Scientia Iranica A (2015) 22(6), 2001–2011

Sharif University of Technology
Scientia Iranica
Transactions A: Civil Engineering
www.scientiairanica.com

Comparison between ANFIS and ANN for estimation of the thermal conductivity coefficients of construction materials

C. Özel[a,*] and A. Topsakal[b]

a. *Faculty of Technology, Department of Civil Engineering, Suleyman Demirel University, 32260 Isparta, Turkey.*
b. *Graduate School of Natural and Applied Sciences, Department of Construction Education, Suleyman Demirel University, 32260 Isparta, Turkey.*

Received 17 April 2014; received in revised form 8 November 2014; accepted 25 April 2015

KEYWORDS
Construction materials;
Thermal conductivity coefficients;
Artificial neural networks;
ANFIS;
Modeling.

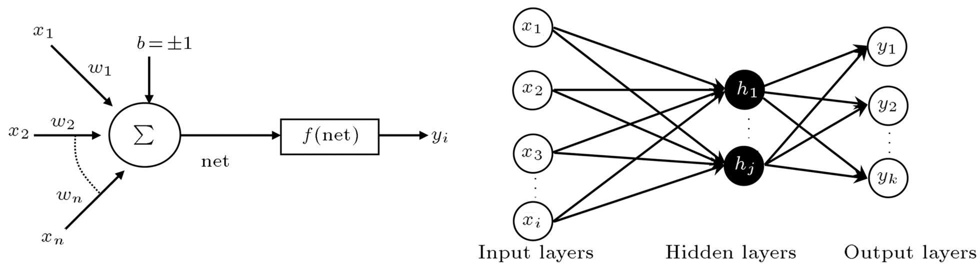
Abstract. Determination of the thermal conductivity coefficient of construction materials is very important in terms of fulfilling the condition of comfort, durability of construction materials, and the economy of country and individual. In this study, linear regression, Adaptive Neural based Fuzzy Inference System (ANFIS), and Artificial Neural Networks (ANN) models were developed to estimate the thermal conductivity coefficient values from the surface density (dry specific gravity/thickness) and unit weight of construction materials. Validations of the developed models were investigated by statistical analyses. In the predictive models, while the lowest determination coefficient (R^2) and the highest Root Mean Square Error (RMSE) were obtained from linear regression, the highest R^2 and lowest RMSE were obtained from the ANFIS model. Results of the ANN model, according to the results of linear regression, showed that while R^2 increased by approximately 6%, RMSE decreased by 30-39%. The results of ANFIS model revealed that while R^2 increased by approximately 12%, RMSE decreased by 59-71%. As a result, it is suggested to be, along with surface density and unit weight with ANFIS which are the most appropriate methods between the used methods, an alternative approach to estimate the value of thermal conductivity.

1. Introduction

Nowadays, provision of clean and renewable sources of energy is required due to energy shortages and growing environmental awareness. The reserves of conventional energy sources are decreasing with every passing day and the environmental impacts of energy sources negatively affect the world. Furthermore, energy resources are limited and production of energy is expensive. Heat energy, a large part of the energy consumed, is the most fundamental and the most needed type of energy. Kindinis et al. [1] stated that 35% of the total energy is consumed by residential and tertiary service building; 81% of this energy, approximately 28% of the total energy, is used to control indoor climatic comfort.

The relationship between obtained data from experimental studies is not always easy to understand or is not always linear. Additionally, some experimental results are foreseeable prior to experiments, based on experience and knowledge. Knowledge discovery uses data mining and machine learning techniques that have evolved through synergy in artificial intelligence, computer science, statistics, and other related fields. There are a number of computational analysis techniques that deal with them. Although there are technical differences, the terms "machine learning", "data mining",

*. *Corresponding author. Tel.: +902462111428*
E-mail addresses: cengizozel@sdu.edu.tr (C. Özel); alpertopsakal@gmail.com (A. Topsakal)



(a) Artificial neural cell structure

(b) A simple artificial neural network

Figure 1. Structure of the network and cells in artificial neural networks.

"heuristic methods", and "knowledge discovery" are often used interchangeably. The use of scientific field of studies based on computers is increasing every day to save time and money in new studies. With the gained experiences or knowledge, it reveals the hidden patterns among obtained experimental data, increases the value of data, converts the data to knowledge, and investigates the validity of predictions [2-5].

In recent decades, Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFISs) have been used in many different fields, from predicting material properties to customer behavior. ANN is a powerful tool for system modeling that has a wide range of applications. However, despite the excellent classification capacities of the latter, its development can be time-consuming and computer-intensive. The most important advantage of the ANN model is that the priority of functional relationship among the various variables is not required. ANN automatically builds a relationship for the network architecture as experimental data through a learning algorithm [6,7].

In this study, to determine the dependence of value λ of building materials on surface density (S) and unit weight (G), regression analyses were conducted, and models to predict the value λ were developed using Adaptive Neural based Fuzzy Inference System (ANFIS) and Artificial Neural Networks (ANN). For this purpose, we prepared 110 different materials to examine the validity of models and to generate the models used. Levels of significance of the relationship and some statistical properties of the correlation coefficients, between the experimental values with estimated values from developed models, were investigated through analysis of variance (ANOVA).

2. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) were designed to simulate some of the brain functions as specific teaching methods. It produced successful results in different areas such as classification, clustering, and sense-data processing [8,9]. An ANN consists of five main parts including the weights and the inputs (Figure 1(a)), total function, activation function, and output [10-12]. There are two types depending on the flow direction of sign in the neural networks, feedforward network, and feedback or recurrent network. The feedforward network, also known as a static network, is the simplest and most primitive structure of ANN. In this network, knowledge only moves to the forward output layer hiddenly and the system does not have memory. However, the feedback network is a network structure that feeds back to the input units or previous layers from the output and intermediate layers. These neural networks have dynamic memories. The output of neurons in this structure not only depends on the current input values, but also depends on previous input values. Therefore, this network structure is particularly suitable for estimation [13]. The least mean square error method (to minimize errors, which adapts the network weight to the mean square error in between the actual output and the model output) is one of the most widely used learning algorithms for feedback [14,15]. The general structure of feedback learning method is the feedback network. This network is multi-layer and feed forward and suitable for classification, projection, and solving interpretation and generalization problems [16]. It consists of many neural cells connected with ANN. Collection of the neural cells is not random. Generally, the network is constituted in such a way that cells are three-layer and are parallel in each layer. There are hidden layers between the input and output layers (Figure 1(b)). Neural cells in the output layer produce the required output as input data in the input layer of the network to process knowledge from the hidden layers [10].

