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Research paper

An application of Artificial Neural Network solution in the apparel industry for Job distribution to subcontractors

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ABSTRACT

In this study, the results of the work distribution made with the TOPSIS method, which is frequently used in the distribution of work to the subcontractor workshops, were estimated using the Artificial Neural Networks Method (ANN). Here, the C* values used in the work distribution with the TOPSIS method were estimated by ANN. The correlation coefficient of the data obtained from the created model was found to be 99.99895% for learning. According to the results, it has been concluded that work distribution can be made by using the ANN method without making complex mathematical calculations in the distribution of work to the contract workshops.

1. Introduction

Outsourcing is one of the strategies developed by businesses to increase their competitiveness, maintain and improve their profitability. The most important factors that increase competition are quality, price, cost and flexibility and these factors cause businesses to try to offer better quality and less costly products and services [1].

Considering the strategies for cost reduction, especially since the 1990s, it is seen that businesses have started to take advantage of outsourcing by having their activities outside of their basic capabilities done by suppliers [2].

According to Halbach's definition outsourcing is an agreement between two manufacturing units; with reference to this, one of the parties (subcontract work-shop) supplies the products (part of the final product or final product) to the other party (main company) within determined period and conditions [3].

The reasons for outsourcing can be listed as follows; increasing flexibility, Focusing on basic abilities (Core activities), Reducing risks, Increasing quality, Downsizing of organization, Reducing cost, Increasing product range, Uncontrollable functions, Saving time, Increasing productivity, Being involved among successful enterprises, Renewing process, Wide and flexible resource pool, Redistributing resources, Resource transfer, Following technological innovations, Overcoming the demands beyond capacity [4–9].

Due to the reasons listed above, companies started to work with subcontractors, and as a result, the main company and subcontractors affiliated to the main company emerged [1].

Subcontracting manufacturers are independent production companies that produce parts in accordance with the recommendation and working technique of the main company [10].

Especially, companies that have a wide range of products and produce and sell in high amounts work with many subcontractors with different features. This causes the need for job distribution to subcontractors according to a certain system [1].

In this study, it was investigated to what extent the results of the work distribution to subcontractors realized by an apparel company using the TOPSIS (Order Preference Technique by Similarity to Ideal Solution) method overlap with the results of the work distribution realized with the Artificial Neural Network (ANN) method and its usability in this field.

When the studies on the use of the ANN method in ready-made clothing are examined It has been seen that the studies are related to predicting the fabric performance and fabric end use [11,12], design of smart sewing machines, and smart sewing environments [13–15], system identification and controller synthesis for sewing machine [16], fabric stitching inspection method proposal [17], sewing fault detection and classification [18], quality control of seams [19], control of sewing parameters [20], modelling and prediction of needle penetration force

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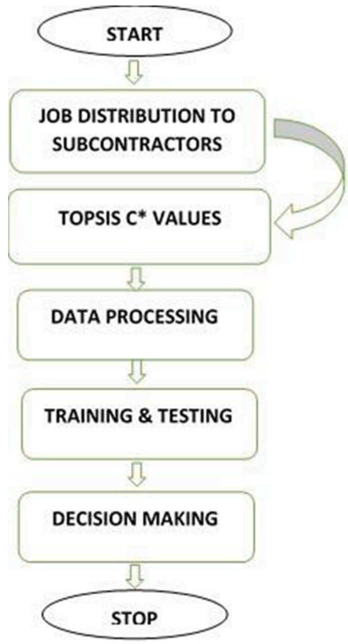

Fig. 1. Subcontractors' performance criteria.

[21,22], predicting of sewing thread consumption [23], predicting of sewing performance [24–26], predicting of strength loss in threads [27], predicting of seam strength [28], prediction and rating of seam pucker [29,30], calculation of optimum fabric lays quantities [31], forecasting of cutting time [32], use of artificial intelligence in cutting and sewing [33].

