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EXPERIMENTAL AND ARTICIAL NEURAL NETWORK BASED STUDIES ON THERMAL CONDUCTIVITY OF LIGHTWEIGHT BUILDING MATERIALS

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Abstract:

The growing concern about energy consumption of heating and cooling of buildings has led to a demand for improved thermal performances of building materials. In this study, an experimental investigation is performed to predict the thermal insulation properties of wall structures of which the mechanical properties are known; by using Levenberg-Marquardt training algorithm based artificial neural network (ANNs) method for energy efficient buildings. The produced samples are cement based and have relatively high insulation properties for energy efficient buildings. In this regard, 102 new concrete samples and their compositions are produced and their mechanical and thermal properties are tested in accordance with ASTM and EN standards. Then, comparisons have been made between the experimental results and the ANN predicted results. It can be concluded that thermal performance of lightweight materials could be predicted with high accuracy using artificial neural network approach.
Key words: *Concrete, thermal properties, mechanical properties, ANN, energy efficient building*

1. Introduction

A great amount of energy consumption is expended through building heating and cooling. It is mandatory to minimize consumption of energy which directly affects energy sources by means of economic and environmental values. The temperature of the living environment which is the one of the most important comfort conditions varies with the surrounding the structure of walls and ceilings as a result of interaction with external atmospheric conditions such as wind speed, solar radiation and the ambient temperature [1]. It is possible to keep the changing temperature in the comfort zones by heating and cooling air within a space. For this reason, it is necessary to heat the living spaces in winter season by giving sufficient amount of moisture, and to cool the spaces in summer season. That is, heating ventilating and air conditioning (HVAC) system has been the most important solution for a more comfortable life. Because capacities of the HVAC systems greatly depend on the types of the walls and roofs used, which are responsible for a major fraction of heat loss or gains for the heating or cooling loads due to their large surface area in many buildings [2]. It is critical both to improve the thermal performance of these structures and to improve thermal comfort of the occupants in terms of reducing the energy use.

In order to describe the thermal performance of the building structures, many studies have been conducted to identify the dynamic thermal characteristics of the components which indicate the magnitude of heat loss and gains through building structures under periodic boundary conditions and are influenced by the effective parameters, which can be categorized as environmental parameters (ambient air temperature, solar heat flux, ventilation etc.), design parameters (orientation, solar absorptivity, emissivity etc.) and thermophysical properties (thermal conductivity, specific heat, density, thickness etc.) [3]. Many investigations declared that those characteristics strongly depend on the thermal conductivity of the building's layer materials [4–11]. Besides, the thermal conductivity of a building wall or roof material are strongly affected by microstructure, mineralogical composition, proportion, supplementary materials, moisture content, and porosity, as shown in Fig. 1. Furthermore, these structures also need to have suitable mechanical properties because they must stand without being damaged from natural causes for many years. Therefore, if these structures having appropriate thermal and mechanical properties are selected, also accurate cooling load calculation is performed, and then suitable HVAC system components can be selected in terms of reducing the energy use. However, it is difficult to determine the ideal thermal conductivity properties of these structures by means of both energy and time efficiency due to the accuracy of test methods and high price of the devices. Hence, this situation leads scientists to search for new solutions.

The mathematical models which are used to describe experiences gathered from data of concrete mixes behaviors are most reliable and accurate as well as recommended methods [13]. These models based on experimental data are generally in regression forms, and called ‘‘Free models” [14]. However, because of more assumptions and less accuracy in regression form, regression methods cannot be used when the problem contains many independent variables. Recently many new modeling methods such as artificial neural networks (ANN), expert systems as a free model can approximate complex and non-linear relation due to any parameters and trial and error process by learning real record relationship without any presumptions [15]. Artificial neural networks (ANN) are a family of massively parallel architectures that produces meaningful solutions to the problems and capable of learning and generalization of examples and experiences, even if the input data is incorrect or incomplete. ANN is a powerful tool to solve for some complex engineering problems.

