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Sustainable Supplier Selection with Adaptive Network - Based Fuzzy Inference System (ANFİS) [1]

Adaptif Ağ Tabanlı Bulanık Çıkarım Sistemi (ANFIS) ile Sürdürülebilir Tedarikçi Seçimi

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Abstract

Choosing the right sustainable supplier is a critical decision problem for businesses. Due to the increase in the number of competitors, the increase in evaluation criteria and the difficulty in defining evaluation criteria, the need for reliable methodologies that work with high accuracy increases as the complexity of the selection problem increases. This article discusses a new approach to the problem of sustainable supplier selection based on the Adaptive Network-Based Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) methods. In the study, firstly the sustainable supplier selection criteria have been reduced to four criteria by the ANFIS method. For sustainable supplier performance evaluation, ANFIS model and ANN model were developed. Multiple regression analysis was performed to compare the performance success of both models. The model with the highest success rate was determined as ANFIS model. At the end of the study, the most suitable sustainable supplier selection was made with ANFIS model.

Keywords: *Adaptive Network-Based Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), Supplier Selection, Sustainability.*

Jel Codes: *C60, C45, M11.*

Öz

Doğru sürdürülebilir tedarikçiyi seçmek işletmeler için kritik bir karar problemidir. Rekabetin artması, karar vermede dikkate alınacak değerlendirme kriterlerinin tanımlanmasının zorlaşması ve değerlendirme kriterlerinin artması nedeniyle, doğru tedarikçinin seçimi karmaşık hale gelmiş, bu nedenle yüksek doğrulukla çalışan güvenilir metodolojilere olan ihtiyaç da artmıştır. Bu makalede, Adaptif Ağ Tabanlı Bulanık Çıkarım Sistemi (ANFIS) ve Yapay Sinir Ağı (YSA) yöntemlerine dayalı olarak sürdürülebilir tedarikçi seçimi sorununa yeni bir yaklaşım getirilmesi amaçlanmıştır. Çalışmada öncelikle sürdürülebilir tedarikçi seçim kriterleri ANFIS yöntemiyle dört kritere indirilmiştir. Sürdürülebilir tedarikçi performans değerlendirme için, ANFIS modeli ve YSA modeli geliştirilmiştir. Her iki modelin performans başarısını karşılaştırmak maksadıyla çoklu regresyon analizi gerçekleştirilmiştir. En yüksek başarı oranına sahip model ANFIS modeli olarak belirlenmiştir. Çalışmanın sonunda ANFIS modeli ile en uygun sürdürülebilir tedarikçi seçimi yapılmıştır.

Anahtar Kelimeler: *Adaptif Ağ Tabanlı Bulanık Çıkarım Sistemi (ANFIS), Yapay Sinir Ağı (YSA), Tedarikçi Seçimi, Sürdürülebilirlik*

Jel Kodları: *C60, C45, M11.*

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1. INTRODUCTION

With the development of information and communication technologies, the transition of businesses from traditional markets to the global market has become inevitable. To maintain their global activities, gain a competitive advantage to hold on in the global market, and ensure the continuity of their activities, they need to provide efficiency and productivity throughout their supply chains (Lin et al., 2009: 6461).

Businesses need to develop sustainable strategies to gain competitive advantage. In this context, sustainable supply chain management is a collaboration management that takes into account sustainable development, environmental, economic and social dimensions derived from the needs of stakeholders and customers, and at the same time ensures the continuity of capital, material and information flows between businesses throughout the supply chain (Toprak et al, 2024: 2).

Businesses that put the concept of sustainability on their agenda in their supply chains gain cost advantage while also gaining corporate reputation. Brand value increases when the company acts with environmental awareness, is sensitive to the environment, engages in activities that do not harm human life and space, and conducts its activities with a sustainable framework and perspective.

Suppliers play an important role in the implementation of sustainable supply chain initiatives and in ensuring social, environmental and economic gains. In particular, suppliers' supply chain management has made them a focal point in terms of social and environmental issues. Since many companies pollute the environment heavily, this concern has forced them to take environmental issues into account in their operations. In addition, as the world population increases and available resources decrease, companies believe that their suppliers need to adapt to today's conditions. Due to the increase in customer knowledge and awareness about the environment, ecological pressures from the market and stakeholders, and strict government controls, companies want to make their supply chains sustainable through supplier selection (Ecer, 2021: 29). A wrong sustainable supplier company can damage the current image of the business, and can also lead to the business becoming subject to legal obligations. In addition to the visible advantages of businesses' success in choosing the right sustainable supplier, there are also many positive effects that are reflected in their financial statements but cannot be seen.