The surface density (dry specific gravity/thickness) (S) and the unit weight (G), which can be determined as the experimental data, were used in modeling for prediction of the thermal conductivity coefficient "λ" of construction materials. Data were normalized (dimensionless) by the $F = (F_i - F_{\min})/(F_{\max} - F_{\min})$ equation before modeling due to different units of the two parameters, where F is a dimensionless value, F_i is the value obtained from the experiment,

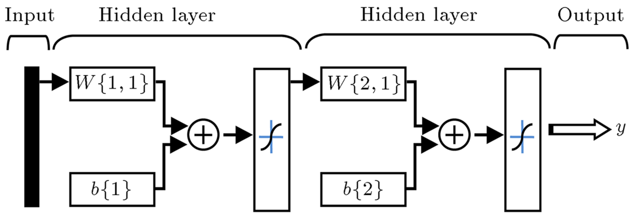


Figure 2. Network structure of the ANN model.

and $F_{\max}$ and $F_{\min}$ are the maximum and minimum values obtained from the experiment, respectively. The number of neurons in the input layer (i), the number of hidden layer neurons (j), and the number of neurons in the output layer (k) are taken as 2, 1, and 1, respectively. In the multi-layer feed-forward ANN model used in this study, the error back propagation algorithm is used to adjust the weights. The structure and properties of the developed model are shown in Figure 2.

3. Adaptive Neural based Fuzzy Inference System (ANFIS)

Fuzzy Logic (FL) has been proposed as a new method instead of the binary logic of Aristotle. This method enabled the description and the determination of uncertain or suspect ideas [17-24]. Fuzzy Models (FM) are used to identify relationships between variables with the help of rules [25]. The results in the FM foresight, even if it seems to be a suitable numerical test perspective, requires the physical configuration associated with input and output variables in terms of the rules with connections of membership functions (MFs). A Fuzzy Inference System (FIS) provides powerful tools for simulation of non-linear behavior with the help of linguistic fuzzy rules and fuzzy logic [26]. There are two main approaches in FIS: "Mamdani" and "Sugeno". The "maximum-minimum" is applied in the Mamdani approach and the uncertain results are obtained from fuzzy installation [27]. The Mamdani method is widely used in order to obtain expert knowledge. However, the Mamdani type of fuzzy inference system requires significant computational processes. On the other hand, the Sugeno method is especially effective in numerical control systems operating with adaptive control systems and also in optimization for the non-linear dynamic systems [28]. Adaptive Neural Fuzzy Inference based System (ANFIS) was first proposed by Jang [29]. While ANFIS is based on the "Sugeno Fuzzy Logic Inference System" and the ability to provide expert knowledge and decision-making like a human, it is used for the "Backpropagation Learning Algorithm" in the application of ANN [29-31]. In addition, ANFIS includes advanced data analysis techniques such as rule-making and numerical grouping [32]. Figure 3 shows the schematic network structure of ANFIS.

Learning the algorithm of ANFIS optimizes both the input variables and the output variables. The learning process that takes place in ANFIS uses a hybrid learning algorithm, which is combined with the use of backpropagation learning algorithm by the least squares method. The hybrid learning algorithm consists of two parts: feedforward and feedback. While the values of resulting parameters, the input parameters in feedforward, are calculated by the least squares method as fixed, the values of input parameters, the results parameters in feedback, are calculated by backpropagation learning algorithm as fixed [33].

ANN is a low-level structure that can obtain successful results with the use of raw data as input. However, the FL draws conclusions using linguistic data obtained by expert knowledge. In fact, fuzzy systems have no learning ability and cannot adapt themselves to a new environment. On the other hand, ANN is capable of learning, but not appreciated by the user. ANFIS draws conclusions using expert knowledge of FL through the learning ability and calculations of ANN [34].

ANFIS modeling, similar to ANN modeling, uses S and G as input sets and the aim is to estimate λ as output. The structure of modeling is shown in Figure 4. The Trimf function is selected, having the smallest error value. As can be seen in Figure 4, the ANFIS model was developed, including two inputs and three membership functions, depending on these inputs.

