International Journal of Heat and Mass Transfer 83 (2015) 337–344

Contents lists available at ScienceDirect

International Journal of Heat and Mass Transfer

journal homepage: www.elsevier.com/locate/ijhmt

Neural network optimization by comparing the performances of the training functions -Prediction of heat transfer from horizontal tube immersed in gas–solid fluidized bed

L.V. Kamble [a,*], D.R. Pangavhane [b], T.P. Singh [c]

[a] Symbiosis International University, Pune 412115, Maharashtra, India
[b] K.J. Somaiya Institute of Engineering and Information Technology, Sion, Mumbai 400022, Maharashtra, India
[c] SIT, Symbiosis International University, Pune 412115, Maharashtra, India

A R T I C L E I N F O

Article history:
Received 20 August 2014
Received in revised form 20 October 2014
Accepted 27 November 2014
Available online 23 December 2014

Keywords:
Artificial neural network
Fluidized bed
Heat transfer coefficient
Training function

A B S T R A C T

This paper describes the selection of training function of an artificial neural network (ANN) for modeling the heat transfer prediction of horizontal tube immersed in gas–solid fluidized bed of large particles. The ANN modeling was developed to study the effect of fluidizing gas velocity on the average heat transfer coefficient between fluidizing bed and horizontal tube surface. The feed-forward network with back propagation structure implemented using Levenberg–Marquardt's learning rule in the neural network approach. The objective of this work is to compare performances of five training functions (TRAINSCG, TRAINBFG, TRAINOSS, TRAINLM and TRAINBR) implemented in training neural network for predicting the heat transfer coefficient. The comparison is shown on the basis of percentage relative error, coefficient of determination, root mean square error and sum of the square error. The predictions by training function TRAINBR found to be in good agreement with the experiment's values.

1. Introduction

Fluidized beds find applications in different industries, such as the coal combustors, boilers, and furnaces; drying solid particles; waste heat recovery heat exchangers; etc. In most applications, fluidized bed consists of a vertically oriented column filled with particles (small or large), and fluid (gas or liquid) pumped upward through a distributor, at the bottom of the bed [1]. The main characteristics of the fluidized bed are its isothermal nature and the high rate of heat transfer between the fluidized bed and the immersed surface [2]. In case of large particles, heat transfer is caused by steady state conduction across a gas layer between the surface and particle and by gas convection, as explained by Ravindranath [3]. The heat transfer between gas–solid fluidized bed and surface immersed in it consists of three additive parts: particle convective part, gas convective part and radiative part [4,5]. The heat transfer coefficient for an immersed surface in a fluidized bed of large particles is mainly controlled by the gas convective part than the particle convective part [6]. The analysis of performance of such thermodynamic systems depends on the computation accuracy. Now a day, computational intelligence is attracting researchers for solving various engineering problems of nonlinear nature. The traditional methods for such analysis include using fundamental equations, employing conventional correlations, or developing unique designs from experimental data through trial and error. To overcome this difficulty, a simple artificial neural network (ANN) method implemented in various heat transfer studies based on databases available from experimentation. The empirical models and correlations developed by conventional methods are complex in nature, difficult to predict nonlinear relationship, less accurate, and need long computing time. Artificial neural network can provide a platform for solving such thermal processes with quick and reliable way of predicting their performance. The changes in the system can continuously be updated easily.

The effect of fluidizing velocity on heat transfer coefficient studied for a horizontal tube immersed in the bed of large particles such as mustard, raagi and bajara. Experimental results for heat transfer coefficient between the bed and single horizontal tube surface is calculated and compared to the theoretical results by developed correlations in author's previous work [7]. The experimental data achieved is implemented in ANN predictions. The other parameters like particle mean diameter, temperature difference between the bed and tube surface are treated as input parameters in neural network (NN) modeling. The multilayer

* Corresponding author. Mobile: +91 9921512503.
E-mail address: klaxmanv@rediffmail.com (L.V. Kamble).

http://dx.doi.org/10.1016/j.ijheatmasstransfer.2014.11.085
0017-9310/

Nomenclature

a	network output
A_t	tube surface area (m^2)
d_p	particle mean diameter (m)
g_k	current gradient.
h	average heat transfer coefficient (W/m^2 K)
I	electric current (A)
k	kth data point
k_g	thermal conductivity of air (W/mK)
N	number of data points
Nu	Nusselt number, hd_p/k_g
Q	heat input (W)
R	coefficient of correlation
R^2	coefficient of determination
T	temperature (K)
T_b	temperature of bed (K)
t_o	target output
T_t	temperature of tube surface (K)
u	superficial fluidization velocity (m/s)
V	electric voltage (V)
X_k	vector of current weights and biases