There are many methods proposed in the literature to solve the problem of choosing the right sustainable supplier for businesses. In addition, there are flexible computational approaches that can detect the nonlinear relationship between variables and alternatives for highly close-to-accurate decisions. These methods are preferred because results can be obtained in a shorter time, they are low cost, they can learn for more accurate results, they are easy to process, and they are fast in decision making. At the same time, inflexible calculation methods that use the tolerance of uncertainties, more effective results can be obtained. At the same time, the determination of sustainability criteria is a critical step towards creating a sustainable supply chain. The determination of sustainable supplier criteria and the complexity of the problem of choosing a sustainable supplier can be expressed as a limitation that prevents the calculations from being verifiable. Due to the existence of these reasons, an application has been performed using the Artificial Neural Network method, one of the flexible computing methods inspired by the working style of the human brain and the Adaptive Network-Based Fuzzy Inference System method, one of the hybrid-neuro fuzzy systems. This study contributes to providing reliable methodologies that work with high accuracy in predicting the sustainable supplier performance of businesses.

2. REVIEW OF THE LITERATURE

Güneri et al. (2011) proposed an ANFIS-based method for supplier input selection and supplier selection problem. The method was carried out in a textile company. Firstly, the selection of supplier criteria was carried out using the ANFIS method. Subsequently, the selection results were tested compered the multiple linear regression method. It has been analyzed that the ANFIS method performs better than the multiple regression method. Khalili-Damghani et al. (2013) proposed a hybrid approach based on ANFIS and Fuzzy Goal Programming (FGP) for supplier selection problem. By applying the ANFIS method, supplier benefits were obtained by taking into account the relationships between the four main criteria. In the second stage, the FGP model was applied according to the objectives and model constraints. Abbasi and Asgari (2014) selected the most important criteria using Delphi method and selected the best supplier among 60 products selected by ANFIS method. The obtained results were analyzed using an ANN method. The ANFIS method performed better than the ANN method. Kılıc et al. (2014) have developed an ANN model to estimate the returns of the BIST100 (Borsa Istanbul 100) index. Weekly time-delayed values of exchange rate returns, gold price returns and interest rate returns were used as inputs. As a result of the study, they analyzed that the returns of the BIST 100 index follow a certain pattern over time. Genc and Paksoy (2016) have analyzed the change in the exchange rate in order to predict market price movements and increase the accuracy rate by developing ANN models. In this context, by creating three ANN models developed, they aimed to determine the best model in exchange rates. The ANN model with three delayed values as input has been determined as the most successful model. Paksoy (2017) conducted a hybrid study using the Markov chain and ANN model in order to predict the direction of the gold price. Gold yields are regulated according to the Markov chain of the second order, ANN models are created; Depending on the change in gold prices in the past period, the yield direction of gold is studied. As a result of the study, meaningful information about the direction of gold yield was analyzed. Okwu and Tartibu (2020) have integrated the TOPSIS (The Technique for Order of Preference by Similarity to Ideal Solution) and ANFIS methods for sustainable supplier selection problem. As a result of the decisions of decision makers according to the sustainability criteria of suppliers and the information obtained, the data were obtained using the TOPSIS method and the selection was made using the ANFIS method. Luo et al. (2009) conducted a hybrid study with Radial-Based Function and ANN methods. Thanks to the developed model, they were evaluated against both qualitative and quantitative criteria. Wu (2009), a hybrid study was conducted with data envelopment Analysis (DEA), decision tree (DT) and ANN models to predict supplier performance. In the study consisting of two stages, DEA was applied at the first stage and the suppliers were classified as efficient or inefficient clusters according to the obtained scores. At the second stage, the DT and ANN models were developed. Golmohammadi et al. (2009) developed a decision-making model that uses neural networks (NNs) to select suppliers. This model used historical supplier performance data for selection of vendor suppliers. The managers' judgments about suppliers were simulated by using a pairwise comparisons matrix for output estimation in the NN. The case study illustrated shows how the model can be applied for suppliers' selection. Kuo et al. (2010) ANN, DEA, ANP methods have implemented supplier selection. Green supplier criteria were defined using Delphi method, weights were determined using ANP method. Later, the ANN and ANP methods were developed together with the DEA to create a model. The ANN-MADA, ANN-DEA, and ANP-DEA models developed have been tested with the ANN model developed. As a result, ANN- MADA model was found to be more effective. Bahadori et al. (2017) aimed to develop a model to select the best supplier using the ANN and fuzzy VIKOR methods. The weights of the criteria were determined using the ANN model, while they developed a supplier selection model using the fuzzy VIKOR method. Wang (2021) developed a back- propagation ANN model for supplier evaluation and selection problem. Gegovska et al. (2020), a hybrid study was conducted with multi-criteria decision-making methods and the ANN method. In the study, the multi-criteria decision-making methods obtained by the survey method and the ANN method supplier selection were carried out in the manufacturing company. The FTOPSIS, FELECTRE, methods determined the same supplier as the supplier with the highest score, while the same supplier with the FAHP method was analyzed as the third place. Hamdan et all (2023), established a new method to forecast the arrivals of real-time e-orders in distribution centers. This enables third-party logistics providers to handle hourly e-order arrival rates more efficiently and develop a new ML forecasting method by integrating ANFIS and time series data feature. Septiyana et al. (2023) In this work, the authors used ANFIS computational intelligence model to develop sustainability index parameters for the water industry.

