


Forecasting Preliminary Order Cost to Increase Order Management Performance: A Case Study in the Apparel Industry

Tüzin Akçınar Günsari, TYH Textile, Turkey*

Aysegül Kaya, TYH Textile, Turkey

Yeliz Ekinci, İstanbul Bilgi University, Turkey

 <https://orcid.org/0000-0001-9478-1271>

ABSTRACT

In this study, the cost estimation to be used in the optimization of proposed order price offer is made by artificial neural network (ANN) method. A case study is performed by the real data of a company, and the forecast results of the traditional arithmetic model used by the company and the proposed ANN-based method are compared, and it is seen that the proposed method results outperform the other. The biggest contribution of this study to companies is to increase the company's order management performance by helping the company to make more accurate pricing due to more accurate cost estimation. Moreover, to the best of the authors' knowledge, this is the first study on forecasting preliminary order cost in the apparel industry and fills an important gap in the literature.

KEYWORDS

Apparel Industry, Artificial Neural Network, Forecasting, Preliminary Order Cost, Ready-Made Garment Sector

INTRODUCTION

The changing dynamics of today's business world point out that data analyzing should be taken into account with importance in all processes of companies. The use of companies' existing data for future forecasts opens a significant horizon for company executives, both in terms of decision-making processes and strategy setting (Guimaraes and Paranjape, 2021).

In the labor-intensive ready-to-wear apparel industry, order costs have a complex structure consisting of many elements. The formation of unpredictable costs on orders makes detailed cost estimation studies both costly and time consuming. The use of data mining techniques in determining the preliminary cost of order and achieving successful results will provide the company with a great competitive advantage and increase order management performance (Pujitha and Venkatesh, 2020).

In some cases, in order to be cautious, the order is missed due to cost estimated higher than its normal value. . In addition, loss occurs as a result of the actual cost value above the estimated cost due to unforeseen extra costs. Both situations cause a decrease in performance for manufacturers producing for global brands in the market.

Due to the fact that the factors that make up the costs consist of many variables and the unpredictable interaction between the variables, difficulties are encountered in estimating the costs,

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*Corresponding Author

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hence the forecasts show low accuracy (Adhikari, Bisi, and Avittathur, 2020). In addition, the dynamic functioning of the sector does not allow high precision calculations in terms of both cost and time constraints. For these reasons, developing high-performance models for order cost estimation is of great importance for supply chain efficiency and company performance (Ngai, et al, 2014).

In general, the entire supply and production process in the textile industry is labor intensive. For this reason, labor costs consisting of human factors have an intense effect on the cost. The fact that the production process is heavily influenced by the human factor rather than the mechanical steps, causes the formation of actual cost data to deviate greatly from the arithmetic and linear preliminary cost estimates (Pujitha and Venkatesh, 2020). In addition, the involvement of external suppliers that are difficult to control over causes deviations from the estimates that are made by linear methods. Based on this approach, in this study, the cost estimation system used by an apparel manufacturer company with arithmetic methods is compared with the cost estimates that will be created by using machine learning and artificial neural networks for the same orders. To the best of our knowledge, this is the first study on forecasting preliminary -order costs in the apparel industry and fills an important gap in the literature.

The article content includes a review of literature of related subject in Section 2. Methodology of the study is explained in Section 3. Structure of the model, performance of the forecasting models and evaluation of results are explained with a case study in Section 4. Conclusion of the study and further research directions are given in Section 5.

LITERATURE REVIEW

Supply Chain Management and Effects of Successful Cost Estimation on Order Management Performance

The importance of order management in ready-made garment (RMG) sector is clear. A comprehensive order management is required in the textile industry in order to manage and fulfill an order profitably. Order management: It is a wide process that includes the management of all variables in the supply chain during the preparation of the order, from preliminary cost offer to the right price to the customer. After the order is received, order management is carried out in coordination with the supply chain management (SCM).

Basak, Seddiqqe and Islam & Akanda (2014) explained the need for working collaboratively in the supply chain as follows. There are four phases of SCM: generation of requirements, sourcing, pricing and post-award activities. In all phases, SCM consists of all parties to fulfill customers' requests not only by manufacturers but also suppliers. (Basak, Seddiqqe, Islam & Akanda, 2014). Ahmad, S., Kamruzzaman, M., & Iqbal, M. (2020) state that since costs are increasing day by day, the only way to increase profit and retain in the competitive market, machine learning techniques should be used to make forecasts. In their study they used ANN to make optimization in the apparel supply chain.

