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Araştırma Makalesi

Prediction Thermal Conductivity of The Novel Developed Light Weight Concrete with Artificial Neural Networks

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ABSTRACT

The dependence on energy is increasing in a growing population and a rapidly developing global world. Around 40% of the energy consumed is consumed in buildings. Building heating and cooling have boosted energy consumption and costs dramatically. As a consequence, in order to boost energy efficiency in buildings, it becomes inevitable to develop new construction materials with thermal insulation properties. Vermiculite, waste basalt powder, molten tragacanth, and cement-reinforced samples were produced for this purpose. Mechanical and thermal conductivity tests were performed on 48 samples produced at various rates. The findings of the experimentally measured thermal conductivity were modelled and compared with the outputs of the created artificial neural network. The Matlab software was used for modelling. The mechanical properties acquired experimentally using the Artificial Neural Networks (ANN) approach were used as an input, and the correlation of the samples with thermal conductivity was investigated. The findings obtained were consistent with one another, and the thermal conductivity values were predicted with an error ranging between 7.6701% and 0.0091%, and the ANN yielded successful results at a rate of 99%.

Keywords: *Expanded vermiculite, waste basalt powder, thermal conductivity, artificial neural networks*

Yeni Geliştirilmiş Hafif Betonun Yapay Sinir Ağlarıyla Isıl İletkenliğinin Tahmini

Öz

Artan nüfus ve hızla gelişen küresel dünyada enerjiye olan bağımlılık giderek artmaktadır. Harcanan enerjinin yaklaşık %40'ı yapılarda tüketilmektedir. Yapıların ısıtılması ve soğutulması ile enerji tüketimi ve maliyeti oldukça artmıştır. Bu nedenle yapılarda enerji verimliliğini arttırmak için ısıl yalıtım özelliğine sahip yeni yapı malzemeleri üretmek kaçınılmaz olmuştur. Bu amaçla vermikülit, atık bazalt tozu, eriyik kitre ve çimento katkılı numuneler üretilmiştir. 48 adet farklı oranlarda üretilen numunelere mekanik deneyler ve ısıl iletkenlik deneyi yapılmıştır. Deneysel olarak ölçülen ısıl iletkenlik sonuçları geliştirilen yapay sinir ağı çıkışlarıyla modellenerek karşılaştırılmıştır. Modelleme için Matlab paket programı kullanılmıştır. Yapay Sinir Ağı (YSA) yaklaşımı ile deneysel olarak elde edilmiş mekanik özellikler giriş olarak kullanılmış ve numunelerin ısıl iletkenlik ile ilişkisi incelenmiştir. Bulunan sonuçların birbirleriyle uyumlu olduğu ve ısıl iletkenlik değerlerinin % 7,6701 ile % 0,0091 arasında bir hata ile tahmin edildiği ve YSA'nın % 99 oranın da başarılı sonuçlar verdiği görülmüştür.

Anahtar Kelimeler: *Genleştirilmiş vermikülit, atık bazalt tozu, ısıl iletkenlik, yapay sinir ağları*

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I. INTRODUCTION

The preference of building materials with low thermal conductivity and low density is a sought-after feature for sustainability in buildings. In recent years, energy costs and price increases in building materials have brought natural materials that are low in costs and resistant to heat conduction to the agenda. [1]. Therefore, lightweight concrete can be produced by using natural lightweight aggregates. Lightweight concrete has become widely used in recent years due to some of its technical, economic and environmental benefits. [2]. Lightweight concrete is a type of concrete produced using cement, water, aggregate and lightweight aggregate. It may contain chemical and mineral additives as in conventional concrete. [3].

Lightweight aggregates used in the production of lightweight concrete are of two types, natural and artificial aggregates. Since the production of artificial lightweight aggregate will be costly, the use of natural aggregates is generally preferred in the production of lightweight concrete. Natural lightweight aggregates are aggregates obtained by crushing volcanic rocks or sedimentary stones. Artificial lightweight aggregates are aggregates obtained as a result of heat treatment of natural stones or as a result of industrial wastes. Aggregates such as pumice, volcanic tuff, and volcanic slag are examples of natural lightweight aggregates. Aggregates such as expanded clay, perlite and vermiculite are used as artificial lightweight aggregates. Experiments are carried out to determine the nature of the correlation between the variables that comprise the facts in manufacturing systems. Experiments are generally carried out by either monitoring outputs through collecting samples from the actual system or simulating system behavior in settings that may reflect the genuine system, it is costly to perform the experiments because the calculations are difficult in these experiments due to too many independent variables, the results of the intermediate values are not known when taking samples for the experiments, and time is required to obtain the results [4].