3. METHODOLOGY

3.1 Artificial Neural Network

ANN is a computer system that simulates the learning function of the human brain and information developed to search for solutions to problems inspired by a natural event (Kılıç et al., 2014: 759). ANN can be applied to solve many problems such as forecasting, modelling, clustering, vehicle routing and classification. ANN offers the possibility of convenient modelling complex data. With ANN, it is possible to identify the problem with the help of historical data and to predict the future situation (Hu, 2002: 75). The most important advantage of ANN is the parallelism feature. The artificial neural network can be adapted to linear or nonlinear models. When the network is trained, it can then be used for other situations (generalization capability). Thanks to the trained network, when circumstances change, the network can be re-trained and solutions to different problems can be found (adaptability). Since the error tolerance is low, in case of loss of information between neurons, the error can be tolerated even if the structure is affected (fault tolerance). In solutions where modelling with missing data is difficult, ANN offers more realistic results than other methods. It is also faster than other methods (Haykin, 1999: 26).

3.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a data learning technique that uses fuzzy logic to convert inputs given through weighted, interconnected neural network processing elements and information links to the desired output to map numerical inputs to an output (Al-Hmouz et al., 2012: 229). ANFIS is an attractive, powerful modelling technique that combines the well- established learning laws of ANN and the linguistic transparency of fuzzy logic theory within the framework of adaptive networks (Abdulshaded, 2015: 46). According to Jang, an adaptive network is a network structure consisting of nodes to which nodes are connected and directional connections. Nodes represent a process, while decouples also represent a decoupled relationship. Some or all of the nodes may be adaptive. The adaptive nature of the nodes means that each of their outputs depends on the parameters related to this node. Thanks to learning, the parameters are updated to minimize the predicted error measure in the parameters (Jang, 1993: 666).

3.2.1. ANFIS Structure

ANFIS is a neural network that is functionally the same as a Takagi Sugeno-type inference model. It is also an adaptive network that uses supervised learning in the learning algorithm. For the Takagi-Sugeno model, two IF-THEN rules were used. If we envisage a single-output model such as "f" with two inputs such as "x" and "y", then two IF-THEN rules will be possible, as follows. The expressions A_1 , A_2 , B_1 , B_2 are the membership function for the inputs x and y. The expressions p_1, p_2, q_1, q_2, r_1, r_2 are linear parameters according to the Takagi-Sugeno model. In the literature, they are also referred to as result parameters (Güneri et al., 2011: 14908; Suparta and Alhasa, 2016: 12).

$$Rule\ 1 = IF\ x\ is\ A_1\ and\ y\ is\ B_1\ THEN\ f_1 = p_1x + q_1x + r_1$$

$$Rule\ 2 = IF\ x\ is\ A_2\ and\ y\ is\ B_2\ THEN\ f_2 = p_2x + q_2x + r_2$$

In the ANFIS model, the values x and y represent the input values, while the values

A_i *and* B_i represent linguistic variables. The f value refers to the output value (Jang, 1993: 668- 670). ANFIS architecture is shown in Figure 1.

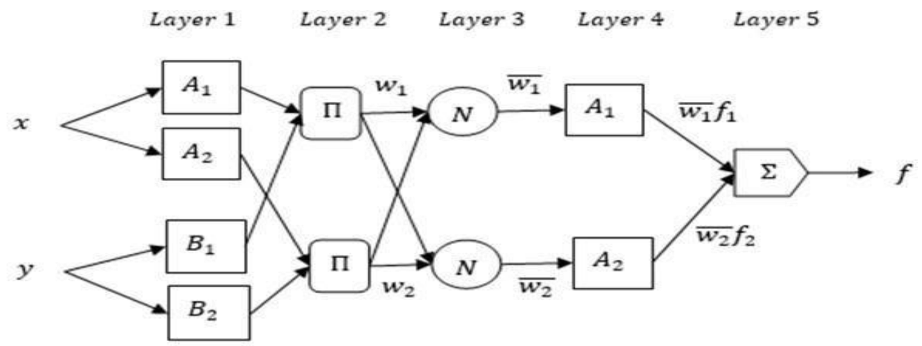

Figure 1. Adaptive Neuro-Fuzzy Inference System Structure

Source: Güneri et al., 2011: 14909; César, et al, 2016: 518)

Layer 1: In the blurring layer, also referred to as the input layer, its inputs are converted to a fuzzy set through membership functions.

Layer 2: The ignition power of each rule is calculated.