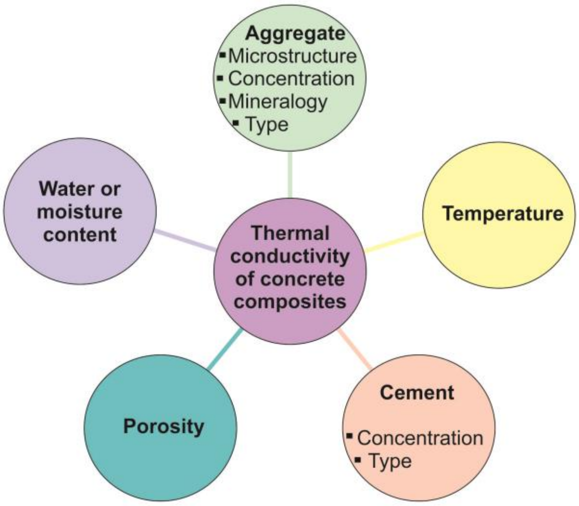

Fig.1. Parameters affecting thermal conductivity of structures[12]

The basic strategy for developing a neural network-based model for material behavior is to train a neural network on the results of a series of experiments using that material. If the experimental result contains relevant information on the behavior of the material, the neural network training will contain sufficient information on the behavior of a material to qualify as a model material [16]. This learning of the neural network not only be able to reproduce the experimental results, but would be able to bring the results of other experiments by the generalization ability.

In the literature, the ANN has been used to predict the effect of material behavior, especially on mechanical properties. Marai M. Alshihri et al. [15] are used the neural networks (NNs) to predict the compressive strength of light weight concrete (LWC) mixtures after 3, 7, 14, and 28 days of curing. The finding of this study indicated that the neural networks models are sufficient tools for estimating the compressive strength of LWC. Furthermore, Guang and Zong, [17] proposed a method to predict 28-day compressive strength of concrete using multilayer feed-forward neural networks. Dias, [18] presented an artificial neural network model for predicting the strength and slump of ready mixed concrete. Eldin and Senouci, [19] employed a neural network for measuring and predicting of the strength of rubberized concrete. Lai [20] predicted the mechanical properties of concrete by ANNs. Moreover, Gencel et al [21] predicted the thermal conductivity of concrete with vermiculite by using artificial neural networks approaches with 20 datasets. The root mean square error, the mean absolute error, and determination coefficient statistics are used as evaluation criteria of the models, and the experimental results are compared with these models.

Therefore, this research aimed to produce new concrete types in order to develop a lightweight construction material with higher thermal insulation property and to predict ideal thermal conductivity values of those produced concrete wall or roof structures by using an ANN method so as to reduce the energy consumption of the buildings. The composite materials were manufactured by reinforcing varying volume fraction of lightweight aggregates in cementitious matrix, which were exposed to the same conditions. The test program was conducted mainly to investigate the effect of pumice (PA), rubber aggregates (RA) and expanded perlite (EPA) on the thermal property of samples by using thermal response method. After experimental test program, an artificial neural network (ANN) method, which is Levenberg-Marquardt algorithm, is constructed for the prediction of thermal conductivity of concretes of which the mechanical properties are known. Then, the actual experimental results were compared with the predicted results. The findings and results are presented in detail in the following sections.