Time and economic factors require businesses to work based on these two key factors in the modern day. At some point, saving time means saving money. Therefore, generalizations must be made utilizing data from past experiments, and solutions to the relevant event must be produced by associating with past instances of experiments that have not previously been done using this generalization. The use of techniques such as genetic algorithms, neural networks, and artificial intelligence to solve problems appears as a result of the works undertaken for this purpose. Recently, particularly with the widespread use of computer technology, the manufacturing of computers capable of processing at high speeds has enabled the use of more sophisticated solution methods. Neural networks, genetic algorithms and artificial intelligence appear as alternatives to the classical methods used [4]. Artificial Neural Networks (ANNs) are parallel and distributed information processing structures inspired by the human brain, linked by weighted connections, and composed of processing elements, each with its own memory. ANNs are computer programs simulating biological neural networks [5]. In recent years, ANN technology, a sub-branch of artificial intelligence, has been used for the complete solution of problems in civil engineering applications. The capability of ANNs to learn directly from examples is their most crucial property in civil engineering applications. Another important property of ANNs is that they complete unfinished tasks properly or almost do, extract accurate information from insufficient data, and produce generalized outcomes from new situations [6]. A specific equation is not required for ANNs. Instead, it requires an adequate quantity of input-output data. It can also train new data continuously to match new data. ANNs are investigated in order to solve problems that include insufficient or inaccurate information [7].

ANNs are often successful in tasks in model selection and classification, function estimation, optimum value determination, and data classification [5]. The function approximation feature of ANN was used in this study. The capability of ANN to learn is its most distinctive property. ANNs are capable of adapting to environmental changes. From an engineering perspective, it is requested to shorten the time necessary for the adaptation process while maintaining the stability of the network's optimal state [8]. The main strategy for developing a neural network-based model related to material behavior is to train the neural network based on the results of a series of experiments using this material. If the experimental results include significant information about the material behavior, the trained artificial network will include sufficient knowledge about the behavior of the material qualified as a material model. Through its generalization capacity, such a trained artificial network will be able to approximate other experimental results in addition to reproducing the experimental results [9]. In the literature, estimation has been made using ANN in many areas. For example; Thermal system design is modeled with artificial neural networks and adaptive network-based fuzzy inference systems for fifty cities in Turkey using the data obtained from the General Directorate of Meteorology (MGM). They used Matlab software for high precision modeling and forecasting of prospective data in thermal systems [10]. Using the estimated temperature values for Turkey, heating degree days (HDD) and cooling degree days (CDD) values were calculated to analyze the energy demand of buildings. In the study, artificial neural network (ANN) and adaptive network-based fuzzy inference system (ANFIS) were used for the estimation of temperature values. [11].

Vermiculite used in this study is a magnesium alumino silicate clay mineral formed by the natural erosion of mica obtained from volcanic magma sources. By processing with high heat, its volume expands, its permeability increases and the volume weight decreases significantly and changes shape. When the vermiculite granules are heated at temperatures of 1000^{o}C and above, the water between the stone layers suddenly evaporates, causing the volume of the granules to increase 15-20 times.. Expanded vermiculite (EV) is used for thermal insulation in the form of loose fill in structures, as well as it is produced in the form of sheets by adding bitumen and various synthetic adhesives and molding. On the other hand, the blocks of waste basalt powder supplied from Diyarbakır-Karacadağ are cut in the factory and sized according to their usage areas. During this cutting process, basalt dusts, which are considered as waste, are formed. These waste dusts are stored in an area by the business owners as inoperable. The properties of Diyarbakır-Karacadağ basalt such as high abrasion resistance, low thermal conductivity, resistance to acids and frost have led to the diversification of usage areas and increased studies on this material. Tragacanth in the samples is a kind of gum obtained by drying the resin under natural conditions from the thorny plant called Astragalus. It is a highly branched, heterogeneous, hydrophilic, carbohydrate polymer. It is 1–3 cm long, at least 0.5 cm wide, as dull white or yellowish strips. It is obtained as a result of cuts made on the bole. It gives high viscosity to the product it is added to the tragacanth and has no smell

The aim of this study is to approximate the experimentally determined thermal conductivity coefficients of lightweight concrete samples based on expanded vermiculite, waste basalt powder and tragacanth-added cement, produced at different rates, using ANN. For this purpose, the thermal conductivity change of lightweight concrete was estimated by means of the MATLAB program, depending on the mechanical test results of the samples. Furthermore, the artificial neural network model used in this study has one hidden layer with eight neurons in it. The output layer's number of neurons is set to one. Activation function was chosen as tangent sigmoid (tansig) for the neurons in the hidden layer and logarithmic sigmoid (logsig) for the neurons in the output layer. The network was trained using the Levenberg-Marquardt (trainlm) learning algorithm. The artificial neural network's performance was evaluated using 6-fold cross-validation. Some of the previous experimental findings were given into the network as a training set, and the network was trained. After the network was trained, the experimental data that had not been given into the network during the training were given into the network as input. The ANN outputs were compared with the experimental data.