Layer 3: Normalization of the calculated ignition power of each rule is performed.

Layer 4: The output value of each rule is calculated.

Layer 5: The total value of the output values is calculated.

3.2.2. ANFIS Learning Algorithm

The learning algorithm of the ANFIS method involves the replacement of neural synaptic weights consisting of a unique input signal and a corresponding desired response (Haykin, 1999: 25). When learning a simple adaptive network, it uses gradient descent, backpropagation, or chain rule algorithms. Today, while gradient descent and backpropagation can still be used as a learning algorithm in a network, the problem of reducing the capacity and accuracy of networks when making decisions can be encountered (Wayan and Alhasa, 2016: 11). At the same time, there is a local minima compression with the gradient descent algorithm, which is known for its slowness (Jang, 1993: 666). For such reasons, a hybrid algorithm combining the gradient descent and least squares method was presented by Jang (Jang, 1996: 1485). For nonlinear parameters, the least-squares method is used whereas the backpropagation gradient descent is applied for nonlinear parameters (Jang and Gulley, 1997: 10). In the ANFIS learning process, there are two transitions, forward transition and backward transition (Tortum et al., 2009: 6201). In the forward transition of the learning algorithm, the result parameters are defined by the least-squares method. In the backward transition, the error signals, which are derivatives of the square error concerning the output of each node, propagate backwards from the output layer to the input layer. In this backward transition, the predecessor parameters are updated by the gradient descent algorithm. The following process is repeated until the ANFIS model reaches the error threshold or until it reaches the number of cycles entered by the user (Haykin, 1999: 772-773).

4. STRUCTURE OF PROPOSED MODEL

In the grid partitioning method used at the stage of creating the ANFIS model, the input area is divided into equal parts, as many as the number of selected subsets. Each separated section represents a fuzzy rule. In our model, where the number of inputs is ten, if two membership functions are defined for each input, $2^{10} = 1024$ rules will be created. In accordance with the Sugeno model of the first order, since n=10, it corresponds to $(10 + 1) \times 1024 = 11264$ linear parameters. It is out of the question to create a reliable model with a lot of parameters and unpredictable inputs (Jang, 1996: 1476). For this reason, it will not be possible to select effective sustainability criteria. In order to create a reliable model, it is necessary to reduce the number of inputs (Jang, 1996: 1496).

An algorithm based on ANFIS model and ANN model for sustainable supplier selection problem is expressed in Table 1. Step 1 includes the ANFIS model and ANN model database development processes. Step 2 includes ANFIS input selection processes. Step 3 includes ANFIS sustainable supplier performance forecast processes. Step 4 includes ANN sustainable supplier performance forecast processes. Step 5-6 includes the processes of comparing the developed models. Step 7 includes ANFIS sustainable supplier selection processes.

Table 1. The algorithm based on ANFIS and ANN methods for sustainable supplier selection problems

Step 1: The stage of determining the decision makers, alternative suppliers, input and output variables
Determination of decision makers
Determination of alternatives
Determination of input variables: Determination of sustainability criteria as a result of literature review and evaluation of decision makers
Determination of the output variable
Obtaining input and output data
Normalization of data
Data is divided into two parts in the hold-out method, 70% training and 30% testing
Step 2: ANFIS input selection and determination of the most effective sustainability criteria
Step 3: ANFIS sustainable supplier performance forecast
Transfer of training, test and control data to the MATLAB ANFIS Editor
Determining the type and number of membership functions
Determination of fault tolerance and number of cycles
Training the network and examination of the error values of the results
Step 4: ANN sustainable supplier performance forecast
Loading input, output and test data into the MATLAB ANN interface
Configuring the network
Teaching data to the network
Verification of the network and examination of the error values of the results
Step 5: Performing multiple regression analysis to compare the prediction performance of the developed ANFIS and ANN models
Step 6: Calculation R^2, MSE, RMSE, MAE, MAPE values and the value of WIA from regression indices using Excel 2010 for comparison of the developed models
Step 7: Making a sustainable supplier selection in the ANFIS model which has reached the most successful performance forecast

5. CASE STUDY

In this section, a multiple regression method has been developed for the purpose of applying models based on ANFIS and ANN methods and comparing performances. Sustainable supplier selection was made using the ANFIS method, which achieved the most successful performance in the models developed according to the determined performance parameters. The marble business where this study was conducted undertakes supply activities of all kinds of natural stones, marble, granite and products made of them as well as meeting its supply activities by purchasing marble blocks for the manufacture of marble. The product that is the most relevant subject of the business in its procurement activities has been selected for this study.