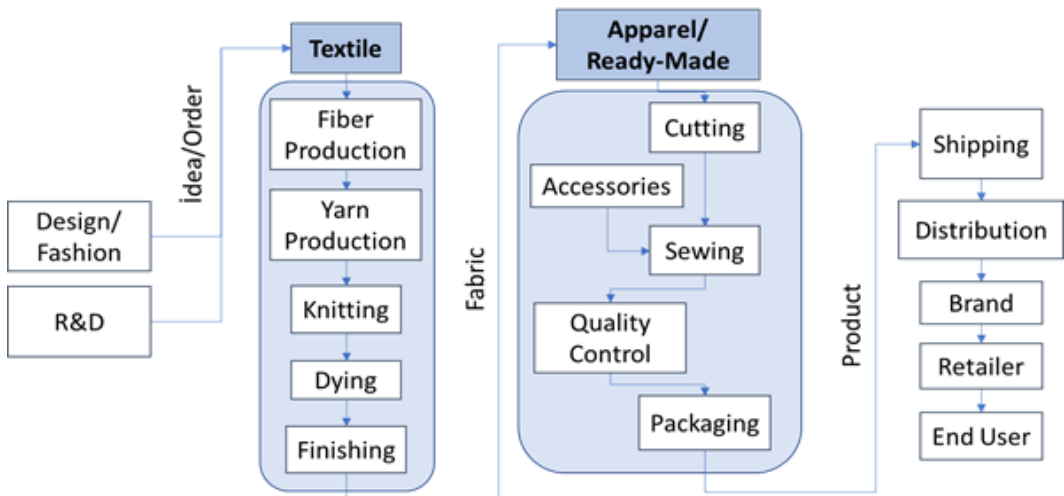
In today's world, wage, supply chain, timeframe, and compliances are key features for ready-made garment (RMG) sector. Even all of them are interrelated and interdependent, the core is having an effective SCM (Hasan, 2017). Miah, Ahmed and Renesa (2018) mentioned about the importance of Supply Chain Management (SCM) in ready-made garment (RMG) sector in their study. Saying that lead time is important in SCM, the authors emphasized that all parties should work in cooperation for an effective SCM. Miah, Ahmed and Renesa (2018) mentioned the importance of supply chain management in RMG sector. The authors, who said that lead time is important in SCM, emphasized that all parties should work in cooperation for an effective SCM. In their study, Barua, Kar and Mahbub (2018) explained that there are many variables that affect RMG exporters and that an effective risk management on factors should be done. One of the risks that needs to be managed is lead time.

In ready-made garment industry, in order to be competitive in the market, lead time is important. Lead time is the period between the placing of the order by the customer and the loading of the final

product by manufacturer (Kader and Md. Khairul Akter, 2014) This time involves raw material procurement, production and loading of the product.

In Figure 1, the order management process of RMG is shown from design, research and development phase to the end user. The field of activity of the company subject to the study, that is, the ready-made garment (RMG) and apparel industry, is shown in the apparel / ready-made box. The box consisting of cutting, sewing, quality control and packaging described in literature as cutting making and trimming (CMT) (Hasan, 2017). While explaining the order management by this figure, we also intend to show the items that make up the order price offer for the product. In addition to the factors here, there are also different factors that affect the order price offer.

Figure 1. Order Management in Ready-Made Garment (RMG) Sector



The estimated preliminary cost, which is formed by calculations made for each of the inputs used by the apparel company, -the manufacturer in the supply chain of the product that reaches the end consumer- affects the price determination policy of the company. Therefore, it will affect the strategic decision of the company by seeing the risk that it will accept. However, determining the deviations in the estimated preliminary cost in the subsequent controls of the company provides a prediction about the performance of the company in order management.