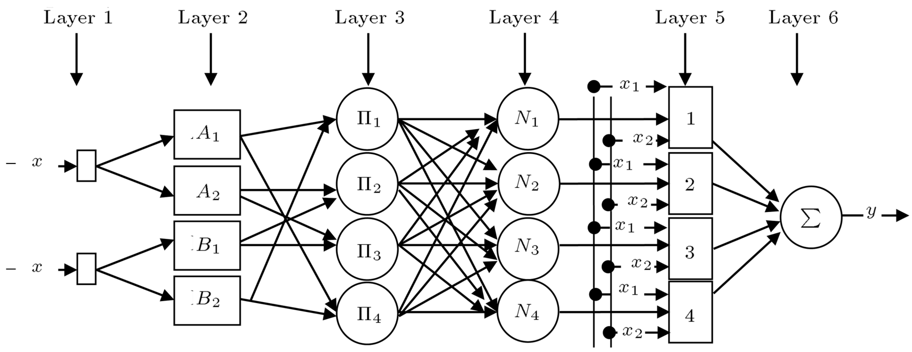
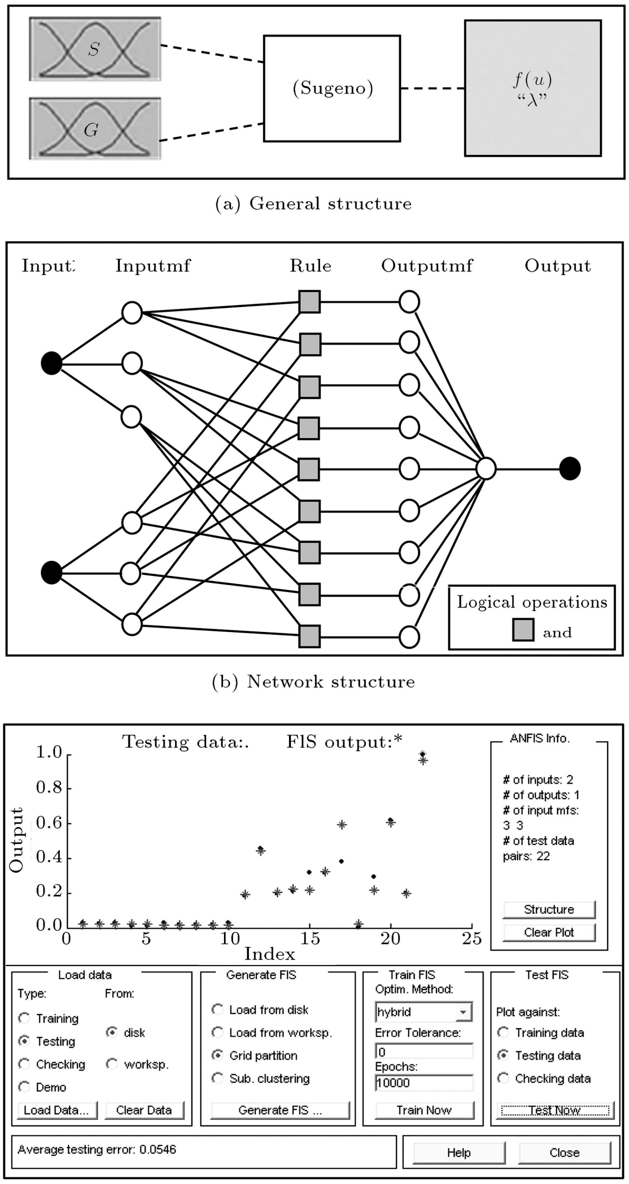


Figure 3. Network structure of ANFIS.



(a) General structure

(b) Network structure

(c) Editor structure

Figure 4. Properties of the developed ANFIS model.

4. Determination of thermal conductivity coefficients (λ)

Many studies have been conducted to determine the heat transfer coefficient of solids, and different methods have been used in these studies. The test method depends on measuring the sensitivity of instruments and the structure and shape of material. The most important and most widely used methods for solids include:

- Continuous Regime Methods: Heat flow measurement (classic or caliber), hot plate (flat or cylindrical), and hot box (caliber or insulated);
- Transient Regime Methods: optical based techniques (laser lighting technology, Angstrom technique (classic and enhanced), adjustable beam technique, and photo-thermal techniques);
- Adiabatic box technique [35].

In this study, the guarded hot plate method according to TS 415 EN 12939 [36] was used to determine the thermal properties of building components. The major advantages of this method include the facts that the test is easy to conduct, and the geometry of samples is simple, in that cubic and measurement procedures can be achieved parallel to the horizontal axis. The greatest disadvantage is that the thermal conductivity of moist samples cannot be determined and conditioning is required for these samples. Therefore, according to TS 415 EN 12939 and TS ISO 8302 [37], the thermal conductivity coefficient determines the steady state of oven dry state. For this reason, before starting to test, the stone-based samples were dried (105°C, 24 hour) to a constant weight under normal atmospheric pressure (1×10^5 Pa). As the samples were plastic-based (expanded polystyrene, extruded polystyrene, etc.), the physical properties were lost at 105°C, and the drying process was applied at 24°C for 24 hours.

In general, a planar surface heat loss decreases depending on increase in thickness of the sample and λ increases depending on the density of material; λ decreases depending on increase in the thickness of material. However, the relationship with λ within these parameters is not linear in either case [38]. Additionally, thermal conductivity values of materials with the same thickness and different density values are different from each other due to differences of thermal bridges in internal structures. Therefore, the unit weight of materials (G) and surface density (function of dry specific gravity with thickness (S) values were calculated and used in this study.

4.1. Samples

The materials, which were construction and insulation materials, for modeling and analyses are given in Tables 1 and 2. These materials are those that are widely used in applications (expanded polystyrene (EPS), extruded polystyrene (XPS), glass wool, bricks, plastering, etc.), mixtures produced in laboratory (lightweight concrete "LC", boards produced with different materials, gypsum, perlite, etc.), and natural materials (natural stone, tufa stone, volcanic tuff, etc.).

In the constituting model to predict thermal conductivity coefficient (λ), 80% of all data (110 materials) was used as a training dataset (88 materials), while the rest of data (22 materials) was used as testing data, analyzing them in order to examine the validity of model and to determine the determination coefficient between the results obtained from the model and test results.

As can be seen in Tables 1 and 2, at the modeling

Table 1. Training data and materials used in modeling.