5.1. Creation of the Database

Step 1: Decision-makers who are considered to be experts in their field have been identified as determined by the business manager. The expert persons appointed by the business manager constitutes the decision committee. In order to implement the study, a data set consisting of inputs and outputs is needed (Jang, 1996: 1493). A literature review was conducted to determine the inputs. The decision-makers were asked to evaluate the suitability of the sustainability criteria for the business, stating "Yes" or "No", such sustainability criteria being identified as a result of the literature review similar to the Amindoust et al. (2012) study. As a result of the evaluations, 10 sustainability criteria were determined by making required eliminations and additions. Sustainability criteria are presented in Table 2.

Table 2. Sustainability Criteria

Sustainability Main Criteria	Sustainability Sub-Criteria	References
Economic	Cost (M) Delivery time (DT) Reliability (R) Quality (Q)	Hoseini et. al., Fallahpour et. al., Guarnieri P. and Trojan P., Kannan D., Weber C. et. al., Zhang et. all. Bai and Sarkis, Sarkis and Talluri
Social	Interests and rights of employees (IRE) Social Responsibility (SR) Employee safety (ES)	Hoseini et. all, Luthra et. all, Guarnieri P. and Trojan P., Awasthi et. al.
Environmental	Waste management (WM) Pollution control (PC) Environmental competencies (EC)	Hoseini vd., Guarnieri P. and Trojan P., Amindoust et. al., Ghadimi and Heavey, Bai and Sarkis, Nikolaou et. al., Zhang et. al.

Sustainable suppliers are the driving force of businesses, representing a part of the total turnover of businesses while being involved in the purchasing functions of businesses. For this reason, the turnover shares of supplier companies were taken into account as an output variable. Taking into account the activities of the previous one-year procurement period for the study; it contains data of six supplier companies for which the business meets its procurement activities during the one-year procurement period.

For quantitative criteria, data defined in the purchasing activities of the enterprise was used, while for qualitative criteria, the decision committee of the enterprise was asked to evaluate the criteria using an evaluation scale from 1 to 10. In order to select effective inputs, the data should be divided into two groups: training and test data to train the model and evaluate the validity of the model (Zhang et al., 1998: 50). For this reason, the data are divided into two parts in the hold-out method, i.e. 70% training and 30% testing (Barak and Sadegh, 2016: 14). The data were normalized to ensure data integrity, improve performance and accuracy (Aylı and Ulucak, 2020: 91).

5.2. ANFIS Input Selection

Step 2: To develop an input model, the command "exhsrch (1,trn_data, test_data, input_name)" is used. In this way, the effect of each input variable on the output is examined. The number "1" in the command describes the effect of each criterion (input) on the share of turnover (output). In one-input model combinations, 10 ANFIS models were trained and the best criterion was calculated as SR (social responsibility). In two-input model combinations, 45 ANFIS models were trained and the two best criteria were determined as SR (social responsibility) and C (cost). In three-input model combinations, 120 ANFIS models were trained and the three criteria with the lowest error values were calculated as C (cost), WM (waste management) and DT (delivery time). In the four-input model combinations, the ANFIS method has trained 210 ANFIS models each having four inputs among ten inputs. In four-input model combinations, the four best criteria were determined as C (cost), DT (delivery time), PC (pollution control) and WS (worker safety), respectively. As a result, four inputs with the lowest RMSE values were determined as SR (social responsibility), C (cost), WM (waste management) and DT (delivery time), taking into account the combinations of one-input models, two-input models, three-input models and four-input models.

5.3. ANFIS Sustainable Supplier Performance Forecasting

Step 3: Because the number of data elements should be greater than the number of modified parameters, two membership functions are chosen for each input in the model (Güneri et al., 2011: 14913). After the FIS training, the membership function types were tested with epoch:40 and the RMSE values were analyzed. Psigmf with the lowest error value (0.038) was determined as the membership function.

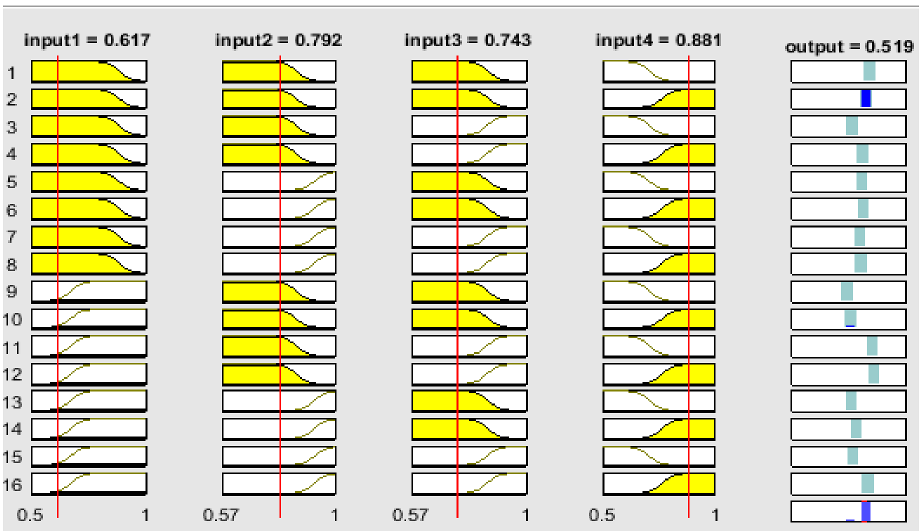

Figure 2. ANFIS Model Rule View

According to Figure 2, the input 1 value is calculated as 0.617, the input 2 value as 0.792, the input 3 value as 0.743, and the input 4 value as 0.881, while the output value is calculated as 0.519. Through simulation in Figure 10, the output can be easily calculated according to different input values.

