PREDICTION OF EFFECTIVE THERMAL CONDUCTIVITY OF MOISTENED INSULATION MATERIALS BY NEURAL NETWORK

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Received: 8 February 2011; **Accepted:** 5 October 2011

ABSTRACT

In harsh climates, utilizing thermal insulation in the building envelope can substantially reduce the building thermal load and consequently its energy consumption. The performance of the thermal insulation material is mainly determined by its effective thermal conductivity, which is dependent on the material's density, porosity, moisture content, and mean temperature difference. The effective thermal conductivity of insulation materials increases with increasing temperature and moisture content. Hence, thermal losses may become higher than the design values. The availability of measured data of the thermal conductivity of insulations at higher temperatures and at elevated moisture contents is poor. In this article the Artificial Neural Networks (ANN) is utilized in order to predict the effective thermal conductivity of expanded polystyrene with specific temperature and moisture content. The experimental data was used for training and testing ANN. Obtained results from the ANN method give a good agreement with experimental data.

Keywords: Artificial neural network; insulation material; expanded polystyrene; Levenberg Marquardt; effective thermal conductivity

1. INTRODUCTION

The decreasing of energy sources cause increasing of need of saving energy in the world. As energy becomes more precious and demand increases, the use of thermal insulations in buildings is being enforced in new building constructions. Many parameters should be considered when selecting thermal insulation including cost, compression properties, water vapor transmission properties and the effective thermal conductivity (k) of the material. The k of insulation materials is the most important property that is of interest when considering thermal performance and energy conservation measures.

The effective thermal conductivity is dependent on the material density, porosity, moisture content, and the mean temperature difference. The effective thermal resistance of insulation materials decreases with increasing temperature and moisture content.

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The impact of operating temperature on the thermal performance of insulation materials has been the subject of many studies. The influence of moisture on heat transfer through fibrous-insulating materials was presented in some articles [1-4]. Vieseh et al. [5] found mathematical models for thermal conductivity-density relationship in fibrous thermal insulation.

Modeling the effective thermal conductivity of heterogeneous or composite materials is of interest in many heat transfer applications. Alternatively, an empirical parameter may be inserted to account for differences in material structure [6,7]. Another common way of estimating effective thermal conductivity for composite materials with known microstructures is to make rigorous numerical simulations using the finite difference or finite element methods [8–10]. Zhao et al. [11] developed a numerical model combined radiation and conduction heat transfer was to predict the effective thermal conductivity of fibrous insulation at various temperatures and pressures. Cheng and Fan [12] reported an improved model of coupled heat and moisture transfer with phase change and mobile condensate in fibrous insulation. However, analytical models are preferred over numerical models in many applications due to their physical basis, rapid and low cost calculation, and reasonable accuracy even when microstructure is uncertain. Many effective thermal conductivity models found in the literature are based on one or more than five basic structural models; specifically, the Series, Parallel, Maxwell–Eucken (two forms) [13] and Effective Medium Theory (EMT) models [14,15].

Fan et al. [16] have developed models for heat and moisture transfer in fibrous insulation (clothing in the first place) that considers phase change and mobile condensate. Bjrk and Enochsson [17] studied Properties of thermal insulation materials during extreme environment changes.

Ochs et al. [18] showed a detail description of modeling and measurement of the effective thermal conductivity of porous bulk materials at temperatures up to 80^{o}C and moisture contents below free water saturation. Consequently, the need for a more realistic evaluation of thermal insulation performance in harsh climatic conditions is undoubtedly necessary for a more accurate assessment of the thermal performance and for a better prediction of energy efficient design.

The computational intelligence techniques, such as Artificial Neural Networks (ANNs), genetic algorithms (GAs), and fuzzy logic have been successfully applied in many scientific research and engineering practices. ANNs have been developed for about two decades and are now widely used in various application areas such as performance prediction, pattern recognition, system identification, and dynamic control and so on. Since ANNs provide better and more reasonable solutions. ANN offers a new way to simulate nonlinear, uncertain or unknown complex systems without requiring any explicit knowledge about the input–output relationship. It can approximate any continuous or nonlinear function by using a certain network configuration [19].