No	Product name	S kg/m^2	G kg/m^3	λ kcal/mh°C	No	Product name	S kg/m^2	G kg/m^3	λ kcal/mh°C
1	EPS*	0.225	11.330	0.045	**45**	Brick*	48.500	1246.000	0.240
2	EPS*	0.751	14.970	0.037	**46**	LC	51.400	1287.000	0.240
3	EPS*	0.791	15.670	0.037	**47**	LC produced with pumice	25.350	509.580	0.150
4	EPS*	0.885	17.000	0.068	**48**	LC produced with pumice	26.360	588.000	0.140
5	EPS*	1.092	21.410	0.061	**49**	LC produced with pumice	29.500	690.000	0.145
6	EPS*	1.128	20.967	0.067	**50**	LC produced with pumice	30.800	705.000	0.146
7	EPS*	1.309	26.190	0.035	**51**	LC produced with pumice	33.000	887.000	0.100
8	EPS*	1.346	27.000	0.032	**52**	LC produced with pumice	61.370	1418.000	0.230
9	XPS*	0.691	27.360	0.037	**53**	LC produced with pumice	63.450	1570.400	0.420
10	XPS*	0.713	28.125	0.036	**54**	LC produced with pumice	32.300	663.000	0.120
11	XPS*	0.970	30.000	0.029	**55**	LC produced with pumice	31.100	780.000	0.150
12	XPS*	0.642	32.000	0.026	**56**	LC produced with pumice	32.110	800.000	0.160
13	XPS*	0.641	31.880	0.028	**57**	LC produced with pumice	32.630	820.000	0.120
14	XPS*	0.650	32.600	0.028	**58**	LC produced with pumice and EPS	19.450	499.000	0.140
15	XPS*	0.664	32.680	0.022	**59**	LC produced with pumice and EPS	33.240	833.000	0.270
16	XPS*	0.668	32.770	0.022	**60**	LC produced with fiber	67.270	1738.000	0.500
17	XPS*	0.668	32.770	0.022	**61**	LC produced with fiber	60.500	1513.000	0.350
18	XPS*	0.972	33.000	0.029	**62**	Board produced with gypsum	9.079	728.700	0.180
19	XPS*	1.500	35.000	0.025	**63**	Gypsum	56.990	1398.000	0.429
20	XPS*	1.530	35.000	0.022	**64**	Gypsum	59.000	1392.000	0.420
21	XPS*	1.510	35.000	0.024	**65**	Board produced with gypsum and perlite	32.010	780.000	0.231
22	XPS*	1.490	35.000	0.026	**66**	Board produced with gypsum and perlite	32.210	785.000	0.226
23	XPS*	1.520	35.000	0.023	**67**	Perlite	65.970	1635.000	0.533
24	XPS*	1.485	35.000	0.027	**68**	Board produced with perlite and cement	71.000	1753.000	0.610
25	XPS*	1.520	35.000	0.023	**69**	Board produced with perlite and cement	70.000	1760.000	0.660
26	Glass wool*	0.880	26.000	0.034	**70**	Board produced with perlite and cement	70.000	1724.000	0.470
27	Glass wool*	0.680	59.000	0.024	**71**	LC produced with perlite	31.710	750.300	0.150
28	Glass wool*	0.750	60.000	0.034	**72**	Mortar (sand and cement)	79.050	1956.000	0.620
29	Glass wool*	0.830	64.000	0.023	**73**	Mortar (sand and cement)	67.870	1686.000	0.610
30	Glass wool*	0.870	68.000	0.031	**74**	Board produced with sand and diatomite	34.800	870.000	0.150
31	Glass wool*	0.970	68.300	0.020	**75**	Mud brick	72.780	1755.000	0.640
32	Glass wool*	0.734	71.620	0.026	**76**	Mud brick with cement	74.560	1754.000	0.680
33	Glass wool*	1.070	76.000	0.034	**77**	Silk plaster*	1.321	275.550	0.061
34	Glass wool*	1.050	78.000	0.025	**78**	Silk plaster*	0.890	180.160	0.042
35	Glass wool*	1.144	78.470	0.037	**79**	Silk plaster*	0.854	168.240	0.056
36	Glass wool*	1.151	79.110	0.035	**80**	Polyurethane board*	0.868	34.500	0.023
37	Glass wool*	1.243	81.330	0.037	**81**	Polyurethane board*	0.815	32.600	0.024
38	Glass wool*	1.184	83.580	0.038	**82**	Polyurethane board*	1.989	66.490	0.033
39	Glass wool*	0.878	86.860	0.032	**83**	Board produced with polyurethane and wood shavings	5.130	101.000	0.083
40	Glass wool*	1.190	88.000	0.033	**84**	Wood shavings boards	16.000	315.000	0.102
41	Glass wool*	1.145	91.410	0.035	**85**	Wood shavings	12.640	1206.000	0.160
42	Glass wool*	1.172	99.610	0.035	**86**	Natural stone	49.000	1190.000	0.185
43	Glass wool*	1.352	101.080	0.034	**87**	Tufa stone	85.200	1469.500	0.515
44	Brick*	47.710	1189.500	0.230	**88**	Volcanic tuff	34.350	1016.800	0.260

* Produced by different companies or products of various qualities of the same company.

and analysis used both different products with materials, such as plastic, concrete, and different materials characteristics. For example, although the lightweight concrete materials between 47th to 52nd samples in table 1, they have different λ values, G and S for each one.

In both the training set and the test set, the values of materials changed within quite a wide range, and differed from each other in the training set (min = 0.225, max = 85.200 for S; min = 11.330, max = 1956 for G; min = 0.020, max = 0.680 for λ) and the test set (min = 0.713, max = 74.770 for S; min = 14.350, max = 1796 for G; min = 0.023, max = 0.680 for λ). Although the training set contained materials such as silk plaster, wood shavings boards, volcanic tuff, and natural and tufa stone, the test set did not contain these materials.

The coding of data used in the training and test series are given in Tables 1 and 2. The λ, S, and G values of these materials are shown for the test series in Figure 5 and for the training series in Figure 6.

Generally, the three properties of materials have

Table 2. Test data and materials used in the analyses.

No	Product name	S kg/m^2	G kg/m^3	λ kcal/mh°C	No	Product name	S kg/m^2	G kg/m^3	λ kcal/mh°C
1	EPS*	0.713	14.350	0.039	**12**	Mortar produced with sand and cement	54.140	1353.000	0.320
2	EPS*	1.420	28.550	0.033	**13**	LC produced with pumice	31.330	788.000	0.150
3	XPS*	0.722	28.620	0.037	**14**	LC produced with pumice	32.460	841.000	0.160
4	XPS*	0.980	33.520	0.028	**15**	LC produced with pumice	31.940	799.000	0.230
5	XPS*	1.500	35.000	0.025	**16**	LC produced with pumice	48.300	1224.000	0.230
6	Polyurethane board*	1.221	82.360	0.039	**17**	LC produced with fiber	69.160	1613.600	0.440
7	Glass wool*	0.924	97.200	0.029	**18**	LC produced with pumice and EPS	0.890	35.000	0.023
8	Glass wool*	0.893	85.380	0.031	**19**	Board produced with gypsum and perlite	31.490	775.000	0.215
9	Glass wool*	0.976	95.320	0.029	**20**	Gypsum	57.590	1412.000	0.428
10	Glass wool*	1.168	69.540	0.038	**21**	Brick	31.250	785.000	0.150
11	Glass wool*	28.920	679.000	0.144	**22**	Mud brick with gypsum	74.770	1796.000	0.680

* Produced by different companies or products of various qualities of the same company.