Although there are many studies on the use of the ANN method in ready-made clothing, no study has been found in this area. In this respect, it can be said that the study is the first study in this field and therefore it is an original study.

2. TOPSIS and ANN process

2.1. TOPSIS method

In the application of this method, the past delivery performances of subcontractors have a significant impact on the distribution of work to subcontractors. These performance criteria are listed in Fig. 1[34]. In determining the criteria, besides the literature research, the opinions of two different outsourcing department managers of an apparel company X from which the data was obtained on the performance criteria of subcontractors were considered.

After determining the factors, it is a very important step for the companies to give weight to the criteria. For example, while price has more weight in cost-oriented companies, the quality factor may weigh more in quality-oriented companies. In the weighting of the criteria determined, 2 different outsourcing department managers working in company X filled out a form to sort the criteria. The ranking method (sorting method) was used in the weighting.

As can be seen from the above, the constant distribution of work to subcontractors is affected by many factors, and the fact that these have different weights is a complex problem for businesses. At this point, multi-criteria decision-making methods are the most effective tools for solving this problem.

With the use of multi-criteria decision-making methods, the main company will make more accurate decisions while distributing orders, and motivate subcontractors to increase their performance. As a result, it will ensure that the order is made at the desired quality, time and cost.

"Multi-criteria decision making" means choosing the highest priority among others; in other words, it means short evaluation, ranking and

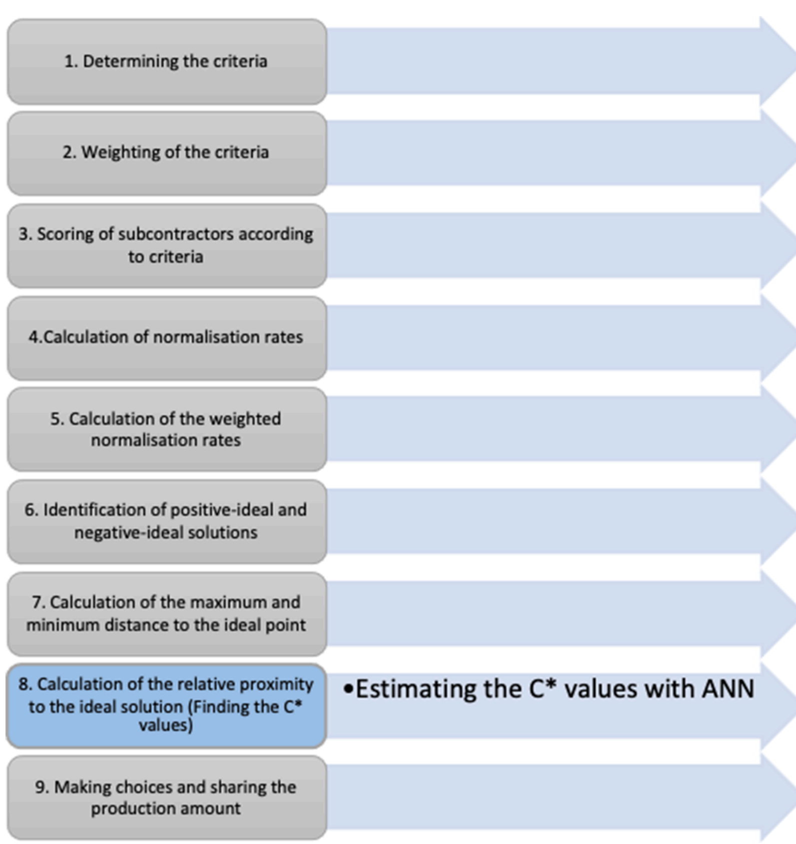

Fig. 2. Stages and implementation of TOPSIS method.