II. ARTIFICIAL NEURAL NETWORKS

Processing or analyzing large amounts of data manually wastes a significant amount of time and effort. Hence, numerous artificial intelligence methods have been developed for predicting future data based on previous data. Artificial neural networks are widely used in almost every aspect of life because they are a computational method that adapts to their environment, are adaptable, can function with insufficient information, can make decisions under uncertainties, and is error tolerant. As in many artificial intelligence methods, it is aimed to learn the way to solve a problem with the data available in artificial neural networks and to use this learned path in solving new data sets or problems [12]. Figure 1 depicts a multi-layered artificial neural network with several neurons linked. The hidden layer is the layer between the input and output layers.

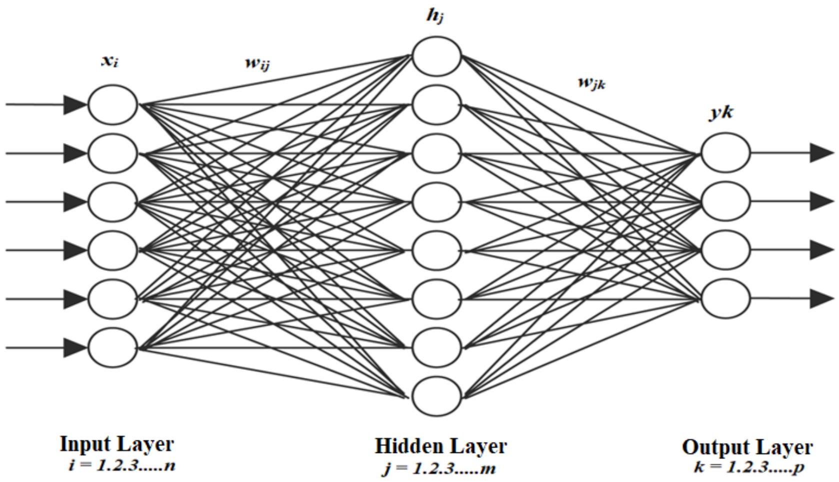

Figure 1: *Artificial Neural Network Model*

Where, the *j*. neuron in the hidden layer is connected to input vectors as $x_{i=}(x_1, x_2, x_3, ...x_n)$.
Where, the net input values in the hidden layer are expressed by the following equation;

$$\text{Net}_j = \sum_{i=1}^{n} x_i\, w_{ij} + \beta_j \tag{1}$$

After the net input of each neuron in the hidden layer is calculated, it is processed by the activation functions they have and transmitted to the output of the neurons.

$$h_j = \psi(\text{Net}_j) = \psi(\sum_{i=1}^{n} x_i\, w_{ij} + \beta_j) \tag{2}$$

Where, the symbols indicate;
x_i = input vectors,
w_{ij} = the weight value on the input *i* and neuron *j* connection,
β_j = bias value,
n = number of input,
$\psi(.)$ = activation function of the hidden layer,
h_j = output of neuron *j* in the hidden layer.

Each neuron in the output layer creates a net input for itself by taking and summing the outputs from the hidden layer with the effect of connection weights w_{ij}. The net input for any neuron in the output layer is;

$$\text{Net}_k = \sum_{j=1}^{m} h_j\, w_{jk} + \beta_k \tag{3}$$

Output, on the other hand, is calculated with the following equation;

$$y_k = \phi(\text{Net}_k) = \phi(\sum_{j=1}^{m} h_j\, w_{jk} + \beta_k) \tag{4}$$

Where, the symbols indicate;
w_{jk} = the weight value on connection between the input *j* and neuron *k*,
β_k = bias value,

$\phi(.)$ = the activation function of the output layer,
y_k = output of the neuron k in the output layer.

An input vector and a corresponding output vector are presented to the network throughout the learning process of artificial neural network. To calculate its output, the network uses weights and thresholds. Initially, this output is often incorrect. During training, adjustments are made. While making these adjustments, the network output is compared with the actual output. This comparison;

$$e = y_g - y_k \tag{5}$$

Where,
y_k = the output value of the artificial neural network,
y_g = actual output value,
e = the error value.

The total error function is calculated with the following equation;

$$E = 0.5 \sum_{k=1}^{p} (y_g - y_k)^2 \tag{6}$$

Training of an artificial neural network is essentially the process of finding the best weights for the network by adjusting the weights. In this process, the backpropagation learning method is used. This algorithm aims to adjust the weights in the network, bringing the artificial neural network's output value closer to the real output value. The gradient descent method is used to accomplish this purpose. The gradient descent method is a strong and versatile optimization method that uses the first derivative to converge the local minimum. The weights are updated until the errors between the outputs of the artificial neural network and the real outputs are at an acceptable level. The testing process begins once the artificial neural network is trained [13].