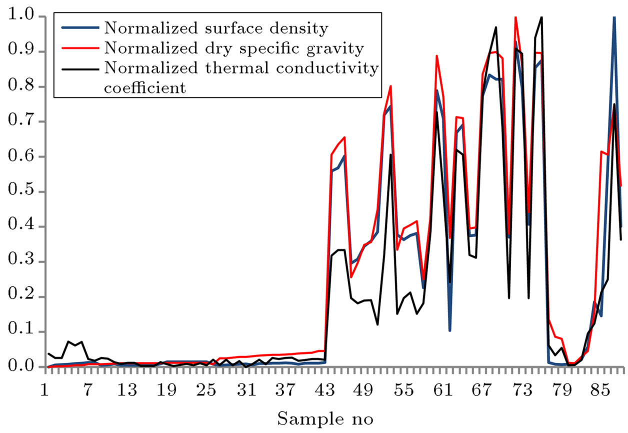


Figure 5. Data used for the training set.

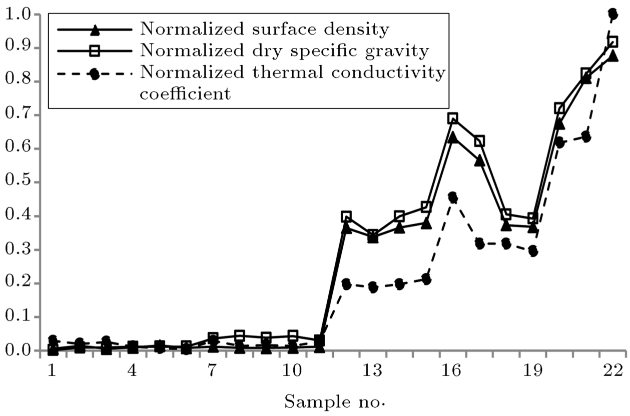


Figure 6. Data used for the test set.

a similar graphical behavior; nevertheless, it is not a valid behavior for all materials, such as those 1-10th and 46-58th samples in the training set, and 1st, 3rd, 8-10th, and 21th samples in the test set.

5. Results of models

The obtained relationships, according to experimental values, are shown in Figures 7 and 8, Tables 3 and 4. As can be seen from the two figures, although the

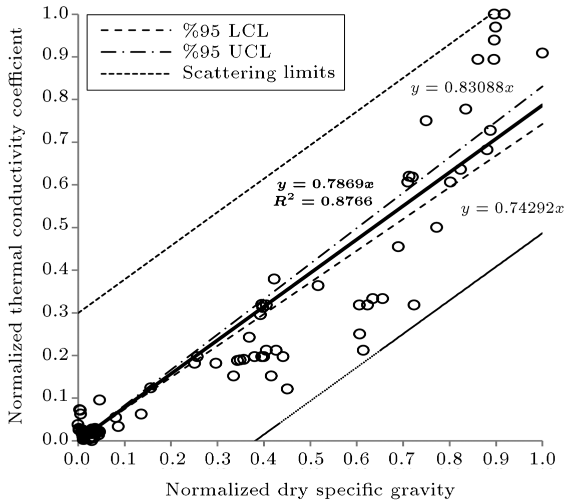


Figure 7. Relationship between G and λ.

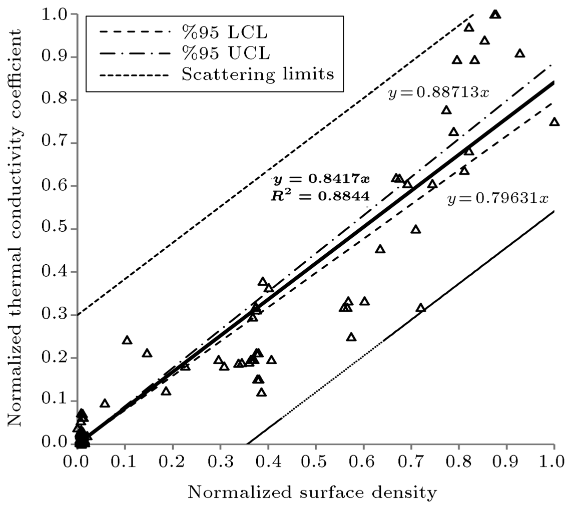


Figure 8. Relationship between S and λ.

determination coefficient (R^2) values are somewhat high, the scattering values are significantly beyond the 95% confidence level.

According to the results of the statistical analyses between G and S with λ, there were no significant

Table 3. Statistical parameters between G with S and λ.

	G		***S***	
	A value for $y = a.x$	**Standard error**	**A value for $y = a.x$**	**Standard error**
Slope	0.78690		0.84172	
95% Lower Control Limit (LCL)	0.74292	0.02219	0.79631	0.02291
95% Upper Control Limit (UCL)	0.83088		0.88713	
Number of points	110		110	
Degrees of Freedom (DF)	109		109	
Sum of Squares for Error (SSE)	1.01674		0.95256	
Pearson's r	0.95929		0.96191	
Determination coefficient (R^2)	0.8766		0.8844	
Adjusted R^2	0.91951		0.92459	
Root Mean Square Error (RMSE)	0.09658		0.09348	

Table 4. ANOVA analysis of G and S with λ.

		DF	**Sum of squares**	**Mean square**	***F* value**	**Prob> *F***
G	Model	1	11.73076	11.73076	1257.603	0
	Error	109	1.01674	0.00933		
	Total	110	12.7475			
S	Model	1	11.79494	11.79494	1349.678	0
	Error	109	0.95256	0.00874		
	Total	110	12.7475			