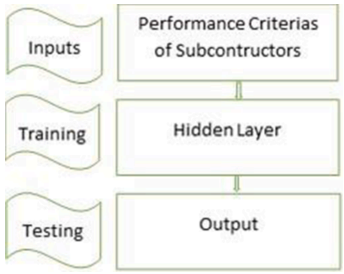

Fig. 3. Flow chart of experimental system

selection [35]. Multi-criteria decision-making (MCDM) is a branch of the most widely used methods of decision-making theory. It includes ones that enable the selection of alternatives, grouping or sorting alternatives by evaluating multiple decision criteria [36].

One of the most used MCDM methods today is TOPSIS (Order Preference Technique by Similarity to Ideal Solution). The TOPSIS method was developed by Yoon and Hwang in 1980 and is one of the most widely used MCDM methods. The basis of this method is that the alternative chosen should be the shortest distance to the ideal solution in the geometric sense and the farthest distance from the negative-ideal solution. The TOPSIS method assumes that each criterion has a uniformly increasing or decreasing utility trend. For this reason, it is easy to identify ideal and negative-ideal solutions. The Euclidean distance approach aims to evaluate the relative proximity of the alternatives to be chosen to the ideal solution. Thus, the order of alternatives can be generated by comparing these relative distances [37]. Fig. 2 shows the stages of the TOPSIS method.

Each of the stages given above is quite complex and takes time. After the C* value is found in the 8th stage, the orders are distributed to the subcontractor workshops in the 9th stage. In this study, the C* value was estimated on a model by using the Artificial Neural Network method of the process up to the 9th stage. In this way, it will be possible to distribute orders to contract workshops much more quickly. The flowchart created for the Artificial Neural Network model used in this study is given in Fig. 3.

The C* values used in work distribution with the TOPSIS method are given in Table 1, which shows the criteria of 15 subcontractors. C* values were calculated after the processes shown in Fig. 2, with the scores each subcontractor received from each criterion. Data from company X was used to calculate the criterion scores of each subcontractor workshop. Company X has recorded the data (quality, term performance, price, etc.) of the previous deliveries of all these subcontractors and information about each subcontractor such as production capacity and distance to the company.

For example, while calculating the quality criterion score of subcontractor A, the past delivery performance values of workshop A were considered. According to the data received from the company X, subcontractor A delivered 85 different models and 6 of these models were found to be unsuccessful in terms of quality. According to these data, Quality (C1) score of subcontractor A calculated as 10 - (6 / 81) = 9,3. The scores of all criteria on the basis of each subcontractor were

Table 1
Technique values of example.

Subconstractors	Criteria										C*
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	
A	9.3	9.3	2.0	10.0	10.0	8.7	8.9	9.0	9.2	8.9	0.5362488
B	9.5	9.6	2.0	10.0	8.0	8.5	9.1	8.8	9.0	8.9	0.5165634
C	9.4	9.2	6.0	6.0	4.0	8.4	8.5	8.1	8.8	8.7	0.4599609
D	9.1	9.7	2.0	10.0	2.0	9.0	8.8	9.1	8.7	9.3	0.4495804
E	9.3	9.1	8.0	4.0	8.0	8.8	8.7	8.5	8.3	8.2	0.5431856
F	9.3	9.2	4.0	6.0	8.0	9.0	8.9	8.7	9.1	8.1	0.4467714
G	9.2	9.6	10.0	2.0	4.0	7.8	8.1	7.9	8.0	7.5	0.4864435
H	9.1	9.4	10.0	2.0	10.0	8.3	8.0	7.9	8.2	7.5	0.5522210
I	8.7	8.8	8.0	4.0	6.0	8.3	8.1	8.2	8.1	8.0	0.5027834
J	9.7	9.5	4.0	8.0	4.0	8.4	8.0	8.3	7.9	9.5	0.4623662
K	8.9	8.5	10.0	2.0	8.0	7.8	7.9	7.9	8.1	8.2	0.5297087
L	9.4	9.7	10.0	2.0	8.0	8.2	7.7	7.9	7.8	8.0	0.5340051
M	9.5	9.1	4.0	8.0	10.0	9.0	9.0	9.2	8.8	9.1	0.5603505
N	8.7	9.1	8.0	6.0	6.0	8.3	8.0	8.1	7.9	8.8	0.5947352
O	9.5	9.5	10.0	2.0	8.0	8.5	7.9	8.5	8.0	7.2	0.5339335
Weight	0.1818	0.1545	0.1545	0.1273	0.1000	0.0273	0.0727	0.0909	0.0273	0.0636	1.00

Table 2
Technique test values of example.