The ANN is an interpolation procedure. Through training, the network “learns” an association between a collection of inputs and their corresponding outputs. In operation, when the network is presented inputs which were not present in the training set, the network will produce a result which is consistent with the training data. The accuracy, fast response and non-iterative solution of ANN led to the use of neural network in many physical problems. Kaveh and Raiessi [20] predicted the deformation of domes under wind load by using ANN. Erzin et al. [21] predicted soil thermal resistivity by ANN also Nouri et al. [22] used ANN for finding Soil profile. Eslamloueyan and Khademi [23] developed a neural network model for prediction of thermal conductivity of pure gases at atmospheric pressure over a wide range of temperatures. Kaveh and Khalegi [24] predicted strength for concrete specimens by ANN. Xie et al. [19] predicted the performance of laminar and turbulent heat transfer and fluid flow of heat exchangers having large tube-diameter and large tube-row by ANNs.

The objective of this study is to investigate the influence of moisture content and mean temperature on thermal conductivity of insulation materials by ANN and experimental data.

2. THERMAL CONDUCTIVITY MEASUREMENTS

During the last two decades, many advances have been made in thermal insulation technology, both in measurement techniques and in improved understanding of the principles of heat flow through insulating materials. Consequently, revisions have been made to the measurement methods of thermal transmission properties. These revisions are considered in the ASTM C518-04 standard [25].

In this study, 300mm×300mm specimens with thicknesses ranging from 50 to 100mm were mounted in the test section between two plates with specific different temperatures during the test. Upon achieving thermal equilibrium and establishing a uniform temperature gradient throughout the sample, thermal conductivity was determined. The temperature control system was thermoelectric. An external computer system equipped with a specialized software controlled the measuring apparatus.

3. MODELING OF THERMAL CONDUCTIVITY

There are three major methods for the modeling of effective thermal conductivity. Type *I* regards the temperature and heat flux profile of two particles which are in contact (unity cell). It is the most complex model in terms of calculation effort and has to be solved numerically. In type *II* the porous material is mapped onto a combination of serial and parallel layers representing thermal resistances of the components as proposed by Krischer and Kast [7]. All primary parameters such as porosity, thermal conductivity of the fluid(s) and of the solid as well as the influence of radiation which is a secondary parameter, are considered. A simplification is represented by type *III*. Analogue to type *I* the unity cell is regarded, but instead of a grid of isotherms and heat flux lines either parallel isotherms or heat flux lines are considered. In this paper, type *II* is considered for using the neural network method. Some primary parameters are considered as input data for the neural network and the effective thermal conductivity is considered as the output of neural network. The density, moisture content and mean temperature are considered as input data. For moisture content the normalized moisture content is used [18]. The moisture content is normalized by free saturation water content mentioned earlier.

4. ARTIFICIAL NEURAL NETWORKS

As discussed by Dumek et al. [26] the neural network is a structure for parallel information processing which may be considered as a "black box" or a transfer function. A block diagram of the model of a neuron is shown in Figure 1. A neuron is a basic information processing and operating unit in a neural network. Specifically, a signal x_i is connected to a neuron with the synaptic weight w_i, and then all input signals weighted by their respective synapses are summed as a net input u. A bias b is applied to the neuron so that the increase or decrease in net input depends on whether the bias is positive or negative. Finally the increased or decreased net input is imported into an activation function. The activation function is so developed that the amplitude of the net output of a neuron is limited. The input-to-output operation of a neuron is formulized mathematically as follows [27]:

$$v^k = \sum_{i=1}^{m} w_i^k x_i \tag{1}$$

$$y^k = \varphi\left(u^k + b^k\right) = \varphi\left(\sum_{i=1}^{m} w_i^k x_i + b^k\right) \tag{2}$$

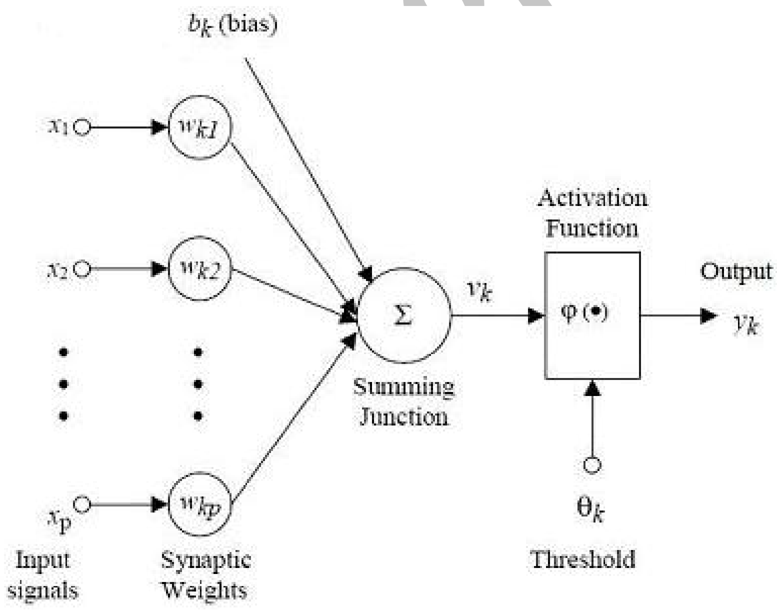


Figure 1. A block diagram of the model of a neuron [27]