A. K FOLD CROSS VALIDATION

The dataset to be tested is divided into k sub-data pieces for the k-fold cross-validation test. Then, k-1 of these sub-data pieces are used in the training of the artificial neural network, while the remaining sub-data piece is used in the testing of the artificial neural network. This process is repeated k times until all feasible sub-data pieces are used in testing of the artificial neural network. Thus, the complete data set is tested, and a conclusion regarding the complete data is reached.

III. EXPERIMENTAL STUDY AND EVALUATION

Vermiculite used in the experiments was supplied from Demircilik vermiculite quarry (in Sivas Yıldızeli). Raw vermiculite was heated at 800°C for 20 seconds to produce expanded vermiculite. The expanded vermiculite was initially subjected to pre-treatments such as drying, grinding and sieving.
In this study, vermiculite and waste basalt powder were sized with particle size less than 200 μm. The specific gravity of vermiculite is 0.22 g/cm^3 and the waste basalt powder is 1.21 g/cm^3. As a waste basalt powder additive, the aqueous wastes generated during the production of the basalt type produced by Dibaz Bazalt Fabrika Ticaret A.Ş. (in Karacadağ, Diyarbakır, Turkey) were dried and ground [14]. Tragacanth resin was ground into a powder using a grinder. 100 g of powdered tragacanth resin, weighed with a balance, was placed in a 5-litre container filled with water and mixed thoroughly. For the preparation of samples, expanded vermiculite at 10 wt.%, 30 wt.%, 50 wt.%, and 70 wt.%, waste basalt powder at 5 wt.%, 10 wt.%, 15 wt.%, and 20 wt.%, and molten tragacanth at 0 wt.%, 0.5 wt.%, and 1 wt.% were put in the mixture bucket together with cement. It was mixed homogeneously in a mechanical mixer. W/C=0.40 was calculated in the production of the samples. In this study, when the effect of tragacanth on the thermal conductivity coefficient is examined, it is that it has a low thermal conductivity coefficient and that the tragacanth in liquid form carries the air-filled pores in its structure to the mixture at the end of drying and creates artificial pores. Mixture percentages and coding of the samples produced

are shown in Table 1. Thermal conductivity tests of the produced samples were performed using plywood molds of 20x60x150 mm and mechanical tests using plywood molds of 100x100x100 mm. The samples were kept in the molds for 24 hours. They were then taken out of the molds through vibration and stored at ambient temperature for 28 days [15].

The samples taken out of the mold were tested for density, compressive strength, porosity, and thermal conductivity. The thermal conductivity coefficients were measured using the Shotherm QTM-D2 instrument, which was developed in accordance with DIN51046 and operates using the hot-wire method, and the thermal conductivity coefficient was measured in the transient regime. 48 events were used in the lightweight concrete produced. Table 2 shows the results, as well as the ANN results.

Table1. *The codes of the ratios as weighted percent of the samples produced*.

The first number	The second number	The third number	Cement Ratio (%wt)
10% expanded vermiculite **(1)**	5% waste basalt powder **(1)**	0.0% tragacanth ratio **(0)**	85%
30% expanded vermiculite **(3)**	10% waste basalt powder **(2)**	0.5% tragacanth ratio **(1)**	60%
50% expanded vermiculite **(5)**	15% waste basalt powder **(3)**	1% tragacanth ratio **(2)**	35%
70% expanded vermiculite **(7)**	20% waste basalt powder **(4)**		10%