5.4. ANN Sustainable Supplier Performance Forecasting

Step 4: After reviewing the literature, in the ANN models developed for supplier selection, advanced feedback propagation network type was preferred most. In this context, the feed-forward back propagation model, which has been widely preferred in the literature and consistent results have been obtained, was determined as the network type (Wei et al., 1997: 670). Another reason why a feed-forward backpropagation network is preferred is that it can be applied to linear or nonlinear models and is easy to use (Ataseven, 2013: 112).

In the literature, there is no general rule for determining the number of hidden layers. In this regard, a trial and error method were applied to determine the number of hidden layers (Chowdary, 2007: 321). For the number of hidden layers, in the trial and error methods performed, the lowest error value was reached in thirteen hidden layers. Therefore, the number of hidden layers was set at thirteen. The Levenberg-Marquardt (trainlm) method, which is one of the methods applicable to nonlinear models whose training function is capable of reaching an absolute minimum, was chosen (Zhang et al., 1998: 48). In machine learning, data partitioning expressed as data split was performed as simple random sampling (SRS) (May et al., 2010: 284). Performance evaluation MATLAB is defined as MSE in the ANN interface. The training of the network was completed in almost a second, with 112 iterations. Training function, learning function and transfer function are shown in Table 3.

Table 3. Training Function, Learning Function, Transfer Function Error Values.

Training function	Learning function	Transfer function	R	MSE	$RMSE$	$MAPE$
trainlm	learngd	logsıg	0.93983	0.004862	0.069729	0.366331
trainlm	learngd	purelın	0.90465	0.007356	0.085768	0.358877
trainlm	learngd	tansıg	0.96578	0.002657	0.051542	0.239289
trainlm	learngdm	logsıg	0.93384	0.004846	0.069611	0.391762
trainlm	learngdm	purelın	0.89958	0.007513	0.086679	0.410249
trainlm	**learngdm**	**tansıg**	**0.96653**	**0.002749**	**0.052435**	**0.235912**
trainscg	learngd	logsıg	0.94214	0.004452	0.066722	0.364634
trainscg	learngd	purelın	0.90492	0.007416	0.086115	0.345773
trainscg	learngd	tansıg	0.94623	0.004148	0.064402	0.337980
trainscg	learngdm	logsıg	0.94780	0.004149	0.064415	0.319148
trainscg	learngdm	purelın	0.90126	0.007409	0.086077	0.408172
trainscg	learngdm	tansıg	0.93466	0.005415	0.073589	0.418127

Based on the information obtained from Table 3, it was decided to create an ANN model with thirteen hidden layers, four inputs and one output, using the training function Levenberg-Marquardt (trainlm), the learning function gradient descent with momentum (learngdm) and the transfer function tangent-sigmoid transfer function (tansıg)

5.5. Evaluation of the Performance of ANFIS Model and ANN Model

Step 5: In order to compare the performance of the developed ANFIS model and the ANN model, multiple regression analysis was performed. While a model can be created with maximum four inputs (independent variables) in the ANFIS method (Yücel, 2010: 81); analysis is performed with an unlimited number of inputs in the ANN method (Ataseven, 2013: 39). In this regard, a comparison of both developed models with a specific single model was made for performance comparison. Regression analysis result is shown in Table 4.

Table 4. Regression Analysis Results

Variables	B	Std. error	$\boldsymbol{\beta}$	t	$\boldsymbol{\rho}$	Durbin-Watson	Tolerance	VIF
Constant	1,598	0.135		-11.208				
SR	0.749	0.083	0.583	9.050			0.306	1.114
C	0.690	0.091	0.486	7.621	0.00	2.079	0.961	1.122
WM	0.476	0.115	0.268	4.150			0.862	1.149
DT	0.142	0.092	0.098	1.541			0.305	1.106
$\boldsymbol{R} = \mathbf{0.861}$	$\boldsymbol{R^2} = \mathbf{0.742}$	95% confidence interval						
$\boldsymbol{F} = \mathbf{51.087}$	$\boldsymbol{\rho} < \mathbf{0.00}$							