While the order price offer to be presented to the customer in the intense competitive environment is of great importance, the deviations in the predictions also create valuable data to be used later by the company management. There are often minor differences in the proposed price offer of different manufacturers. The high order quantity and low profit rate for the producer cause the cost calculations made on the unit to be high risk when applied to the general order. For all these reasons, the most accurate estimation of the order cost will provide the most accurate price offer, providing manufacturers with high performance in order management and create a competitive advantage. (Darvishi, Yaghin, and Sadeghi, 2020).

Manufacturer companies prepare their price offers to their customers in two approaches, based on market and cost. These approaches depend on the customer and the company's strategic decisions (İçli, 2016). In this context, the cost-based offer is taken into account. For a new product in the RMG sector for export, an estimated preliminary cost is calculated before the price to be given to the customer and the final price offer is reached with the target profit ratio.

Previous Studies on Cost Estimation

To the best of our knowledge, this is the first study on forecasting product costs in the apparel industry and fills an important gap in the literature. However, there are some studies in the literature which forecast preliminary order costs in the construction industry.

The construction industry has some similarities with the textile industry. Firstly, both of the industries are project based sectors. Secondly, both require considering several pieces of costs which make up the total cost. Juszczak and Leśniak (2019) studied on cost estimation for construction projects by using artificial neural networks (ANN). In their study, they start with solving a regression problem and end up with 3 ANN model. Another construction example is that of Salari, Aria and Asgari (2015). They studied with ten construction projects and used fuzzy logic with earned value management (EVM) approach. In their study, they compare the results of two estimation models. The first method is estimate at completion (EAC) approach and the second method is their original method, which is called extended estimate at completion (EEAC). Their findings show us that the new approach is relatively better than traditional one in terms of change in the time value of money and delay in client payment.

Bisen and Dikmen (2012) stated in their study that estimating the cost in structure projects in the construction sector includes many unpredictable variables, so forecast using artificial neural networks model will give better results than expert opinions.

Dogan (2005), based on the cost of the 29 buildings built in the construction sector in Turkey, has made preliminary cost estimation with the help of artificial neural networks. The method he used is similar to the method used in this study. The estimation structure consisting of one hidden layer which calculates the estimated cost per square meter by using 8 different attributes.

In the study of Alqahtani and Whyte (2013), ANN was used to forecast life cycle costs of construction projects. They choose 3 hidden layers model with 20 projects data. Moreover, in Yemen, Hakami and Hassan (2019) studied preliminary construction cost estimation by using ANN with one hidden layer and 136 different projects. As a result of their study, they found the MAPE value as 0.14%. Lastly, in Vietnam, Luu and Kim (2009) studied apartment project's construction cost prediction by using ANN. They choose three layered feed-forward networks with one hidden layer and 7 nodes and applied this method into 5 real-case apartment projects. Their study's MAPE result is 8.5%. Roxas, C. L. C., Ongpeng, J. M. C. (2014) applied ANN to estimate the total structural cost of building construction projects in the Philippines. They used data from a total of 30 building projects and found successful results.

Based on the literature review, it is seen that ANN is the most widely used method in forecasting preliminary order cost. due to the presence of variables that are unpredictable and due to the fact that the interactions of the variables with each other are not clearly known.

Artificial Neural Networks

Artificial neural networks (ANN) emerged in the late nineteenth and early twentieth centuries and were used in interdisciplinary studies. First studies did not include mathematical models, instead they emphasized general theories (Lek and Park, 2008).

Artificial neural networks, commonly known as neural networks, work like a human brain. Also, the human brain works like a complex, non-linear and comprehensive computer with neurons such as artificial neural networks. The principle of artificial neural networks is similar to the human brain. In this context, both artificial neural networks and the human brain can only see the inputs of the problem and the outputs of the solution, rather than the elaboration of the process (Haykin, 1999; Rafiq, Bugmann & Easterbrook, 2001). By details it is meant interneurons that work to calculate the solution. Neural networks learn in trials and act like an expert while generating possibilities, a unique property. (Albino & Garavelli, 1998).

Artificial neural network models are data prediction models that are created based on the brain working system in the human body, the communication and interaction between neurons and other

neurons (Hou et al, 2022). It is based on the assumption that a variable creates a hidden connection with its interaction with other variables and that different inputs that affect the output are formed as a result of this hidden connection. (Singh, Kumar, and Sharma, 2010). A node that operates similarly to a biological nerve cell has multiple inputs, but only one output that it can send to other nodes in the network. The learning process of an artificial neural network consists of creating a weight matrix that will calculate the correct output at an acceptable level according to the input values applied to the nodes in the input layer. Since a node is affected by more than one node, insufficient or corrupt data on the influencer nodes will not affect the overall performance of the system. Artificial neural networks are a suitable model against errors that may arise while working with missing or corrupted data (Walczak, 2019).