Table 2. *Experimental and ANN results*

Dataset number	Sample code	Density (g/cm3)	Porosity (%)	Compressive Strength (MPa)	Experimental Thermal conductivity (k) (W/mK)	ANN Thermal conductivity (k) (W/mK)
1	**110**	1.972	0.301	39.90	0.5220	0.5186
2	**120**	1.676	0.338	36.47	0.4810	0.4727
3	**130**	1.570	0.385	31.73	0.4020	0.4088
4	**140**	1.348	0.416	30.76	0.3920	0.3902
5	**310**	1.911	0.319	37.30	0.5040	0.5123
6	**320**	1.706	0.354	35.05	0,4670	0.4508
7	**330**	1.428	0.397	30.37	0,3830	0.3780
8	**340**	1.137	0.445	25.37	0.2820	0.2784
9	**510**	1.607	0.364	31.67	0.3950	0.3987
10	**520**	1.342	0.403	28.96	0.3580	0.3569
11	**530**	1.218	0.419	26.27	0.3040	0.2968
12	**540**	1.014	0.446	23.89	0.2580	0.2571
13	**710**	1.466	0.401	30.35	0.3770	0.3767
14	**720**	1.280	0.417	28.81	0.3540	0.3588
15	**730**	1.089	0.443	26.17	0.3020	0.2964
16	**740**	0.89	0.466	22.85	0.2510	0.2575
17	**111**	1.878	0.322	35.17	0.4680	0.4690
18	**121**	1.596	0,361	33.71	0.4330	0.4303
19	**131**	1.496	0.412	29.00	0.3620	0,3621
20	**141**	1.284	0.445	28.42	0.3530	0,3362
21	**311**	1.820	0.341	34.00	0.4540	0.4494
22	**321**	1.625	0.379	32.77	0.4210	0.4259
23	**331**	1.360	0.425	27.88	0.3450	0.3424
24	**341**	1.083	0.476	23.77	0.2540	0.2511
25	**511**	1.531	0.389	28.86	0.3550	0.3566
26	**521**	1.278	0.431	27.58	0.3220	0.3264
27	**531**	1.160	0.449	24.17	0.2730	0.2607
28	**541**	0.966	0.477	22.62	0.2320	0.2390
29	**711**	1.396	0.420	27.76	0.3390	0.3331
30	**721**	1.219	0.447	26.57	0.3190	0.3139
31	**731**	1.037	0.473	24.16	0.2720	0.2658
32	**741**	0.848	0.498	21.67	0.2260	0.2260

33	**112**	1.784	0.359	32.66	0.4060	0.4208
34	**122**	1.517	0.303	30.26	0.3760	0.3851
35	**132**	1.421	0.458	26.47	0.3140	0.3218
36	**142**	1.219	0.496	21.88	0.2280	0.2241
37	**312**	1.729	0.379	31.09	0.3940	0.3848
38	**322**	1.544	0.421	29.82	0.3650	0.3643
39	**332**	1.292	0.473	25.86	0.2990	0.2926
40	**342**	1.029	0.529	21.53	0.2230	0.2059
41	**512**	1.454	0.433	26.46	0.3080	0.3179
42	**522**	1.214	0.480	25.13	0.2790	0.2838
43	**532**	1.102	0.499	22.81	0.2370	0.2378
44	**542**	0.917	0.530	21.47	0.2020	0.2103
45	**712**	1.326	0.467	25.52	0.2940	0.2956
46	**722**	1.158	0.497	24.55	0.2770	0.2780
47	**732**	0.985	0.527	22.72	0.2360	0.2386
48	**742**	0.806	0.554	20.27	0.1960	0.2036

A. DATASET CLUSTER

The artificial neural network model used in this study had one hidden layer and the number of neurons in this layer is eight. The number of neurons in the output layer was chosen as one. Activation function was chosen as tangent sigmoid (tansig) for the neurons in the hidden layer and logarithmic sigmoid (logsig) for the neurons in the output layer. The network was trained using the Levenberg-Marquardt (trainlm) learning algorithm. The artificial neural network's performance was evaluated using 6-fold cross-validation. The MATLAB® R2019a software was used to conduct all analyses for the ANN designed in this study. The maximum error produced by the ANN was 7.6701%, the minimum error was 0.0091%, and the mean error (arithmetic mean) was 1.7616%. The aggregate ratio, density, compressive strength, porosity, and thermal conductivity were determined in the input layer, and all input parameters were inputted as described above using the ANN model. Table 3 shows the use of these input parameters for the training and test sets.

Table 3. *6-fold cross-validation table*

Input Data	Use Cases of Data for Training and Testing		
48 input sets (density, compressive strength, porosity, thermal conductivity)	1	9-48 Training Set	1-8 Test Set
	2	1-8:17-48 Training Set	9-16 Test Set
	3	1-16:25-48 Training Set	17-24 Test Set
	4	1-24:33-48 Training Set	25-32 Test Set
48 output sets (thermal conductivity)	5	1-32:41-48 Training Set	33-40 Test Set
	6	1-40 Training Set	41-48 Test Set

The thermal conductivity coefficient decreased when the ratio of expanded vermiculite, waste marble powder, and molten tragacanth in the sample increased, as shown by the data in Figure 2. This is due to the fact that these aggregates formed pores in the sample. Furthermore, when the effect of tragacanth on the thermal conductivity coefficient was examined, tragacanth had a low thermal conductivity coefficient, and the tragacanth in liquid form transmitted the air-filled pores in its structure to the mixture at the end of drying, creating additional artificial pores. Figure 3 shows the thermal conductivity data acquired by ANN. In both situations, the findings were found to be in agreement.