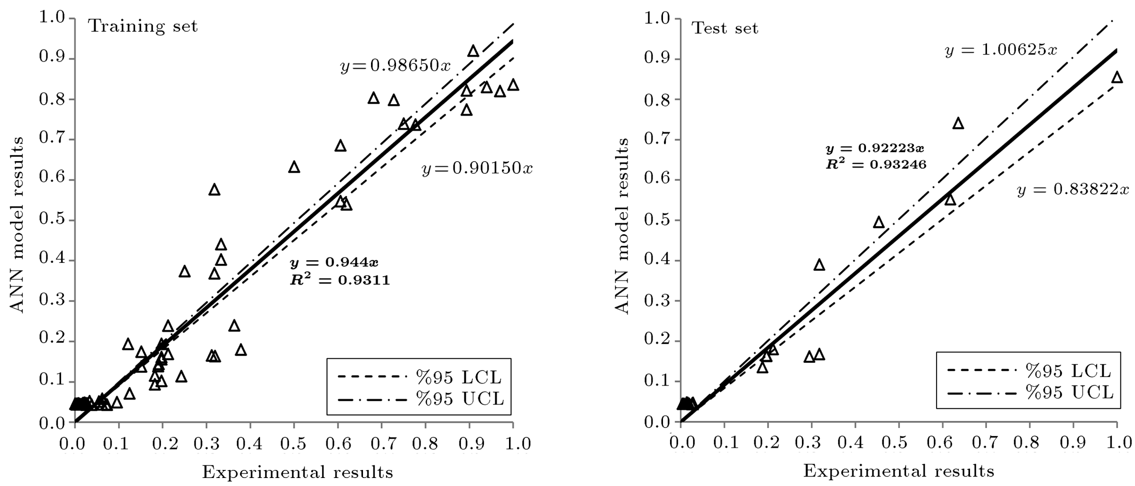


Figure 9. Relationships between the experimental and test data in the ANN model.

difference. In particular, R^2 and RMSE values for both the parameters were very close.

According to the analysis of variance (ANOVA) analysis, shown in Table 4, the significance level for $P < 0.01$ (F values) is statistically significant (non-random) [$F(1, 109) = 1257.60315$, $P < 0.01$ for G; $F(1, 109) = 1349.67862$, $P < 0.01$ for S].

5.1. Results of the ANN model

The relationships between experimental results of the ANN modeling are shown in Figure 9. Both the relationship between the training set and the experimental results ($R^2 = 0.9311$) and the relationship between the test set and the experimental results ($R^2 = 0.93246$) were acceptably high values and quite close to each other.

Although the statistical analyses of experimental λ in both the training and test series obtained close values (Table 5), based on the relationships of the linear analyses, R^2 values increased, but the RMSE values decreased. However, because of the decrease in the number of data in test series, the obtained standard error values increased.

According to the results of ANOVA analysis,

Table 5. Statistical analysis of λ between experimental results and ANN model results.

	Training set		Test set	
	A value for $y = a.x$	**Standard error**	**A value for $y = a.x$**	**Standard error**
Slope	0.944		0.92223	
95% Lower Control Limit (LCL)	0.9015	0.02138	0.83822	0.0404
95% Upper Control Limit (UCL)	0.9865		1.00625	
Number of points	88		22	
Degrees of Freedom (DF)	87		21	
Sum of Squares for Error (SSE)	0.4098		0.08383	
Pearson's r	0.9784		0.98044	
Determination coefficient (R^2)	0.93110		0.93246	
Adjusted R^2	0.95678		0.95941	
Root Mean Square Error (RMSE)	0.06863		0.06318	

Table 6. ANOVA analysis of λ between experimental results and ANN model results.

		DF	**Sum of squares**	**Mean square**	**F value**	**Prob>F**
Training	Model	1	9.18029	9.18029	1948.977	0
	Error	87	0.4098	0.00471		
	Total	88	9.59009			
Test	Model	1	2.08012	2.08012	521.065	2.22045×10^{-16}
	Error	21	0.08383	0.00399		
	Total	22	2.16395			

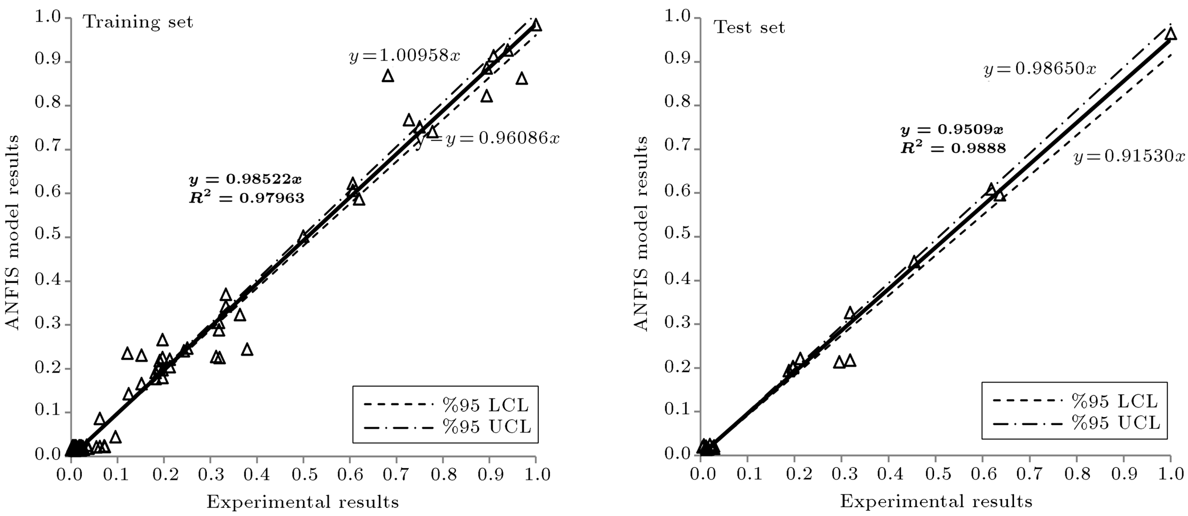


Figure 10. Relationships between the experimental and test data in the ANFIS model.

shown in Table 6, depending on the increase in standard error, given in Table 5, the significant values of test series slightly increase. Additionally, the significance level for $P < 0.01$ is statistically significant (non-random) [$F(1,87) = 1948.97729$, $P < 0.01$ for the training set; $F(1,21) = 521.06494$, $P < 0.01$ for the test set].

5.2. Results of the ANFIS model

The relationships between the experimental results and the ANFIS modeling results are shown in Figure 10. Both the relationship between the training set and the experimental results ($R^2 = 0.97963$) and the relationship between the test set and the experimental results ($R^2 = 0.9888$) were higher than the previous

Table 7. Statistical analysis of λ between experimental results and ANFIS model results.