Nerve cells in the input layer transmit information from the environment to the hidden layer. There may also be one or more hidden layers. The data transmitted from the input layer is processed by the activation process in hidden layers and transmitted to the output layer. The output layer creates the output values synchronized with the information received (Saatçioğlu and Özçakar, 2016). There are 5 basic elements of artificial neural networks cells that try to imitate the working system of the human brain. These are inputs, weights, addition function, activation function and outputs.

Learning in artificial neural networks is provided by finding weight values that can represent different properties of a group. First, the initial values of the link weights between the neural network nodes are determined. After experimenting with the specified inputs and getting results, this system uses hidden nodes, which gives the coefficient between neurons. As the number of attempts increases, the coefficient will change, so a more suitable estimate will be obtained. (Lek and Park, 2008)

METHODOLOGY

In this study, Artificial Neural Networks with one hidden layer are used. As the activation function, generalized reduced gradient (GRG) -one of the non-linear optimization algorithms- is utilized. The methodology of the study was composed by using Günaydın and Doğan (2004) and Kaya (2019)'s study.

When data normalization is done, construction of the first weight matrix between the inputs and the hidden layers is created. To do that, initial weight values are used as 1. After creating first weight matrix, outputs of the calculation become the inputs of the hidden nodes. This process creates values for the next layer by using weight matrix and *tanh* function. Then, second weight matrix is shaped, and this matrix allows us to transform hidden nodes into single output node. Then, final neural network output is calculated. In this stage the same *tanh* function that is used for output of hidden nodes is used. Lastly, scaling and error calculation operations are performed. (Hegazy ve Ayed, 1998). Scaling is used for transforming values to original range.

After finding ANN results, MAD (Mean absolute deviation), MSE (Mean squared error), RMSE (Root-mean-square deviation) and MAPE (The mean absolute percentage error) values are used to evaluate the performances of the models (Khair, Fahmi, Hakim & Rahim, 2017). Formulae of the performance measures are given below. (Shim, 2000). In the formula, *n* means total number of cases, *t* means related case, *A* means actual value (cost in our study) and *F* means forecast value.

$$MAD = \frac{\sum_{t=1}^n |A_t - F_t|}{n}$$

$$MSE = \frac{\sum_{t=1}^n (A_t - F_t)^2}{n}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (A_t - F_t)^2}{n}}$$

$$MAPE = \frac{\sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|}{n} \times 100$$

CASE STUDY

In this study, estimated preliminary cost and actual cost data for previous orders of a ready-made garment company and all kinds of information regarding orders were available. Many variable data that are assumed to affect the order costs can be obtained from the ERP system of the company.

Only unit consumption is considered in the cost of raw materials and auxiliary materials to be used in each product. Various supply problems, process errors and rework costs regarding quality assurance are ignored in this study. The production costs of the raw materials supplied for each order also vary according to the product. The machinery to be used in production processes, sewing techniques, other processes such as printing and embroidery on the product, the density of the production facility, the location of the production facility also vary according to the order. The study does not include all kinds of unpredictable changes and errors caused by human beings in production that will occur in each order regarding labor cost. However, labor cost is added to the product at every stage of the production process. In the study, the actual order data of an apparel company managing the supply chain was used. The production process of the company starts with the supply of yarn in accordance with the order, then the production of the fabric with the appropriate knitting technique in various external suppliers and simultaneously the provision of the necessary accessories. The production process is completed after the raw materials provided are transformed into a product by passing through cutting, sewing, packaging and other various workmanship stages in the production facilities.