Subconstractors	Criteria										C*
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	
A	8	9	2	10	10	9	9	9	9	9	0.5421959
B	10	10	2	10	8	9	9	9	9	9	0.530978
C	9	8	6	6	4	8	9	8	9	9	0.457455
D	9	10	2	10	2	9	9	9	9	9	0.4635248
E	9	9	8	4	8	9	9	9	8	8	0.5376994
F	9	9	10	6	10	9	9	9	9	8	0.717791
G	9	10	10	2	4	8	8.1	8	8	8	0.4779465
H	9.1	9	10	2	10	8	8	10	8	8	0.5467382
I	9	8.8	8	4	6	8	8	8	8	8	0.4947356
J	10	10	4	8	4	8	8	8	8	10	0.4767266
K	9	9	10	2	8	8	8	8	8	8	0.51867
L	9	10	10	2	8	8	8	8	8	8	0.525436
M	10	9	4	8	10	9	9	9	9	9	0.5717541
N	9	9	8	6	6	8	8	8	8	9	0.5890157
O	10	10	10	2	8	9	8	9	8	7	0.5258015
Weight	0.1818	0.1545	0.1545	0.1273	0.1000	0.0273	0.0727	0.0909	0.0273	0.0636	1.00

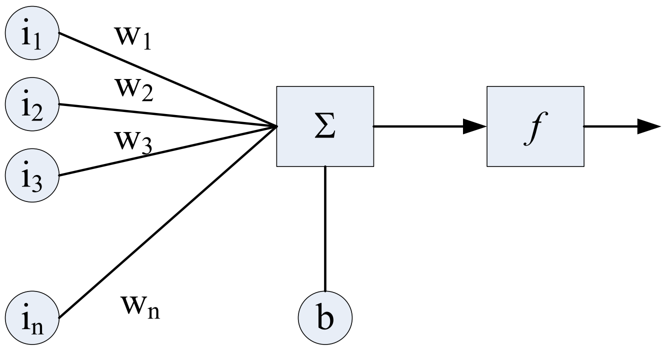

Fig. 4. The ANN model.

calculated in this way and the values in Table 1 were obtained.

The values of the criteria of 15 companies to be used for estimation by ANN for testing purposes are given in Table 2. When the accuracy of the data obtained from the created model was checked, the Artificial Neural Network model was trained with the C* values obtained by the TOPSIS method, and the C* values were estimated using different criteria values for a different 15 subcontractor companies.

2.2. *Artificial Neural Network*

Artificial Neural Network can be defined as a highly connected array of elementary processors called neurons. The ANN model is shown in Fig. 4. The basis of neural networks is the artificial neuron, as in Fig. 4. An artificial neuron consists of: input signals (i), a set of real value weights (wi), an activation level ($\sum$wixi), a threshold function (f).