2. Experimental Procedure Instructions

2.1. Concrete Mixtures, Materials and Test Methods

Several materials were used to obtain different lightweight building elements. The materials were locally available ordinary Portland cement (PC) (CEM I 42.5R), silica fume (SF), fine aggregate, coarse aggregate, RA, PA, EPA and superplasticizer (SP). Both river sand and uncrushed gravel were employed as the fine and coarse aggregates, respectively. Crumb rubber consisting of particles ranging in a size from 4.75 mm to 0.075 mm was generated from waste tire without steel fibers with a cracker mill process. Perlite is a siliceous volcanic glass, whose volume can expand substantially under the effect of heat. When it is heated above 870 °C, its volume increases 4–20 times of the original volume [22]. Pumice is a porous volcanic rock with amorphous structure and composed mainly of SiO_2. It is widely used in many industries [23]. Due to their low density and high thermal and sound insulation capacity, both pumice and expanded perlite are suitable materials to produce lightweight concrete (ASTM C330/330M, ASTM C 332). In accordance with ASTM C136, the gradation of aggregates was selected to be ideal region depending on the maximum grain size. Due to the fact that the gradation of aggregates has a significant impact on the property of the concrete composition, in this study, single and uniform grain size was used, as shown in Fig. 2.

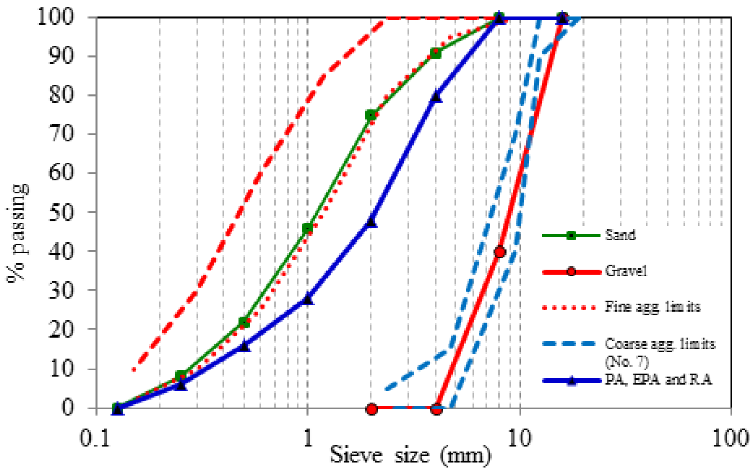

Figure 2. Sieve analyses of aggregates

Concrete mixtures were designed to have a constant water–cementitious material ratio (w/c) of 0.48 and total cement content of 350 kg/m^3. Normal aggregates were replaced by PA, EPA and RA at different volume fractions vary between 10% and 50%. In total, 102 concrete samples were produced and their mechanical tests which are the compressive strength, bulk density, porosity are performed on air dry samples aged 28 days. The compressive strength test was carried out in accordance with ASTM C39 at a loading rate of 0.24 MPa/s on 100 x 100 x 100 mm cube specimens by a testing machine with a maximum capacity of 3000 kN. The thermal conductivity test was performed on same state with the age of 35 days according to EN 12667. In this study, ISOMET 2104 device (Fig. 3) was used to measure thermal conductivity of concrete samples on the basis of TPS method and the values of the device ranges for the measured parameters are presented in Table 1. In the TPS technique, the source of heat is a hot disc made out of a bifilar spiral, which also serves as a sensor for temperature increase in the samples. In comparison with stationary or steady state methods, the advantage of transient methods is that some of them give a full set of thermophysical properties within a single rapid measurement. All test result measurement values presented in the tables are based on the average values ± a tolerance limit (less than 4%) in order to cover the range of all properties as measured for different samples of the same category.

Table 1. Values of device range for measuring parameters

Measurement	Measurement range	Accuracy
Thermal conductivity coefficient	0.015–6 W/m K	5 % of reading + 0.001 W/m K
Specific heat capacity	4 x10^4 – 4 x10^6 J/m^3 K	15 % of reading + 1.103 J/m^3 K
Operating temperature	From -20 – +70 °C	1°C

Fig. 3. The thermal property measurement device used in this study.