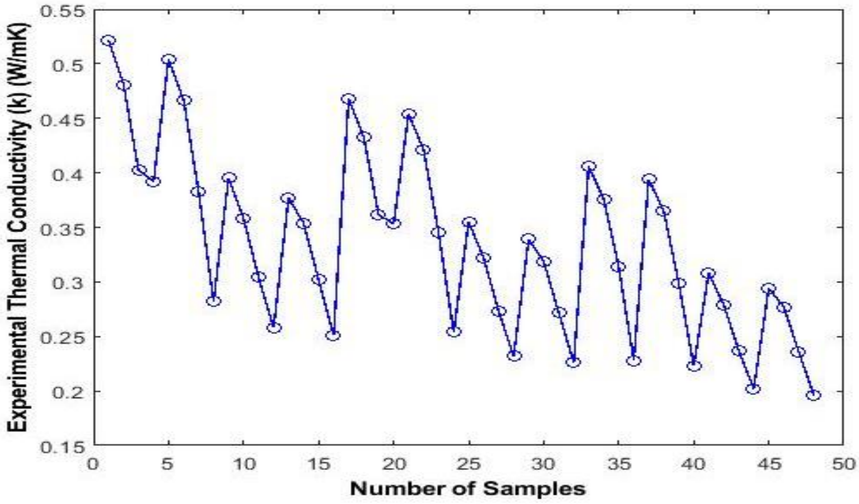

Figure 2. Experimental thermal conductivity graph by Dataset Number

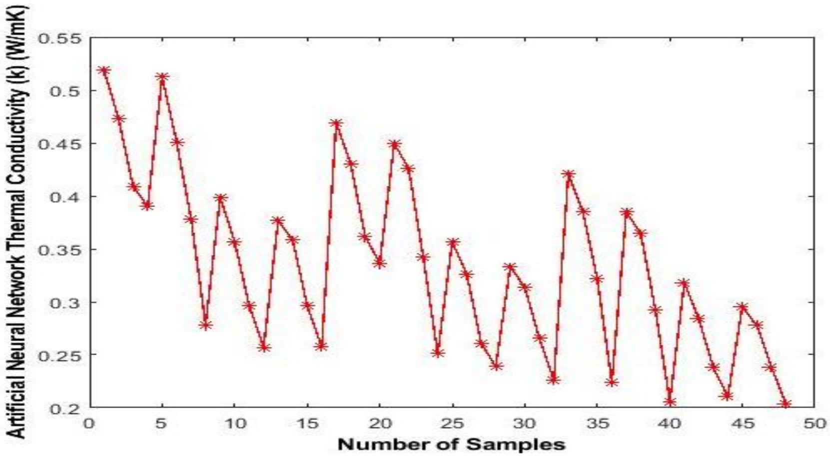

Figure 3. Thermal conductivity output graph obtained as a result of ANN according to Dataset Number

Experimental data were very close to the expanded vermiculite, waste marble dust and melt tragacanth rates with the obtained modelling, the thermal conductivity of each lightweight concrete containing 10-70% expanded vermiculite, 5-20% waste marble dust and 0-1% molten tragacanth were estimated and given graphically. Figure 4 shows the effect of the variation of expanded vermiculite, waste marble dust and melt tragacanth ratio on the thermal conductivity coefficient together with the data tested using the trained mesh.

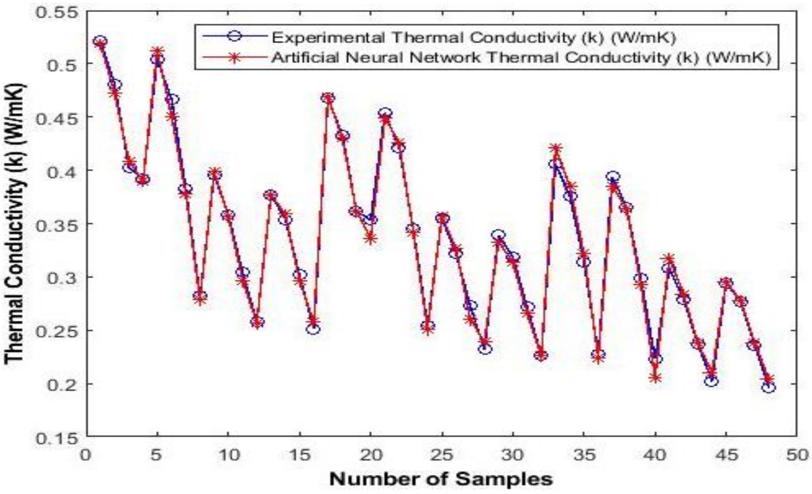

Figure 4. *Experimental And Artificial Neural Network Thermal Conductivity Graph*

Figure 5 shows the difference between the values generated by ANN and the experimental values. The maximum rate of difference was discovered to be 0.17104 in sample no: 40, which comprised 30% vermiculite, 20% waste basalt powder, and 1% molten tragacanth mixtures, as shown in the Figure. Furthermore, the minimum difference rate was observed to be 0.000021 in sample no: 32, which contained 70% vermiculite, 20% waste basalt powder, and 0% molten tragacanth mixture. The rate of difference between the data in all other mixture rates ranged between ± 0.005563 on average.