Figure 2 illustrates a typical full-connected network configuration. Such an ANN consists of a series of layers with a number of neurons (in Figure 2). Each connection between two neurons with a real value is called weight. Neurons are gathered together into a column called a layer. Among various types of ANNs, the feed-forward or multilayer perception neural network is widely used in engineering applications. The input information is propagated forward through the network while the output error is back-propagated through the networks for updating the weights.

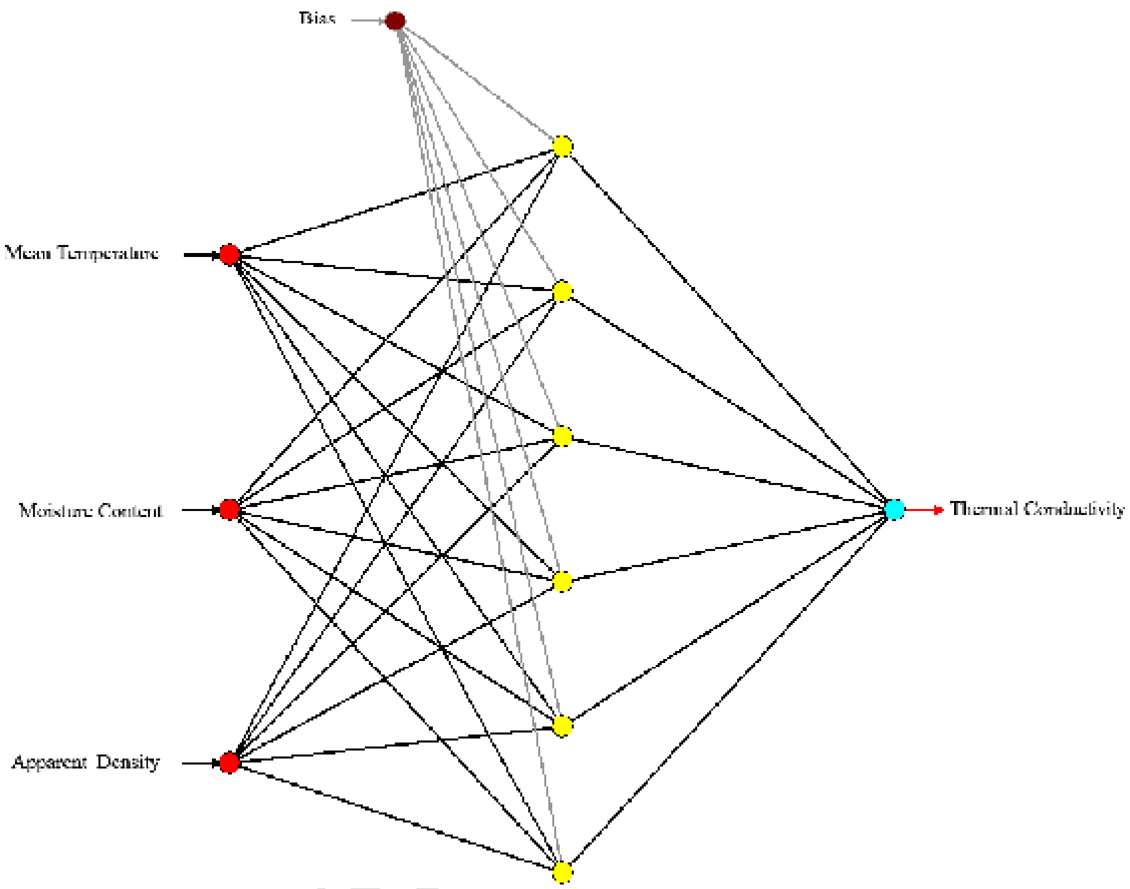
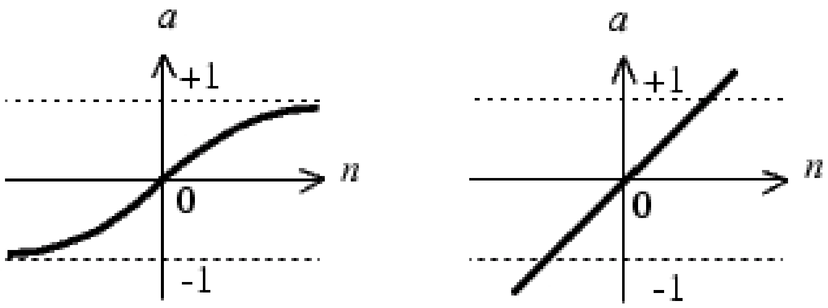