The earliest example of neural computing is the McCulloch-Pitts neuron [38]. The inputs to a McCulloch-Pitts neuron are either excitatory (+1) or inhibitory (-1). The activation function multiplies each input by its corresponding weight and sum the results; if the sum is greater than or equal to zero, the neuron returns 1, otherwise, -1. McCulloch and Pitts showed how these neurons could be constructed to compute any logical function, demonstrating that systems of these neurons provide a complete computational model [39–41]

The historical emergence of networks with continuous activation functions suggested new approaches to error reduction learning. The Widrow and Hoff [42] learning rule is independent of the activation function, minimizing the squared error between the desired output value and the network activation, neti=WXi. Perhaps the most important learning rules for continuous is the delta rule [31,32,43]. The mean squared network error is found by summing the squared error for each node:

$$Error = (1/2)\sum_{i}(d_i - O_i)^2 \quad (1)$$

Artificial Neural Networks (ANN) or simply Neural Network (NN) are simplified to imitate central nervous system been motivated by the computing performed by human brain. ANN is defined as a data processing system consisting of a large number of simple highly interconnected processing elements (artificial neuron) in architecture inspired by the structure of cerebral cortex of the brain [44]. Artificial Neural Networks (ANN) are an abstract simulation of a real nervous system that consists of a set of neural units connected to each other via axon connections which are very similar to the dendrites and the axons in biological nervous systems [45,46]

Each layer employs several neurons and each neuron in a layer is connected to a neuron in the adjacent layer with different weights. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer linearly weighted by the interconnect values between neurons. The neuron then produces an output signal by passing the summed signal through a sigmoid function.

Table 3
Suggested network design for ANN model.

ANN Model **Data Division**	Random	
Training	Levenberg-Marquardt	
Performance	MSE	
Epoch	29 iterations	
Regression	Training	0.99895
	Testing	0.98494
Input	10	neurons
Hidden Layer	16	neurons
Output Layer	1	neuron

The ANN is trained to respond to the corresponding target vectors and training continues until the average error between the desired and actual output of the ANN over the training set is less than a predetermined threshold [47,48]

2.3. *ANN structure*

Data were organized so that more reliable results could be obtained and changed into numerical values in order for the network to understand them. Before the separation of the data to be used during the training and testing, data selections were carried out randomly. Thus, the system is trained with data reflecting the parameters of the whole system and random data were selected to be able to achieve the best result.

As training algorithm that determines the application process and one of the significant factors, back propagation algorithm Levenberg-Marquardt was used. Marquardt parameter accelerates the zero-error approach of the neural network. In return for the given input, the output calculated by the network is compared with the real (desired) output. The gap between the output of the network and the real output is calculated as error. The average of the total of the fault is attempted to minimize. This value to be minimized MSE (Mean Squared Error) enable the network to have smaller weight and performance values that is one of the factors affecting the training performance [49]. In this study, the best result was obtained by the use of mean squared error function.

The construction of Artificial Neural Network Architecture for C* values forecaster as suggested is as follows:

The input layer consists of ten neurons. The hidden layer consists of sixteen neurons (this number was determined from studying the network behavior during the training process taking into consideration some factors like convergence rate, error criteria, etc.) The output layer consists of one neuron that it represents the predicted C* values forecasting.

3. Results

The training process is a vital part of creating an intelligent system that can accurately predict the C* values used in work distribution with the TOPSIS method. Error back propagation algorithm is used to train the proposed network (Table 3).

Ten training data were used in the training process so that only a few models may be needed to update the network weights and thresholds as needed.

MSE values obtain from the secret phase number of test result and mean squared error results and absolute change values were provided. The closer the absolute error closes to zero, the better the system reflects the truth.

In Fig. 5(a) and (b), the training and validating as a function of epochs are shown. The network is trained within 29 epochs met the goal of error of 0,000000001. The best validation performance is 3.7541e–07 at epoch 2.