When the data of the manufacturer is examined, there are big differences between the preliminary order costs estimated by arithmetic methods and the actual order costs. The current cost formulation is based on simple algebra and the formula is given below:

$$\text{Product Price Offer} = \text{Estimated Preliminary Cost} + \text{Targeted Profit}$$

$$\text{Estimated Preliminary Cost} = \text{Fabric Cost} + \text{Accessory Cost} + \text{Print \& Embroidery Cost} + \text{CMT} + \text{General Expenses}$$

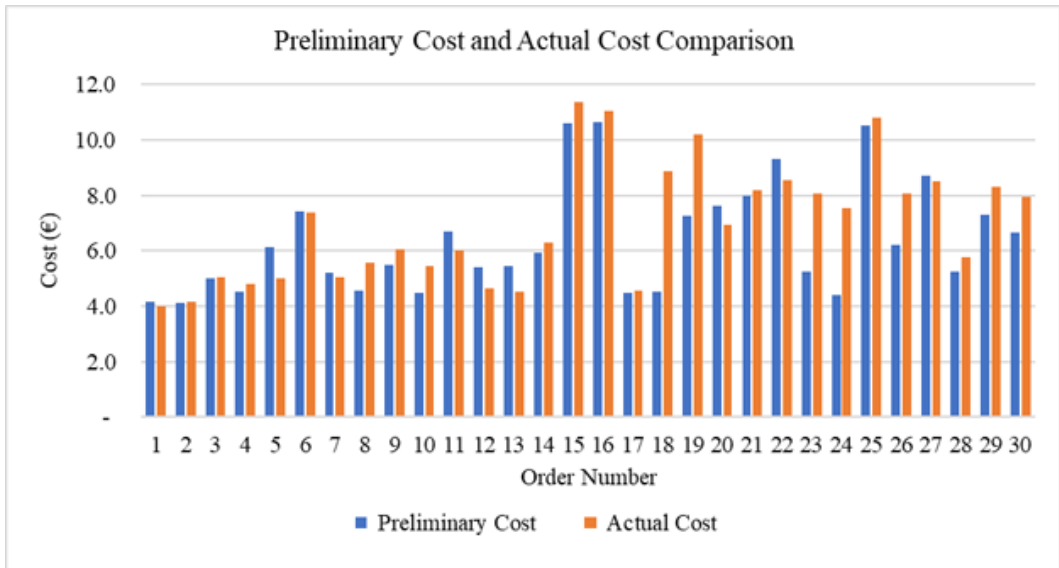
In the formulation CMT means cut, make, and trim. Cut is used for shaping the fabric, make is used for sewing operations and trim is for making corrections and final controls of the product. Instead of using the formula above which is arithmetic method of estimating preliminary cost, the purpose of this study is to forecast the preliminary cost by using ANN.

The orders belonging to a certain customer group of the company were selected and the data regarding the orders was listed. Data about the orders consist of yarn type, yarn composition, fabric color, knitting type, accessories, product group, fabric finishing process, printing-embroidery, extra operations and lead time. Considering that the estimated preliminary costs calculated with the classical calculation method (arithmetic calculation) deviate significantly from the actual costs, it is important to forecast the preliminary cost accurately.

Figure 2 shows the comparison of the preliminary cost calculated with the current arithmetic formula used by the company and the actual cost of 30 orders selected from the orders used within the scope of the study. The blue bar represents the preliminary cost (arithmetic method estimate),

i.e. the price offer, while the red bar represents the actual cost of the order after completion. Details of this figure are given in Table 4, where actual cost and arithmetic method estimate (preliminary cost in this figure) are listed for each order. The MAPE of the actual and forecast values given in Figure 2, is 12.95%.

Figure 2. Comparison of Preliminary Cost Based on Current Calculation and Actual Cost



Structure of the Model

In this study, it is aimed to estimate the preliminary costs of an apparel (a company that does CMT in Ready-Made Garment Sector) company using the company’s actual order data. For this purpose, factors affecting order costs were determined with the information obtained from company managers. A certain customer group suitable for this purpose was determined and the existing orders of these customers were examined. Accordingly, the model has been structured with 10 variables: yarn type, yarn composition, fabric color, knitting type, accessories, product group, fabric finishing process, printing-embroidery, extra operations and lead time. After the input variables were determined, the data of the relevant customer and order were extracted from the company’s ERP system. The information about the order obtained has been evaluated. The variations between variables were determined and their numerical equivalents were used in the model.