3. Construction of Neural Network Model and Parameters

Neural networks algorithm is extremely useful tool for solving complex engineering problems especially recognizing patterns, fitting a function and clustering of data. Basic ANN structure has three inputs, hidden and output layer. Connection between all layers is achieved by weights that show how strong the connection is between layers. All input neuron cell node collect data from world and multiplies by a weight. The neuron will combine these inputs with reference to a threshold value and activation function. There are number of activation functions in use with ANN such as logistic or hyperbolic tangent function. In training process, the error between experimental result of sampled concrete and output was evaluated. The calculated error was propagated backward through the neural network layers, and every neuron weights are updated, it can be described a neuron by the following equations:

$$o = f\left(wx + bias\right) \tag{1}$$

where *w* and *x* defines weights and input that defines

$$w = w_1, w_2, \ldots.., w_n \tag{2}$$

$$x = x_1, x_2, \ldots.., x_n \tag{3}$$

The transfer function:

$$net = \sum_{i=1}^{n} w_i x_i + b \tag{4}$$

Bias, b has the effect of increasing or decreasing the net input of the activation function. On the field artificial neural network, the sigmoid function is a type of activation function and is used excessively in neural networks application. Sigmoid function which refers to the special case of the logistic function is defined by the formula:

$$C_j = f\left(net_j\right) = \frac{1}{1+e^{-(net)}} \tag{5}$$

In this study, ANN architecture was designed as an input layer with 4 neurons and an output layer with one neuron, where every layer in network has 3-5-4 neurons; respectively. Data collected from experimental setup were divided into two parts: training and testing. Matlab – Neural Network Toolbox was used for design, train and simulate. It provides user-friendly and simple graphical user interface(nntool GUI) to efficiently design of several neural network. Using this program, a neural network model was constructed, trained and tested using the available test data of 102 different concrete samples gathered from experimental setup. The data used in neural network model are arranged in a format of four input parameters that cover the bulk density, porosity, compressive strength, and the percentage of aggregate content (%). A basic neural model where consist of 4 inputs and a single output used in this study as shown in Fig. 4.

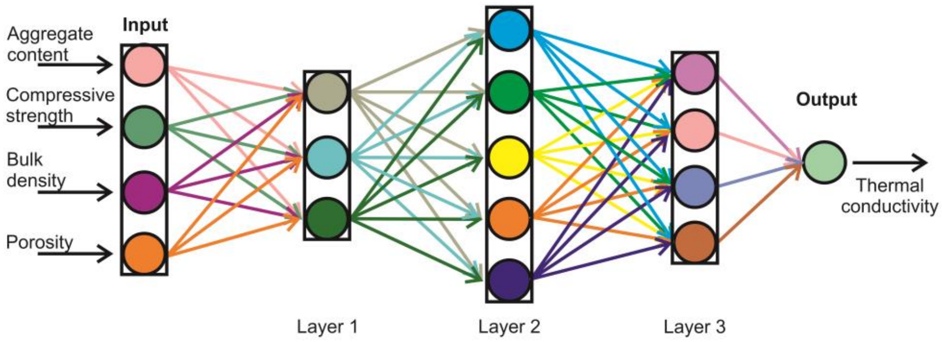

Fig. 4. Structure of ANN model used in this study

In ANN model, Levenberg–Marquardt (LM) algorithm was selected as learning algorithm. Since there is no best option to select number of hidden layer and neurons, several combinations were tried. After trial procedure, optimal results were obtained with 3-5-4 neuron structure, respectively. The quality and speed of training process could improve using normalization that shown by the following formula:

$$x_i = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{6}$$

where x, x_i, x_{max} and x_{min} are original, normalized, maximum and minimum values, respectively.

4. Result and Discussion

The results of the experimental tests gathered from the mechanical and thermal properties of AEC, PC, EPC and RC and mixtures prepared, in contrast with the control mixture, NC are shown in Table 2.