The current ANN model has been retested with 10 main criteria values for 15 subcontractors. Error values expressing the difference

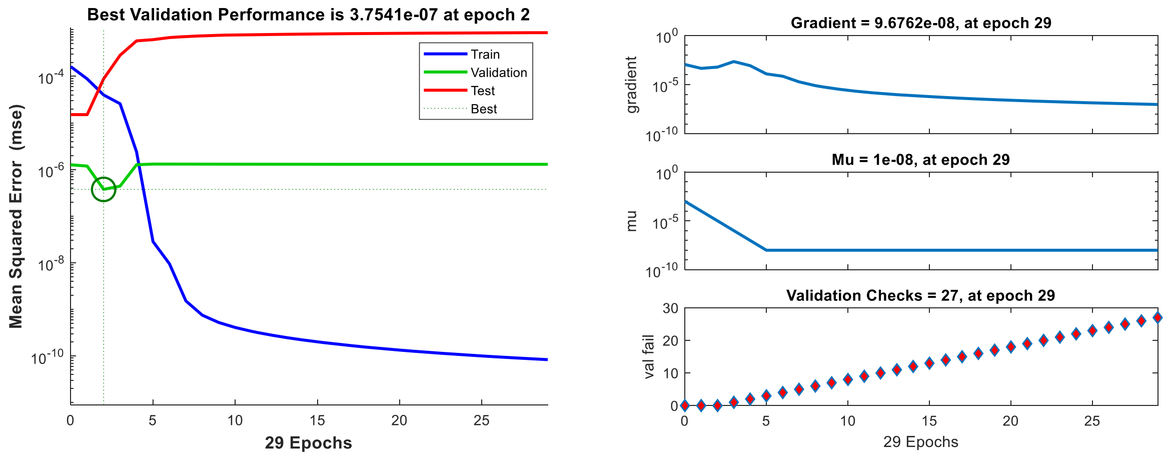

Fig. 5. (a) Training performance of ANN model, (b) Training state of ANN model.

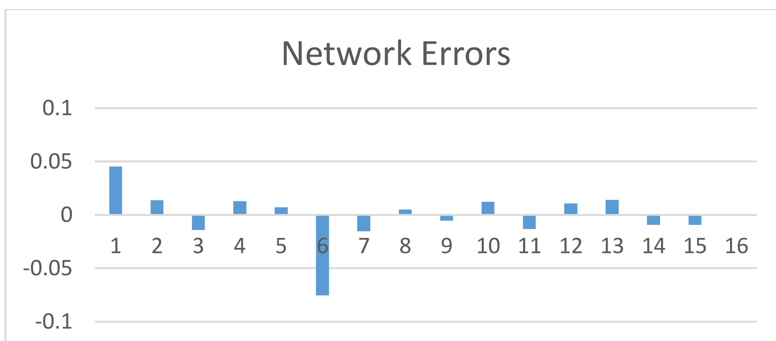

Fig. 6. Figure Network Errors.