In the establishment and creation of the model, the studies of Kaya (2019) and Günaydın and Doğan (2004) were taken as basis. In addition, the work of Ugurlu and Pali (2019) was taken into consideration for the CMT processes of the company where the case study was applied.

As a result of the literature review and interviews with experts, the factors affecting the order cost are listed as follows:

1. Lead time: It refers to the number of days from the time the order is approved and entered into the ERP system until the loading stage. This variable is introduced as numerical variable in the ANN model.
2. Yarn type: It belongs to the yarn types used in the order. There are three types available; which are 30/1, 40/1 and 50/1. These are introduced as categorical variables in the model.

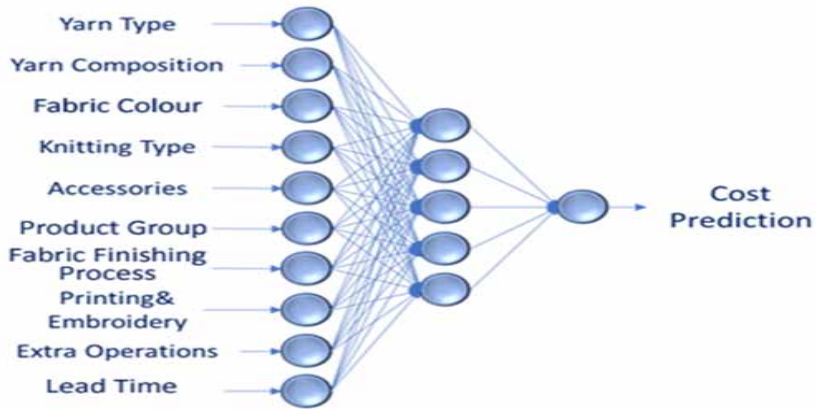
3. Yarn composition: Refers to the mixture of the yarn used in the order. There are eight types used in the manufacturing process. This factor is a categorical variable, as well.
4. Knitting type: It describes the knitting type of the fabric used in the order. Five knitting types are available in the dataset, namely single jersey, interlock, rib, fleece and terry. Therefore, this variable is also a categorical variable.
5. Fabric colour: Refers to the color of the fabric used. In the dataset, three types are available for this criterion, which are solid colours, mélange and roller printed. Fabric colour is another categorical variable used in the ANN model.
6. Fabric finishing process: It indicates the properties that are applied to the fabric after the dyeing stage. This categorical variable includes three types of processes; namely brush, mercerized and non.)
7. Accessories: It refers to the items used in the production as auxiliary materials (other than fabric). In this categorical variable, there are seven types in the dataset; which are no-accessories, standard accessories, native lace, imported lace, button, zipper, ribbon-cord-rubber.
8. Printing & Embroidery: This factor covers details in the production, such as printing / embroidery. Five types are available in the dataset; printing, foil printing, embroidery, no-embroidery or print, and stone sticking. This variable is also a categorical variable.
9. Product group: It describes the product group the order belongs to. There are eleven cases in this categorical variable, which are basic dress, dress, t-shirt, hoody, pants, cardigan, top-bottom set, robe, zippered jacket, and top-bottom set with shirt for men.
10. Extra operations: This categorical variable refers to the extra operations applied to the product. There are six types of operations available in the dataset; namely no-extra operation, button/buttonhole, line following, baby overlock/watermelon seeds/crochet, rib and adjustable buckle.

Output variable was used as the actual cost in the ANN model. This variable is a numerical one, and the following formula is used for normalization for numerical data in this study (Vafaei, Ribeiro and Camarinha-Matos, 2018):

$$Normalized\ Value = \frac{2x(Value - Column\ Min)}{(Column\ Max - Column\ Min)} - 1$$

For the categorical variables, *Dummy Encoding* is used. The reason for using this approach is because it is the most widely used method in ANN models. The ANN network, that is used in this study is illustrated in Figure 3. Each circle represents a neural cell, nodes as hidden layers. The circles in the first column show the input layer. Those in the second column are hidden, while the circles in the third column show the output layer. In the ANN model, a single output does not occur as a result of a single connection, as in the human brain, a factor is affected by more than one factor and affects the output in different ways. As can be seen in the figure explaining the working principle of ANNs, a node has more than one input and a single output is formed as a result of other hidden relationships and connections. In the background of the resulting output layer, a network of relationships is formed with hidden layers (Günaydın and Doğan, 2004).