In multiple regression analysis, when analyzing with a limited number of inputs, there should be no multiple linear connections between the independent variables (Bayır, 2006: 97). Since $\rho < 0{,}05$ is valid for each variable, the model is statistically significant (Kul, 2014: 12). The explanatory power of the developed multiple regression model (R^2) was calculated as 0.74. In the case of high correlation ($R >$ %75), there will be a problem of autocorrelation or multiple correlations (Vupa and Gürünlü Alma, 2008: 42). For this reason, Durbin-Watson and VIF values were examined. The Durbin-Watson d test tests autocorrelation (Durbin and Watson, 1971: 4) while the VIF value tests multiple correlations (Gujarati, 2001: 423). In the literature, the Durbin-Watson test also referred to as the d test, is in the $0 < DW < 4$ value range. Values close to 2 are evaluated as no autocorrelation, while analysis results between the values of 1-3 are interpreted as there is no significant decorrelation (Field, 2013: 309). In our study, there is no autocorrelation according to the calculated d value. Allison considered the VIF value to be $VIF < 2{,}5$ (Allison, 1999: 172) while Anderson accepted this interval as $VIF \leq 4$ (Anderson, 2010: 7). According to Ringle et al., when the VIF value was examined, the VIF was determined to be $VIF \leq 5$ (Ringle et al., 2015: 125). Hair et al. accepted the value interval as $VIF \leq 10$. However, they think that each researcher should determine the correct threshold value himself. Because the assumed threshold values are still capable of allowing linearity (Hair et al., 2014: 200). In this study, the VIF value interval was taken as $VIF \leq 2{,}5$. Since the calculated VIF value is $VIF \leq 2{,}5$, there is no multiple correlations. As a result, the multiple regression model is considered successful in explaining the output values and the model conforms to the prediction (Bayır, 2006: 100).

Step 6: The average of the actual output values and the output values calculated using the ANFIS method were calculated as 0.26 and 0.25, respectively. ANFIS model and ANN model have a standard error value of 0.022. Actual outputs with 0,26 average value will be in the range of 0.2174-0.3085 with a probability of 95%, while ANFIS model outputs with 0,25 average value will be in the range of 0.213-0.302 with a probability of 95%. Statistically, at the 95% confidence interval, the output values and the ANFIS model output values are similar. The ANN model outputs were taken from the ANN interface and compared with the actual output values. When the average and standard error values were examined, the average of ANN model output values were calculated as 0,26 and the standard error value was calculated as 0,022. ANN model outputs will be in the range of 0,220-0.310 with a probability of 95%. Statistically, in the 95% confidence interval, actual output values and the ANN output values are similar. Average value and standard error value are shown in Table 5.

Table 5. Average Value and Standard Error Value

Output value	**Average Value**	**Std. error**
Actual output value	0.263	0.022
ANFIS output value	0.258	0.022
ANN output value	0.266	0.022
MLR output value	0.263	0.019

Multiple regression analysis is used to compare the performance success of ANFIS and ANN models. Comparing of the outputs of develop models using performance parameters are shown Table 6.

Table 6. Comparing of the Outputs of Develop Models Using Performance Parameters

	R^2	**MSE**	**RMSE**	**MAE**	**MAPE**	**WIA**
ANFIS	**0,93**	**0,003**	**0,053**	**0,033**	**0,16**	**0,964**
ANN	**0,94**	**0,001**	**0,057**	**0,032**	**0,18**	**0,966**
MLR	**0,73**	**0,010**	**0,105**	**0,087**	**0,26**	**0,990**

The value of R^2, which is specified as the coefficient of determination, should be in the range of $0 \leq R^2 \leq 1$ (Yüzer, 2004: 272). It should be understood that if the coefficient of determination approaches one, the accuracy of the actual values increases with the developed model (Aylı and Ulucak, 2020: 93). In this context, it is analyzed to what extent the input variables (independent variable) predict the output variable (dependent variable), that is, what percentage it explains (Unver, 1996: 283). According to the R^2 values calculated in our study, the ANFIS model is 94%, the ANN model is 93%, and the multiple regression model is 73% of the input variables, explaining the output variables.

MSE, MAE, RMSE values that have not been standardized, and the model to be considered successful, these parameters are expected to be close to zero (Ji and Gallo, 2006: 824). The lowest MSE, MAE and RMSE values calculated in our study were captured by the ANN model, ANFIS model and ANN model, respectively. The MSE, MAE and RMSE values of the ANN model and the ANFIS model are close to each other.

According to Lewis, models with MAPE value of below 10% are accepted as "high degree prediction", models between 10%-20% as "good degree prediction", models between 20%-50% as "acceptable prediction" and models with 50% and above as "unreliable prediction" (Chen et al., 2003: 445; Çuhadar et al., 2009: 107; Karahan, 2015: 170).