Greek symbols

α_k	learning rate
ΔP	pressure drop (N/m^2)
ΔT	temperature difference between bed and immersed surface (K)

perceptron (MLP) developed by Rosenblatt is the popular network in many heat transfer applications [8–10]. The MLP consists of several artificial neurons arranged in two or more layers. The neurons are information-processing elements that are fundamental for MLP operation. The inputs of each neuron added and the result is transformed by an activation function that serves to limit the threshold of the neuron output. The output of each neuron is multiplied by a weight of concern neuron, before being input to every neuron in the following layer. The network adapts changing the weight by an amount proportional to the difference between the desired output and the actual output. The process of weight updating is called learning or training. The training process is achieved by applying a back propagation (BP) procedure. There are several training algorithms using BP procedure [11–18], with individual advantages, such as calculation rate, requirements of computation and storage. Boniecki et al. [19] developed neural model to predict ammonia emission from the composted sewage sludge. For all of the selected models, the correlation coefficient reached the high values of 0.972–0.981. The neural models developed by Boniecki et al. [20] to forecast the cows' milk yield proved to be the best predictive tool and optimized with the conjugate gradients algorithm. The sensitivity analysis performed for input variables in network decides the dominant input variable in the developed network. Krzywanski and Nowak [21] developed a model to predict local heat transfer coefficient in the combustion chamber of the circulating fluidized bed boiler by ANN approach. It is shown that neural networks gives quick and accurate results to the input patterns provided as compared to the numerical models developed previously. Neural network based heat convection algorithm was successfully implemented by Zang and Haghighat [22] to predict local average Nusselt numbers along the duct surfaces. This algorithm was also integrated with a transient three-dimensional heat transfer model based on finite element analysis of heat conduction to develop a new thermal modeling method for heat exchanger.

It is noted that no single algorithm suits best to all the problems. The performance of each algorithm depends on the process to model, the learning sample and training mode. The success of modeling NN depends on selecting the training function. The aim of this work is to study training algorithms selected in the study that use the BP procedure to optimize an ANN modeling. At first the experimental setup is described, and then ANN model and training algorithms implemented in the study are explained. In this work, authors are comparing the performance of five training functions TRAINSCG, TRAINBFG, TRAINOSS, TRAINLM and TRAINBR based on percentage relative error, root mean square error (RMSE), coefficient of determination (R^2) and sum of square because of error (SSE).

2. Materials and procedure

2.1. Experimental set up

The schematic diagram of experiment's set up shown in Fig. 1, consists of a rectangular fluidized column that is 0.1 m × 0.15 m in cross section and 0.4 m height, with a horizontal brass tube installed at a height of 100 mm from the distributor plate. The air was used as a fluidizing gas at atmospheric pressure. The quality of fluidization improved by providing tapered diffuser and plenum section, thus minimizing the acceleration effects because of the high flow rate. The setup was instrumented for measuring the bed temperature, surface temperature of heat transfer tube, air flow rate and electrical energy supplied to the tube. The particles chosen were mustard, raagi and bajara of diameter, 1.8 mm, 1.4 mm and 2.0 mm respectively. Drying these food grains using fluidized bed is one of the growing areas where much investigation can be carried out by using ANN modeling. The static bed height was 150 mm and the duct supported by a perforated distributor plate 4 mm thick at the bottom, which consisted of many small holes. A stainless steel screen with the mesh was placed above the distributor to gain more homogeneous distribution of the gas flow. The heat transfer tube was 110 mm in length and its outer diameter was 27.5 mm. The cartridge heater inserted inside the bare single tube, and the heat input to the tube was controlled by a variable direct current power supply. The heat input was determined by measuring voltage (V) and current (I). The temperature of the bed measured at three different heights in the bed, while two thermocouples were mounted on tube surface at equal distance to measure tube surface temperature. The pressure difference across the bed was measured by using a water tube manometer. A constant heat input of 52.2 W was maintained throughout the experiment. The plenum chamber was made up of 1.5 mm thick mild steel plate and was fixed to a flange at its top end to accommodate the distributor plate. A centrifugal blower of 0.75 kW capacities provided the air for fluidization.

2.2. Experimental heat transfer coefficient

The experimental heat transfer coefficient h (W/m^2 K) was calculated from simple relation of heat energy supplied:

$$Q = hA_t(T_t - T_b) \tag{1}$$

where Q was the measured tube heat input (W), A_t is surface area of tube (m^2), T_t is tube surface temperature (K) and T_b is bed temperature (K).