Figure 2. A fully connected feed-forward neural network (the ANN having one hidden layer with six hidden neurons and one output layer with two outputs)

There are many ways to design and implement ANNs. However, it is difficult to find an optimal network, considering the uniqueness of a real problem. Thus, a priori choice, such as selection of network topology, training algorithm and network size should be made based on experience.

It is a very common way to use the back-propagation algorithm to train artificial neural networks. The main idea of this algorithm is to minimize the cost function by the steepest descent method to add small changes in the direction of minimization. It simply consists of back-propagating the output errors to the network by modifying the weight matrices, that is, adding a correction weight Δw to a synaptic weight w. More descriptions of the Back-Propagation (BP) algorithm can be found in references [28-29]. Varying the learning rate dynamically or using momentum terms can improve the convergence speed. The mathematical background, the procedures for training and testing the ANN, and the description of the BP algorithm can be found in the reference [27]. Although the BP algorithm needs a long time to converge, the algorithm has gained a remarkable popularity in the neural network community since it is relatively easy to implement in engineering applications as well as in thermal and energy applications, see [19–24]. Also the BP algorithm might provide solutions to difficult problems [27]. Thus in this study the BP is implemented to train the network. There are three basic types of activation functions: Threshold function, Piecewise linear function and Sigmoid function [27]. The tan-sigmoid function and linear function are used in this paper respectively between input layer and hidden layer and between hidden layer and output layer. The curves of each function are shown in Figure 3.



tan-sigmoid function linear function

Figure 3. The activation functions used in this study

The development of an ANN model involves three basic steps: the generation of data required for training, the training and testing of the ANN model and the evaluation of the ANN configuration leading to the selection of an optimal configuration. The procedure used for the development of the ANN model is outlined next section.

4.1 Training artificial neural network

In order to predict effective thermal conductivity, attempts should be done to develop some ANN configurations and finally find a relative optimal or good configuration for prediction. As aforementioned, the feed-forward network structure was used in our study as shown in Figure (2). It employs an input layer of 3 neurons corresponding to each of the input density, moisture content and mean temperature and an output layer consisting of one neuron representing the output parameter *k*. In the training stage, to identify the output precisely, the number of neurons was increased from 3 to 9 based on the trial and error method in the hidden layer. Among them, the network with 7 neurons and a single hidden layer has provided the best results. Therefore, the results provided in the following sections are based on this configuration.

The Levenberg-Marquardt back propagation algorithm [27, 30] was used for training. This algorithm resembles the quasi-Newton methods. Newton's method is an alternative to the conjugate gradient methods for fast optimization. The basic step of Newton's method is

$$w_{k+1} = w_k - \mathrm{A}_k^{-1} \mathrm{g}_k \tag{3}$$

where w_k is a vector of current weights and biases, g_k is the current gradient and A_k^{-1} is the

Hessian matrix (second derivatives) of the performance index at the current values of the weights and biases. Newton's method often converges faster than conjugate gradient methods. Unfortunately, it is complex and expensive to compute the Hessian matrix for feed-forward neural networks. There is a class of algorithms that is based on Newton's method which doesn't require the calculation of second derivatives. These are called quasi-Newton methods. These methods update an approximate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient.

The Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed-forward networks), then the Hessian matrix can be approximated as

$$H = J^T J \tag{4}$$

and the gradient can be computed as

$$g = J^T e \tag{5}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard BP technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$w_{k+1} = w_k \text{-} [J^T J + mI]^{-1} J^T \mathrm{e} \tag{6}$$

When the scalar m is zero, this is just Newton's method, using the approximate Hessian matrix. When m is large, this becomes gradient method with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, m is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced in each iteration of the algorithm.

5. RESULTS AND DISCUSSION

The experimental data of expanded polystyrene is used for training neural network. Some data is left for the test of neural network. The history diagram of mean squared error versus the number of epochs is shown in Figure 4.

