature data

In the early investigations, estimation of heat generation q_v was attempted for the surrogated data. In actual practice, experimental temperature contains inherent noise and this has motivated the authors to carry out an estimation process for the noise added or perturbed temperature data. Hence, in this study 0.5% and 1% noise is added to the surrogated data and estimation of heat generation is
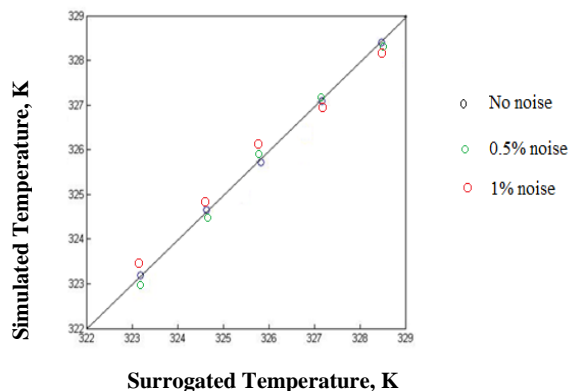
Fig. 12 Parity plot showing agreement of simulated temperature with surrogated temperature.

is carried out. Table 8 shows the retrieved value of heat generation and the simulated temperature obtained by the inverse method for the noise added data. As seen in Table 9, the proposed method is capable of estimating the unknown heat generation using ANN with a maximum error of 4% and 7% between the retrieved value for 0.5% and 1% noise and actual value of heat generation q_v. The parity plot shown in Fig.13 further corroborates the agreement of the simulated and surrogated temperature.

Table 9 Retrieved heat generation q_v, W/m^3 for noise added surrogated temperature

S. No	Actual q_v (W/m^3)	q_v retrieved by adding 0.5% noise (W/m^3)	q_v retrieved by adding 1% noise (W/m^3)
1	200000	191595	187520
2	300000	318475	279330
3	400000	383891	423840

Fig. 13 Parity plot showing agreement of simulated temperature with the noise added surrogated temperature

4. CONCLUSIONS

In a novel approach, the unknown volumetric heat generation (q_v) has been estimated for the surrogated temperature of the Teflon cylinder using artificial neural network as an inverse model. The forward model for the three dimensional conjugate heat transfer has been solved using the commercially available software ANSYS 14. A simple ACFD model has been proposed. ANN and ACFD are used to replace the forward model to save computational cost. ANN method was also used as an inverse model to estimate qv from the surrogated temperatures obtained from CFD simulations. A maximum error of 0.39% was observed between temperature obtained from CFD and ANN and a maximum error of 0.37% between temperature obtained from CFD and ACFD. The unknown heat generation retrieved for the surrogated as well as noise added temperature data was under the reasonable limit. Finally, it has been concluded that the well trained ANN method is a powerful technique for the estimating the volumetric heat generation from surface temperature data.

NOMENCLATURE

ANN	artificial neural networks
ACFD	asymptotic computational fluid dynamics
CFD	computational fluid dynamics
g	acceleration due to gravity (m/s^2)
h	heat transfer coefficient (W/m2K)
k	thermal conductivity (W/mK)
MRE	mean relative error
q_v	volumetric heat generation (W/m^3)
$q_{v,ref}$	reference volumetric heat generation (W/m^3)
R^2	correlation coefficient
T	temperature (K)
T_∞	ambient temperature (K)

Greek Symbols

α	thermal diffusivity (m^2/s)
β	Boussinesq approximation
υ	kinematic viscosity (m^2/s)
ρ	density (kg/m^3)
φ	$(q_v/q_{v,ref})^{0.89}$

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