	Training set		Test set	
	A value for $y = a.x$	Standard error	A value for $y = a.x$	Standard error
Slope	0.98522		0.9509	
95% Lower Control Limit (LCL)	0.96086	0.01226	0.9153	0.01712
95% Upper Control Limit (UCL)	1.00958		0.9865	
Number of points	88		22	
Degrees of Freedom (DF)	87		21	
Sum of Squares for Error (SSE)	0.13465		0.01505	
Pearson's r	0.99333		0.99661	
Determination coefficient (R^2)	0.97963		0.98880	
Adjusted R^2	0.98656		0.99292	
Root Mean Square Error (RMSE)	0.03934		0.02677	

R^2. In addition, especially the 95% confidence interval of relationship between the experimental values and the predicted values of the test set is achieved by the ANFIS model (Figure 10). Although the 95% confidence interval could not be obtained in the training set, greatly reduced scattering values were obtained.

The results of statistical analyses between the experimental λ and the model result in training and test series are shown in Table 7 for the ANFIS modeling. Like other modeling results, they have been obtained close to each other. The standard error value of slope obtained from the ANN modeling was bigger than that obtained from the ANFIS modeling. According to the relationships obtained from both linear analyses and ANN analyses, while the R^2 values increase, the RMSE values decrease. According to the linear regression from ANFIS modeling, the R^2 values of training and test data increased approximately 12%, according to the ANN modeling results, and the R^2 values experienced an approximately 6% of increase. Additionally, according to the linear regression results, the RMSE values decreased 59% for the training sets and 71% for the test sets.

As shown in Table 8, the best results for ANOVA analysis were obtained from the ANFIS modeling. The significance level for $P < 0.01$ was statistically significant [$F(1,87) = 6460.83471$, $P < 0.01$ for the training set; F (1, 21)=3086.11917, $P < 0.01$ for the test set].

6. Conclusions

The most important conditions for achieving renewable energy in buildings take into account the economics of energy consumption with effective design using new technologies and high quality construction materials. In order to optimize heating energy, heat loss should reduce in the opaque components and the heat should be provided, to the maximum degree, from other energy sources [38]. In addition, determination of the heat transfer coefficient of construction materials can provide comfortable conditions.

In this study, linear regression relationships between the values of thermal conductivity with surface density and the unit weight parameters of construction materials were investigated ($R^2 = 0.8766$ for G, $R^2 = 0.8844$ for S). In order to predict thermal conductivity using the inputs of these parameters, ANFIS and ANN models have been developed. As a result of the developed ANFIS and ANN models, determination coefficient between the predicted model values and the actual values for the test set were obtained as

Table 8. ANOVA analysis of λ between experimental results and ANFIS model results.

		DF	Sum of squares	Mean square	F value	Prob > F
Training	Model	1	9.99948	9.99948	6460.835	0
	Error	87	0.13465	0.00155		
	Total	88	10.13413			
Test	Model	1	2.21145	2.21145	3086.119	0
	Error	21	0.01505	7.16579×10^{-4}		
	Total	22	2.2265			

0.98880 and 0.93246, respectively. Furthermore, the validity of models in the inputs and output parameters was examined by statistical analysis. According to the results of all analyses (linear-ANN-ANFIS), it was concluded that statistical relationships were not random or significant ($P < 0.01$). The lowest RMSE was obtained from the ANFIS model; also, the highest R^2 for both the training sets and the test sets were obtained from the ANFIS model at the 95% confidence level. According to the analyses and evaluations, it was concluded that the thermal conductivity coefficient of construction materials can be determined as "Unit Weight" and "Surface Density" values by ANFIS. Although various algorithms to train the networks of ANN can be developed, those that can be implemented to predict problems should be trained by data [5,24]. Due to the fact that ANFIS has a combined learning algorithm, combination of decision-making specialty like to human of Fuzzy Logic together with predict ability of ANN, it can be given more positive results than only the ANN or linear regression.