In this context, according to the MAPE values calculated in our study, the ANFIS model and the ANN model are characterized as "good degree prediction" in the range of 10%-20%, while the multiple regression model is evaluated as "acceptable prediction" with a MAPE value between 20% -50%.

The WIA value is in the range $0 < WIA < 1$. The WIA value also expressed as the "d value" or the "index of agreement", assumes that the model reaches the correct prediction results as it approaches one (Wilmott et al., 2011: 2088). The WIA value measures the degree of regression, and the larger it is, the higher the level of accuracy of the prediction results (Wang and Xu, 2004: 265).

For the model to be considered successful, the value of R^2 must be the highest and the values of the MSE, RMSE and MAE parameters should approach zero. The WIA value is expected to approach one. While the ANFIS model significantly outperforms both models for the RMSE value; it is possible to say that the results of the ANN model and the ANFIS model are very close when examining the MAE values. As regards the WIA value, it is possible to say that a consistent model has been developed for all three models. According to the performance parameters, all three models can be considered as successful. As a result, the model with the highest success rate was determined as the ANFIS model.

5.6. ANFIS Sustainable Supplier Selection

Step 7: As a result of the ANFIS model developed, the company with the most appropriate score for the business is analyzed thanks to the "evalfis" command. In the study, the situation of the company choosing between five supplier companies is examined. In this context, the scores that each company receives according to the input variables constitute the input data. The scores obtained by the supplier companies according to SR (social responsibility), C (Cost), WM (waste management) and DT (delivery time) criteria are input data. The data set used in the application was introduced to the program in the previous steps. When the data of the five supplier companies are entered into the program with the appropriate command, the most suitable sustainable supplier company for the enterprise is determined. Output values have been converted to percentage values for a better evaluation. Sustainable supplier selection result is shown Table 7.

Table 7. Sustainable supplier selection results.

Supplier	ANFIS Output	Turnover Share Percentage
Supplier 1	0,1294	10.09
Supplier 2	0.3300	25.73
Supplier 3	0.0599	4.67
Supplier 4	0,6029	47.02
Supplier 5	0.1600	12.47

When the turnover share variable, defined as the output variable, is expressed in percentages, the first supplier with an output of 0.12 has a 10% share in the enterprise. The second supplier with an output of 0.33 has a percentage of 25% in the enterprise. The third supplier, which has an output of 0.05, has a percentage of 4% in the enterprise. The fourth supplier with an output of 0.60% has a 47% percentage in the enterprise. The fifth supplier with an output of 0.16% has a percentage of 12% in the enterprise. The sustainable supplier with the highest percentage of turnover share is the fourth enterprise with a 47% share. As a result, the fourth supplier is the most suitable sustainable supplier company for the enterprise because it has the highest turnover share.

6. CONCLUSION

In the new world order, instead of businesses acting only to obtain maximum profit (economic interest), it is demanded to establish a "win-win" relationship with maximum social interests. It is out of the question for businesses focused solely on economic benefits to be able to compete and exist in the market if they ignore environmental and social benefits.

In order to create an effective and efficient sustainable supplier chain and develop sustainable partnerships, the suitability of sustainable supplier selection is very important. In this context, when sustainability is mentioned at the enterprise level, it is mentioned about the relationship of the enterprise with all its elements. In this article, an approach to sustainable supplier selection based on ANFIS and ANN methods is proposed. In order to evaluate the efficiency of the developed models, multiple regression analysis was developed by applying the same data to be compared with a single model.

From this point of view, this study was carried out taking into account the suppliers to whom the marble enterprise receives procurement services. Supplier data for the past year have been taken into account for quantitative criteria. For qualitative criteria, decision-makers who are considered to be experts in the field determined by the business manager were asked to evaluate qualitative criteria. Thanks to the models developed based on the ANFIS and ANN methods, the share of turnover of suppliers has been estimated. In order to compare and evaluate the performance of the developed models with a single model, multiple regression analysis was performed to analyze the determined performance parameters. The ANFIS model we have developed has been determined as the most successful model according to the performance parameters and according to the values of R^2, MSE, RMSE, MAE, MAPE and WIA.

For future work, it can be applied to the problem of sustainable supplier selection using different sectors, different sample sizes or different criteria. In our study, the fuzzy rule base developed by the program was used. A fuzzy rule base can be developed in future studies. Multi-criteria decision-making approach methods can be applied instead of ANFIS input selection. By developing different learning algorithms, hybrid studies can be performed.

In addition, our suggestion for future studies is that instead of sustainable supplier selection, green supplier selection, digital supply chain, reverse supply chain and circular supply chain applications can be used. Thus, the performance of the ANFIS model in these applications, which have similarities but different criteria, can be revealed.

DECLARATION OF THE AUTHORS

Approval of ethical committee: All procedures performed in studies comply with the ethical standards of comparable institutional and/or national research committees.

Declaration of Contribution Rate: The authors have equal contributions.

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