Figure 3 Principle of artificial neural network used in this study



Performances of the Forecasting Models

Trials were conducted by making various variations such as the number of orders, the number of training and testing set, sorting the variables according to their order of importance and lower and upper limits, and the use of different orders. With the experience gained in the first trials, care was taken to ensure that the training group was inclusive and diverse in the sample.

In Table 1, features of 3 different orders are given. As can be seen in Table 1, there are different types of products and this makes it difficult to make meaningful estimations. For example, the features of 128th order are 30/1 yarn number, 95% viscose 5% elastane yarn composition, pink fabric color, no fabric finishing process, local labels and standard accessories used, has print, trousers as product group, no extra operation and finished within 102 days. Therefore, meaningful groups were formed from the available data by grouping and forecasts were made with these groups.

Table 1 Features of 3 Orders

Order No	128	53	90
Yarn Type	30/1	40/1	50/1
Yarn Composition	95% Viscose 5% Elastane	100% Modal	82% Viscose 14% Polyester 4% Elastane
Fabric Color	Pink	Beige Colored Background- Print	Mélange
Knitting Type	Single Jersey	Interlock	Single Jersey
Fabric Finishing Process	-	Mercerized	Brushed
Accessories	Local Labels / Standard Accessories	Button	Local Labels / Standard Accessories
Printing & Embroidery	Print	Embroidery	-
Product Group	Trousers	Dress	Cardigan
Extra Operation	-	Overlock- Crochet	-
Lead Time	102	88	97

The model used consists of 3-layer neural network with 1 input, layer, 1 output node and 1 hidden layer. Trials were made in sets of 30 orders. After each trial, the selection of orders was rearranged according to the results. If a result with a high error rate was obtained, the differences in the selected order set and the order characteristics were examined. It is understood that generating order sets with similar criteria gives better results for ANNs to make more accurate predictions. Table 2 below provides details of the trials. A total of 44 trials were made with these orders. In 44 trials, the training set consisted of an average of 25 orders, and the test set consisted of an average of 5 orders.

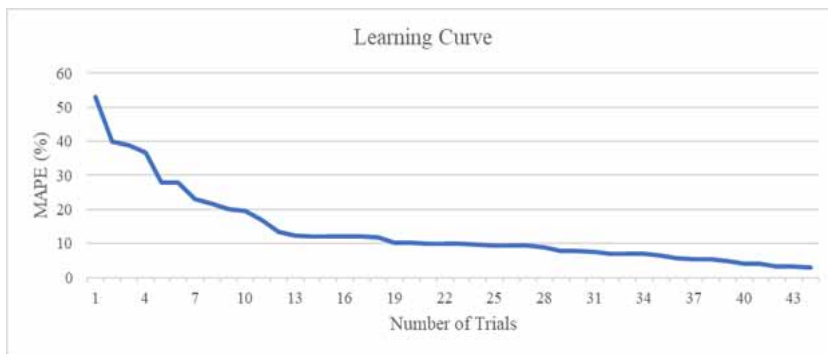
In this study, many trials were run, and the dataset contents were reconstructed according to the results of these trials and the model was run over and over again. If the selected group has a situation that will cause a high rate of deviation in the model, they are excluded from the training set. Trials were made by structuring the dataset as 80% train set and 20% test set. As the number of trials increased and the outputs were reviewed, it became possible to make forecasts with smaller error rates.

When the results of the 44 trials are examined, it is seen that ANN learned as the number of trials increased, as in other studies in the literature. The learning curve of the trials conducted in this study is shown in Figure 1. It is possible to say that the model can obtain more accurate results by increasing the number of trials.

Table 2. Details of the dataset

Number of Cases (Orders)	30
Number of Trials	44
Number of Orders in Training Set	25
Number of Orders in Testing Set	5

Figure 4 Learning Curve



As a result, it was seen that the mean absolute percentage error (MAPE) in the train set was 4.91%, while it was 1.38% in the test set and overall MAPE is 4.32% (Table 3).

When the forecast results were reviewed, it was observed that there were unusual situations such as delays or customer deadline changes in orders that the forecast deviated the most from the actual cost. It has been observed that the presence of orders in the train set that are not reflected in general, increases the model's error rate.