Table 2. Mechanical and thermal properties of produced concrete wall samples*

Types of concrete	Compressive strength, σ_c (MPa)	Bulk density, ρ (kg m-3)	Porosity, ϕ (%)	Thermal conductivity, λ (W m-1 K-1)
NC	51.85	2345.09	9.69	1.96
AEC	48.11	2288.86	8.41	1.91
EPC10	31.21	2139.09	12.86	1.51
EPC20	19.02	1885.52	18.37	1.22
EPC30	10.01	1559.44	23.28	0.70
EPC40	8.15	1376.56	26.12	0.50
EPC50	4.88	1168.63	28.20	0.36
PC10	33.46	2005.34	11.23	1.54
PC20	23.39	1851.02	16.55	1.29
PC30	13.07	1559.95	22.05	0.76
PC40	9.90	1400.72	24.20	0.54
PC50	9.51	1329.97	27.28	0.41
RC10	42.04	2244.30	9.19	1.72
RC20	30.41	2148.07	11.43	1.44
RC30	19.04	2033.93	12.23	1.22
RC40	9.51	1874.62	14.19	0.89
RC50	4.53	1644.98	16.35	0.62

* These properties are the average of the six specimens for each test.

Various performance indices are used to evaluate the convergence of experimental values in order to predict values. Root mean-square error, mean absolute percentage error, mean absolute error and coefficient of correlation (R^2) are performed in various studies. The mean absolute percentage error (MAPE) and R^2 performance indices were used in this study. The mean absolute percentage error was calculated by following equation:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|o_i - t_i|}{t_i}.100 \tag{7}$$

where t_i is target mean value, o_i is output value and n total data number.

After experimental setup was performed, an artificial neural network (ANN) method, which is Levenberg-Marquardt algorithm, is selected for prediction of thermal conductivity of concretes of which the mechanical properties are known. A comparison between the results of experimental study and ANN predicted values are depicted in Fig. 5. MAPE values of predicted data, which shows the percentage value of absolute error, was calculated as 3.17. The correlation coefficient R^2 was calculated as 0.997. The results indicate that ANN makes good predictions for both training and testing periods. Therefore, it can be concluded that the prediction of the artificial neural network has proceed in the correct manner.

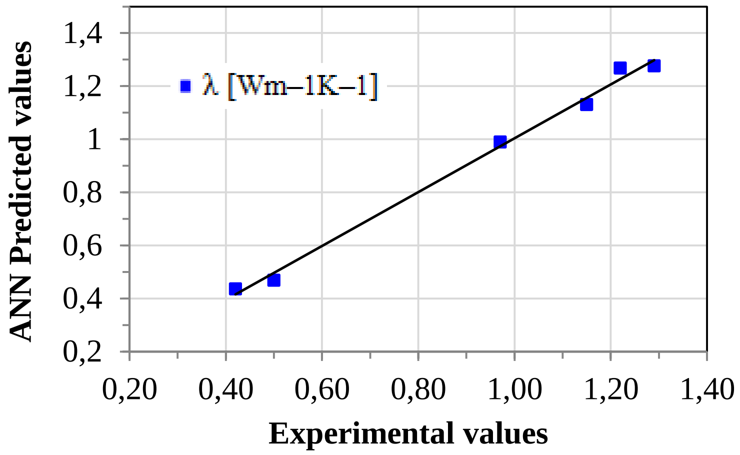

Fig. 5. Correlation between actual (experimental) and ANN results

5. Conclusion

In this study, an experimental investigation is carried out to predict the thermal insulation properties of building wall structures of which the mechanical properties are known, by using an artificial neural network (ANNs) method in order to provide energy efficiency in buildings. Levenberg-Marquardt training algorithm based neural network was designed to predict thermal conductivity properties of lightweight building materials. Since there is no specific rule to determine the number of neurons and hidden layer, the neural network were optimized by trial/error method and the best results were obtained with 3-5-4 hidden layered structure. The value of the mean absolute percentage error (MAPE) 3.17 and correlation coefficient R^2 were calculated as 0.997, respectively. The estimated performance indices show that the error is in acceptable limits. The actual experimental results were compared with the predicted results, ANN estimation is pretty good and can strongly be suggested to decrease time consuming and complicate laboratory experiment.

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