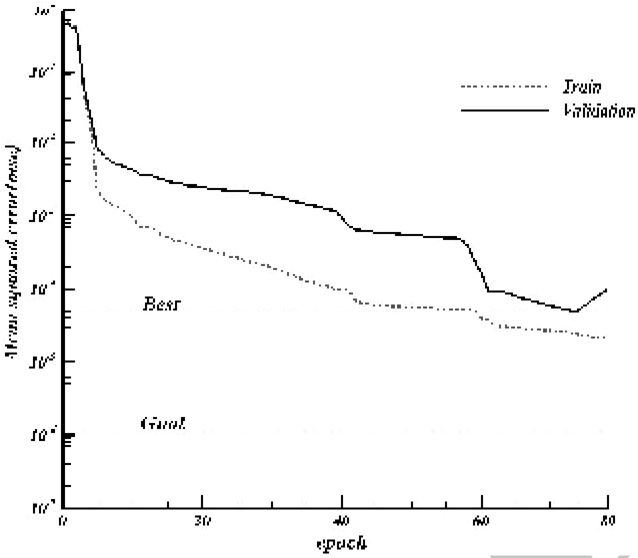


Figure 4. History diagram of mean squared error of neural network for this case

The thermal conductivity values trained by ANN compared to experimental data are shown in Figure 5 and 6. In Figure 5 the thermal conductivity is plotted versus density and mean temperature with constant moisture content around zero and in Figure 6 the thermal conductivity is plotted versus normalized moisture content and mean temperature with apparent density. The network is trained with 70% of the experimental data. It can be clearly seen that both predicted results trained by neural network are very close to the corresponding measured data. The maximum average relative error between the trained predictions and measured data is less than 0.5% for Figure 5 and is less than 1% for Figure 6.

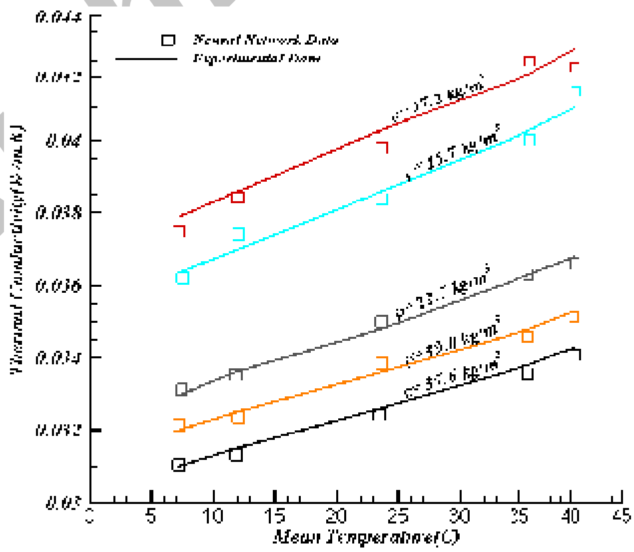


Figure 5. Comparison of thermal conductivity trained by ANN to experimental data in variant temperature and density for EPS boards

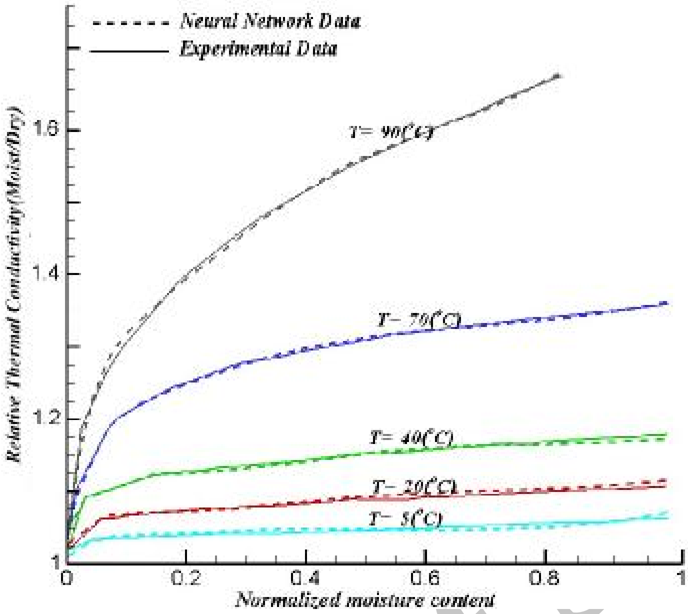


Figure 6. Comparison of thermal conductivity trained by ANN to experimental data in temperatures and normalized moisture contents for EPS boards

In Figure 7 the predicted results of neural network for variant temperatures and densities are illustrated. The figure shows the neural network can predict the effective thermal conductivity of EPS with good accuracy. The maximum relative error between predicted result and experimental data is 5% and the average relative error is less than 1.7%.