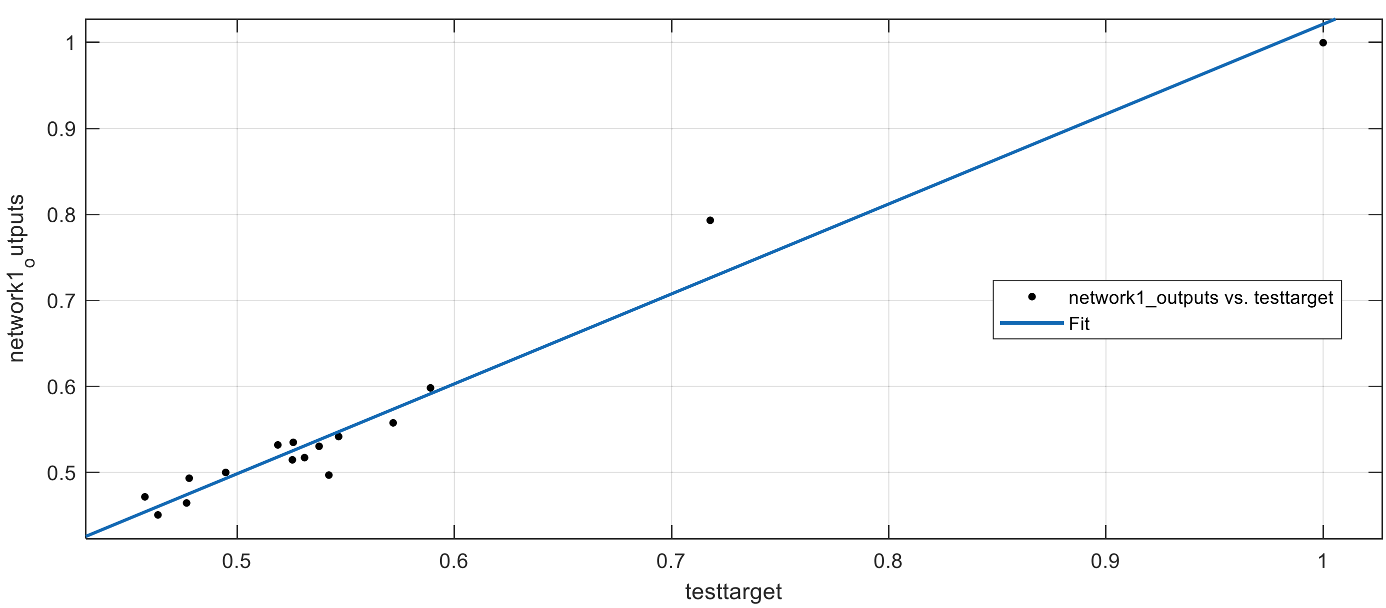

Fig. 7. Comparison between target and forecasting outputs.

between target and forecast values are shown in Fig. 6. Fig. 7 shows the comparison between target and forecast output. It can be seen from the figure that the target and tested output are approximately the same.

The aim of ANN model is to increase learning and to minimize the error level. The higher the number of secret phase, the more time is required. Fig. 8 shows regressions curve of C* testing values of ANN model.

4. Conclusion

As a result of the training, mean absolute error made in Artificial Neural Network with single-layer is 5.8945e–04. This is a good value for

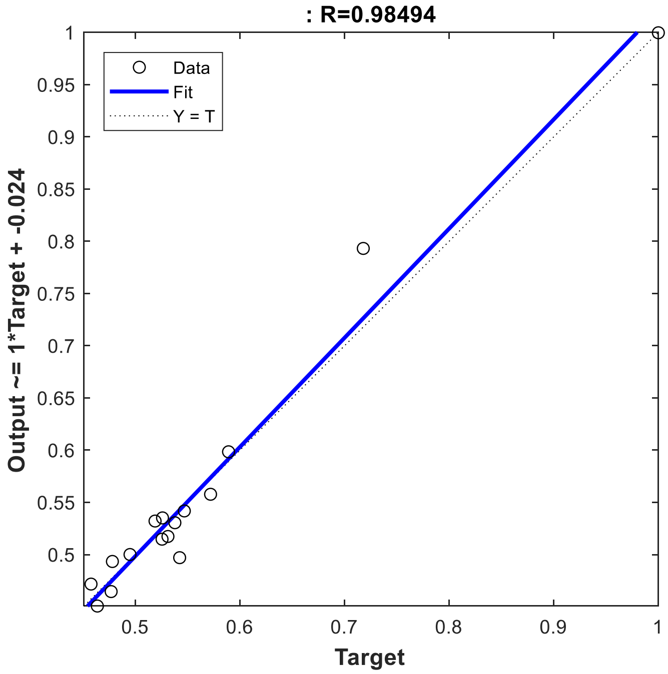

Fig. 8. Tested regression of C* values.

the trained system. The aim here is to draw the error rate closer to zero. The fact that criteria of subcontractors' changes in time, this is reflected its parameters. When TOPSİS and ANN method are compared, ANN method gives as quick and reliable results of C* values.

With this new approach, it has been concluded that work distribution can be made by using the ANN method without making complex mathematical calculations in the distribution of work to the contract workshops. The performance can be enhanced by using more training patterns collected from field study. The results obtained were estimated with an accuracy of 98% by the order distribution process made with the TOPSIS method.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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