Table 3. ANN Results

MAPE of Training Set	4.91%
MAPE of Testing Set	1.38%
MAPE of Data Set	4.32%

Table 4. Cost Comparison

Order No	Actual Cost	ANN Forecast	Arithmetic Method Estimate
1	4,02	4,10	4,17
2	4,17	4,12	4,11
3	5,04	4,14	5,03
4	4,82	4,92	4,52
5	5,03	5,13	6,12
6	7,39	4,09	7,43
7	5,06	4,09	5,23
8	5,59	5,70	4,55
9	6,04	6,16	5,48
10	5,47	5,58	4,49
11	6,00	5,88	6,69
12	4,66	4,75	5,41
13	4,52	4,43	5,47
14	6,29	6,16	5,95
15	11,38	11,20	10,63
16	11,07	11,20	10,64
17	4,56	4,65	4,51
18	8,86	9,04	4,54
19	10,21	10,41	7,29
20	6,94	6,80	7,63
21	8,21	8,13	8,00
22	8,56	8,73	9,33
23	8,06	7,90	5,24
24	7,54	7,69	4,41
25	10,82	10,60	10,54
26	8,06	8,18	6,20
27	8,52	8,52	8,70
28	5,76	5,85	5,27
29	8,30	8,13	7,31
30	7,95	8,10	6,67

Evaluation of the Results

The ANN results are compared with company's current calculation method (arithmetic method). In Table 4, results are shown in order of actual cost, the cost estimated by the ANN model and the cost calculated by the company with arithmetic method. It is seen that the cost forecasted by the algorithm for 3 orders deviates significantly from the actual cost (order number 3, 6 and 7). When these 3 order details were examined, it was seen that there were different problems experienced during the production process.

The comparison of MAD, MSE, and MAPE of the arithmetic method and ANN results is shown in Table 5. As can be seen in Table 5, ANN has better results than the method currently used by the company. The mean absolute percentage error (MAPE) is 4.32% in proposed methodology which uses ANN, whereas 12.95% in company's simple arithmetic calculation method. The performance increase by the proposed methodology will have a direct positive impact on the performance of order management and profitability of the company.

Table 5 Comparison Between the Results of ANN and Arithmetic Method of Company

Performance Measure	ANN	Arithmetic method
MAD	0.28	0.94
MSE	0.44	1.97
MAPE (%)	4.32	12.95

CONCLUSION AND FURTHER RESEARCH DIRECTIONS

Although the textile industry has a fast process flow, it needs scientific methods in the stages of both taking the order, producing the order and delivering it to the customer. The dynamics of the sector where competition is at the forefront, it is seen that it is important to give the best price offer for both the customer and the manufacturer. In this direction, while taking the order, forecasting preliminary cost is important both in receiving and producing the order. To the best of our knowledge, this is the first study on forecasting preliminary order cost in the apparel industry and fills an important gap in the literature. In this study, the preliminary cost and actual cost in the company were compared using past data of a company, and in line with this, cost estimation was carried out using ANN.

As a case study, a certain customer of a company and a certain product group belonging to that customer are selected. These orders are categorized according to their characteristics. The information of the selected orders was evaluated over 10 different variables, and the data was organized and made ready for ANN. The results of the ANN-based proposed methodology and the current method used by the company are compared for a set of 30 orders. It is found that, the mean absolute percentage error (MAPE) is 4.32% in proposed methodology, whereas 12.95% in company's simple arithmetic calculation method.

It has been observed that the selected product group has a direct effect on the estimation. Similar products should be trained together in the dataset in order to get accurate results. Moreover, the variables that are used as input are found important in increasing the performance of the models. The most significant variable in forecast is seen as the product group, followed by yarn type. The biggest contribution of this study is that with more accurate cost estimation, the company will gain competitive advantage by giving more accurate price offers. Moreover, late price offers may cause the order to be missed. With this study, it is possible to create the price offer in seconds. Thus, the company will gain a competitive advantage with the rapid creation of the offer. Hence, the performance of the order management process will be increased in terms of accuracy, time and profitability.

For future work, the integration of this study into the ERP system will be beneficial for the company. For further studies, different machine learning methods can be applied and compared.

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