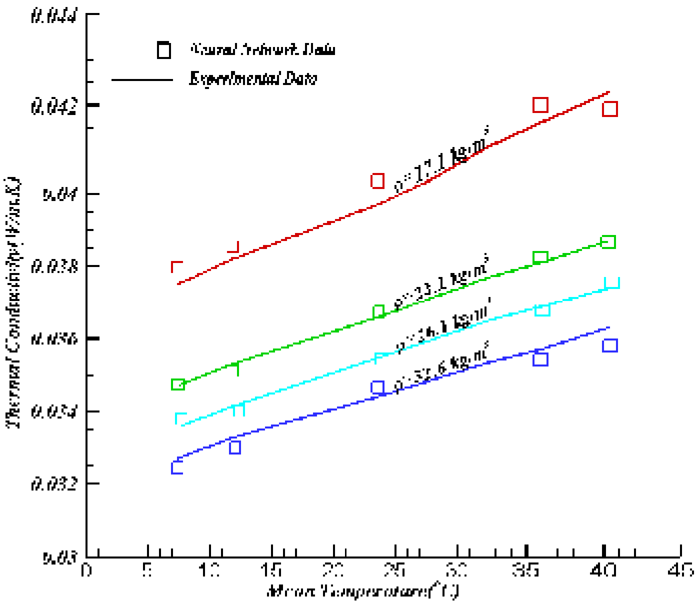


Figure 7. Comparison of thermal conductivity predicted by ANN with experimental data in various temperatures and densities for EPS boards

In Figure 9 the prediction results of neural network for variant normalized moisture content and mean temperature are illustrated. The results show that the neural network can predict the effective thermal conductivity of expanded polystyrene with good accuracy. The maximum relative error between predicted result and experimental data is 4% and the average relative error is less than 1.3%.

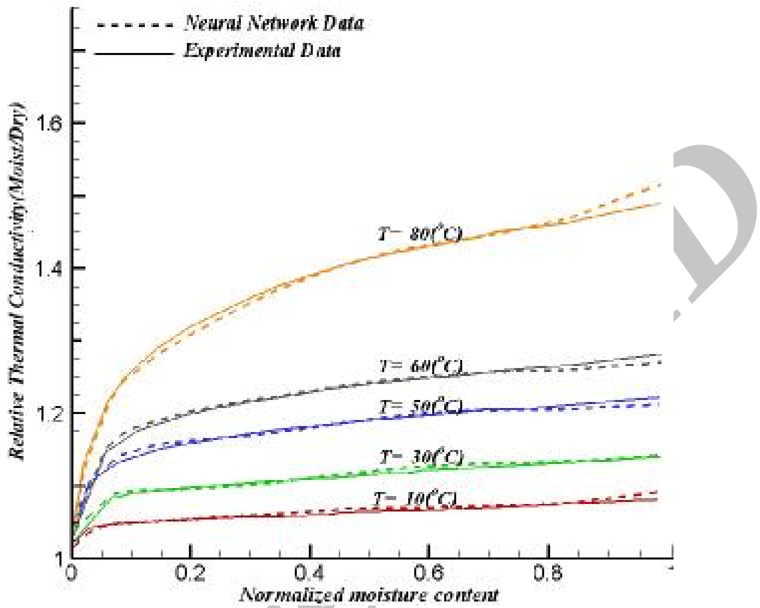


Figure 9. Comparison of thermal conductivity predicted by ANN with experimental data in variant temperatures and normalized moisture contents for EPS

6. CONCLUSION

In this paper the effect of moisture content and temperature on effective thermal conductivity of EPS was studied by experimental methods. The experimental results show that the effect of these parameters on effective thermal conductivity is significant. For finding a model that can predict the effective thermal conductivity, the neural network was employed. The feed-forward network by Levnberg- Marquadet training method is used for modeling. The results show high accuracy of ANN prediction for different cases. The maximum relative error between predicted results and experimental data is only 7% and the average of errors is less than 2% that shows the ability of neural network for predicting effective thermal conductivity. It can be substituted for complicated numerical models and cost and time consuming experimental methods.

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