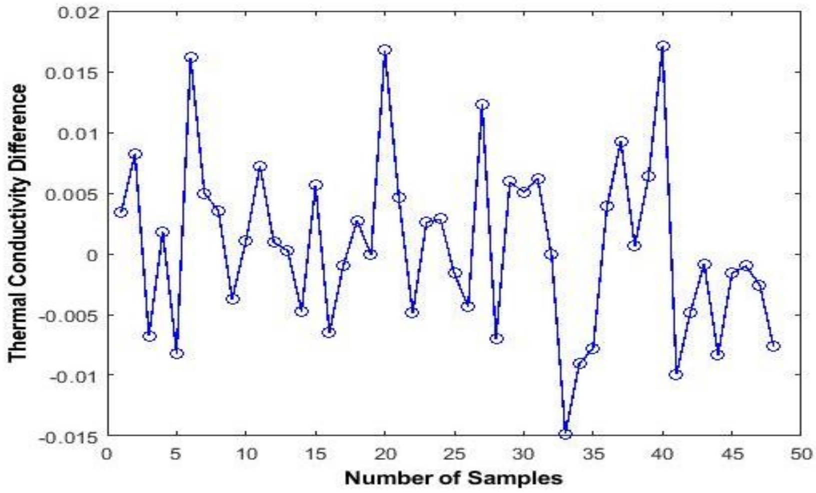

Figure 5. *Difference graph between thermal conductivity obtained from experimental and ANN according to Dataset Number*

Figure 6 also shows the rate of error between the estimated value and the experimental data. The maximum error rate was detected in sample no: 40, which composed of 30% vermiculite, 20% waste basalt powder, and 1% molten tragacanth mixture, as shown in the figure, and the maximum error rate was 7.6701%. Furthermore, the minimum error rate was 0.0091% in sample no: 32, which composed of 70% vermiculite, 20% waste basalt powder, and 0% melted tragacanth mixture. The rate of error between the data in all other mixture rates also ranged between ± 1.7616 % on the average. As can be seen from here, the model created was quite reliable.

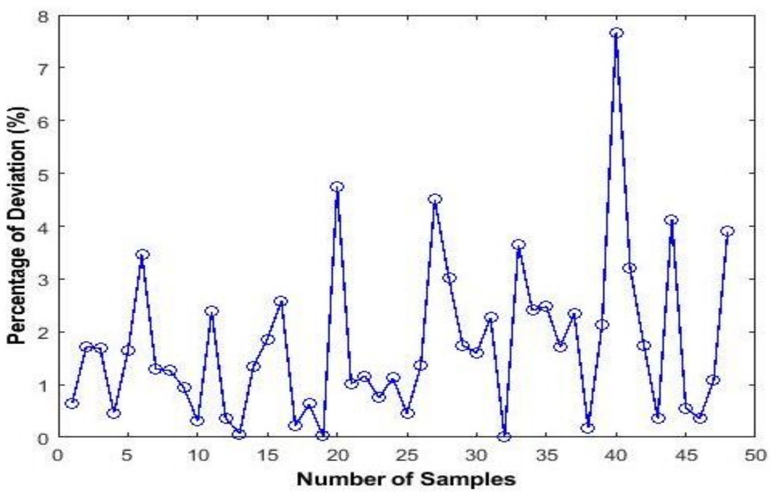

Figure 6. *Percent error graph between thermal conductivity obtained from experimental and ANN according to Dataset Number*

For the experimental data, the backpropagation network algorithm was trained and tested with an error value of 10-4. As a result, the convergence value of the network’s training and test values, as shown in Figure 7, was determined to be 99%. Due to the high reliability of the trained values of the network, the thermal conductivity values were tested for 10-70% vermiculite, 5-20% waste marble dust, and 0-1% melt tragacanth rates, and the convergence degrees of these values were 99%, as shown in Figure 7.