References

1. Kindinis, A., Corgnati S.P., Bianco, E. and Yılmaz, Z. "An approach to active solar cooling system: Italy and Turkey for the sample application", *The Chamber of Mechanical Engineers, Mag. Plant Eng.*, **117**, pp. 12-20 (2010) (in Turkish).
2. Özel, C. and Polat, H. "Prediction of elastic modulus of polypropylene fiber containing concrete by fuzzy logic", *e-Journal of New World Sci. Acad. Eng. Sci., 1A0197*, **6**(4), pp. 789-807 (2011).
3. Terzi, S., Saltan, M. and Küçüksille, E.U. "Backcalculation of pavement layer thickness using data mining", *Neural Comput. & Applic.*, **23**, pp. 1369-1379 (2013).
4. Yücel, K.T. and Özel, C. "Modeling of mechanical properties and bond relationship using data mining process", *Adv. Eng. Softw.*, **45**, pp. 54-60 (2012).
5. Terzi, Ö. "Estimating daily pan evaporation using data mining process", *Scientia Iranica, Transactions A: Civil Engineering*, **20**(4), pp. 1077-1084 (2013).
6. Amani, J. and Moeini, R. "Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network", *Scientia Iranica, Transactions A: Civil Engineering*, **19**(2), pp. 242-248 (2012).
7. Zhu, B., He, C.H. and Niu, Y. "Using group method of data handling to model customer choice behavior", *Scientia Iranica, Transactions E: Industrial Engineering*, **21**(3), pp. 1051-1060 (2014).
8. Kohonen, T. "An introduction to neural computing", *Neu Netw*, **1**, pp. 3-6 (1988).
9. Gencel, O., Kocabas, F. and Diaz, J.J.C. "A comparative modeling study to estimate wear of concrete", *Neural Comput & Applic*, **24**, pp. 649-662 (2014).
10. Terzi, Ö. and Keskin, M.E. "Daily pan evaporation using artificial neural networks approach. Turkish Chamber Civil Engineers", *TeknikDergi*, **16**(4), pp. 3683-3693 (2005).
11. Esmaeili, M., Osanloo, F.R., Bazzazi, A.A. and Taji, M. "Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting", *Engineering with Computers*, **30**, pp. 549-558 (2014).
12. Doğan, E. and Akgüngör, A.P. "Forecasting highway casualties under the effect of railway development policy in Turkey using artificial neural networks", *Neural Comput & Applic*, **22**, pp. 869-877 (2013).
13. Aşkın, D., İskender, İ. and Mamızadeh, A. "Dry type transformer winding thermal analysis using different neural network methods", *J. Fac Eng. & Arc Gazi Univ*, **26**(4), pp. 905-913 (2011).
14. Rumelhart, D.E. and McCleland, J.L. "Parallel distributed processing explorations in the microstructure of cognition", MA: MIT Press, Cambridge (1986).
15. Wang, S. and Archer, N.P. "A neural network technique in modelling multiple person decision making", *Comp Oper Res*, **21**(2), pp. 127-142 (1993).
16. Rogers, J., *Object-Oriented Neural Networks in C++*, Academic Press, San Diego (1997).
17. Dubois, D. and Prade, H., *Fuzzy Sets and Systems: Theory and Applications*, Academic Press Inc. Ltd., London (1980).
18. Do, J., Song, H., So, S. and Soh, Y. "Fuzzy Methodology application for modeling uncertainties in chloride ingress models of RC building structure", *Comp & Conc*, **2**(4), pp. 325-343 (2005).
19. Do, J.Y. "Fuzzy inference based cover thickness estimation of reinforced concrete structure quantitatively considering salty environment impact", *Comp & Conc*, **3**(2), pp. 145-162 (2006).
20. Topcu, I.B. and Saridemir, M. "Prediction of rubberized concrete properties using artificial neural network and fuzzy logic", *Const. & Build Mat*, **22**, pp. 532-540 (2008).
21. Ramezanianpour, A.A., Shahhosseini, V. and Moodi, F. "A fuzzy expert system for diagnosis assessment of reinforced concrete bridge decks", *Comp & Conc*, **6**(4), pp. 281-303 (2009).
22. Terzi, S., Morova, N. and Karaşahin, M. "Determining of flexible pavement condition rating deduct value with fuzzy logic algorithm", *Int Sympn Innov Intel Syst & Appl*, pp. 161-168, Trabzon, Turkey (2009).
23. Jalal, M., Ramezanianpour, A.A., Pouladkhan, A.R. and Tedro, P. "Application of genetic programming (GP) and ANFIS for strength enhancement modeling of CFRP-retrofitted concrete cylinders", *Neural Comput & Applic*, DOI 10.1007/s00521-012-0941-2 (2012).
24. Gençoğlu, M., Uygunoğlu, T., Demir, F. and Güler, K. "Prediction of elastic modulus of steel-fiber reinforced concrete (SFRC) using fuzzy logic", *Comp & Conc*, **9**(5), pp. 389-402 (2012).

25. Dağ, A., Alkan, B. and Çıra, C.S. "Investigation of applicability of fuzzy modeling approach in thickness estimation of cement row materials", *e-Journal of New World Sciences Academy, Eng Sci*, **6**(1), pp. 88-97 (2011).
26. Demir, F. "A new way of prediction elastic modulus of normal and high strength concrete-fuzzy logic", *Cem & Conc Res*, **35**, pp. 1531-1538 (2005).
27. Özel, C. and Soykan, O. "ANFIS model for the prediction of compressive strength of concrete for fresh concrete properties", *Suleyman Demirel Univ Int J Tech Sci, Const Techy*, **4**(1), pp. 30-45 (2012).
28. Negnevitsky, M., *Artificial Intelligence; A Guide to Intelligent Systems*, Second Edition, Addison-Wesley Press, New York (2005).
29. Jang, J.S.R. "ANFIS: Adaptive-network based fuzzy inference systems. IEEE Transactions on Systems", *Man and Cybernetic*, **23**, pp. 665-685 (1993).
30. Elmas, Ç., *Fuzzy Logic Controllers*, Seçkin Publ, Ankara, Turkey (in Turkish) (2003).
31. Sobhani, J., Najimi, M., Pourkhorshidi, A.R. and Parhizkar, T. "Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models", *Build. Mat.*, **24**, pp. 709-718 (2010).
32. Ok, Y., Atak, M. and Akçayol, M.A. "A simple neuro fuzzy model for ISE 100 index prediction", *J. Fac Eng. & Arch Gazi Univ*, **26**(4), pp. 897-904 (2011).
33. Şentürk, S. "A different approach to factorial design with adaptive neuro fuzzy inference system", *J. Inst Sci & Tech Dumlupınar Univ*, **22**, pp. 57-74 (2010).
34. Hocaoğlu, F.O. and Kurban, M. "Adaptive network-based fuzzy inference system and the sun times forecast for Eskişehir region", *Electrical-Electronics-Computer Engineering, 11th National Conference and Exhibition*, Istanbul (in Turkish) (2005).
35. Yeşilata, B., Turgut, P. and Işıker, Y. "Composite building materials thermal property measurement-1: Evaluation of existing measurement techniques", *Eng. & Mach*, **48**(654), pp. 2-9 (In Turkish) (2007).
36. TS 415 EN 12939, "Thermal performance of building materials and products - Determination of thermal resistance by means of guarded hot plate and heat flow meter methods - Thick products of high and medium thermal resistance", *Turkish Stand Inst*, Ankara, Turkey (2005).
37. TS ISO 8302 "Thermal insulation; determination of steady-state thermal resistance and related properties; guarded hot plate apparatus", *Turkish Stand Inst*, Ankara, Turkey (2002).
38. Özel, C. "Exterior wall detailed proposals of suitable for conditions of region with construction materials produced in Isparta region", M.Sc. Thesis, Süleyman Demirel University, Graduate School of Applied and Natural Sciences, Department of Construction Education, Isparta, Turkey (In Turkish) (2001).

Biographies

Cengiz Özel is an Associate Professor at the Faculty of Technology in Suleyman Demirel University, Isparta, Turkey. He received his MS and PhD degrees in Construction Education in 2001 and in Civil Engineering in 2007, respectively, from Suleyman Demirel University. His research interests include rheology and workability of fresh concrete and the thermo-physical and thermo-mechanic properties of construction materials.

Alper Topsakal obtained his MS degree in Construction Education from Suleyman Demirel University, Isparta, Turkey, in 2013. His research interests include construction materials.