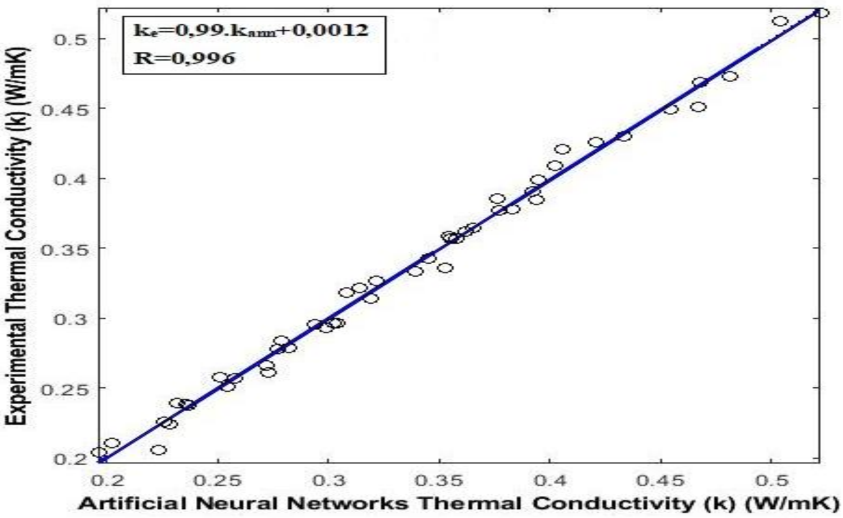

Figure 7. *Regression graph between experimental and ANN thermal conductivities*

IV. CONCLUSION

The experimental thermal conductivity values obtained due to the different rates of expanded vermiculite, waste marble powder, and molten tragacanth substitute in the lightweight concrete mixture were found to be compatible with the thermal conductivity values obtained with the artificial neural network approach model. Experimental studies are studies that take a long time, may cause environmental problems and financial consequences by using materials, and also need the employment of technical experts. As a consequence, by employing artificial intelligence models such as artificial neural networks, these losses and needs in experimental studies may be decreased to a lower rate by achieving findings that are extremely close to experimental study results. Because the thermal conductivity values of the lightweight concrete to be made with materials at different rates affect the compressive strength of the generated samples, it is vital in practice to be able to predict these lightweight concretes based on their intended application. This study also supports the idea that artificial neural networks, the most common artificial intelligence techniques, are a significant tool that can be used safely in this field to get the needed data while spending less material, labor, and time. Aside from the parameters used in this study, some other values of concrete samples to be made with other materials may be modelled in a much shorter time and with very little input in a much faster and economic manner. It was observed that problems that can be solved experimentally in a very long time were solved in a very short period and with a very low error rate using ANN. When the ANN results were analyzed, it was observed that the maximum error rate was “7.6701%” and the minimum error rate was “0.0091%”.

V. REFERENCES

[1] Duaij, J. A. A., El-Laithy K. and Payappilly R. J., “A value engineering approach to determine quality lightweight concrete aggregate,” *Cost Engineering*, c.39, ss. 21-26, 1997.

[2] V. Khonsari, E. Eslami, and A. Anvari, “Effects of expanded perlite aggregate (EPA) on the

mechanical behavior of lightweight concrete," *in Proceedings of the 7th international conference on fracture and mechanics of concrete & concrete structure (FraMCoS-7),* Jeju, Korea, ss. 1354–1361, 2010.

[3] S. Chandra and L. Berntsson, "Applications of lightweight aggregate concrete," *Science, Technology,* 2002.

[4] Ö. Hasgül, A. S. Anagün "The use of artificial neural networks in the analysis of experimental Results and An Application for Concrete Strength Testing," *V. National Production Research Symposium*, Istanbul, ss. 133-139, 2005.

[5] Ç. Elmas, "Artificial intelligence applications," 5th edition, Ankara, Turkey: *Seçkin Publishing*, ss.1-480, 2007.

[6] M. Sarıdemir, "Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks," *Advances in Engineering Software,* c. 40, ss. 350-355, 2009.

[7] S.C. Lee, "Prediction of concrete strength using artificial neural networks," *Engineering Structures,* 25, ss. 849–857, 2003.

[8] J. Hertz, A. Krogh, and R. Palmer, "An introduction to the theory of neural networks," *Lecture Notes*, vol. 1. *Studies in the Sciences of Complexity*. Addison-Wesley, Redwood City,1991.

[9] A. Öztas, "Predicting the compressive strength and slump of high strength concrete using neural network," *Construction and Building Materials*, c. 20, ss.769–775, 2006.

[10] Işık, E., Inallı, M., "Artificial neural networks and adaptive neuro-fuzzy inference systems approaches to forecast the meteorological data for HVAC: The case of cities for Turkey," *Energy,* 154, ss. 7-16, 2018.

[11] Işık, E., İnallı, M., Celik, E., "ANN and ANFIS approaches to calculate the heating and cooling degree day values: The case of provinces in Turkey," *Arabian Journal for Science and Engineering,* 44(9), ss. 7581-7597, 2019.

[12] E. Öztemel, "Artificial neural networks," 3rd edition, Istanbul, Turkey: *Papatya Publishing*, ss. 1-44, 2012.

[13] M. Khandelwal, "Prediction of thermal conductivity of rocks by soft computing," *International Journal of Earth Sciences*, c.100, s. 6, ss.1383-1389, 2011.

[14] F. Koçyiğit, F. Ünal, Ş. Koçyiğit,"Experimental analysis and modeling of the thermal conductivities for a novel building material providing environmental transformation," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects,* c. 42, s.24, ss.3063-3079, 2020.