Black Sea Journal of Engineering and Science
doi: 10.34248/bsengineering.1296187

Open Access Journal
e-ISSN: 2619 – 8991

Research Article
Volume 6 - Issue 4: 325-329 / October 2023

DETERMINATION OF HARNESS PRODUCTION TIME AND DEFECTIVE PRODUCT FORMATION RISK FACTORS WITH ARTIFICIAL NEURAL NETWORK

Gülşah KURNAZ[1], Naci MURAT[1]*

[1]*Ondokuz Mayıs University, Department of Industrial Engineering, Faculty of Engineering, 55139, Samsun, Türkiye*

Abstract: The aim of this research is to estimate the projected production times of the cable harnesses produced for the tender in a company operating in the aviation and defense industry in our country by artificial neural network. For this, artificial neural network model has been formed for the number of work order, the number of cable harness module, the number of cable harness pin, the number of cable harness label, the number of cable harness back shell, the number of cable harness heat shrink tube, and the number of cable harness terminal variables which may have an effect on the projected production times of cable harnesses for the tender. Multiple linear regression analysis method is used to compare the predictive power of this model and the most appropriate method for estimating the projected production time of cable harnesses for the tender is provided. The aim of the research is to determine the effect of cable harness connector type, cable harness label type and personnel competence level risk factors on the formation of faulty cable harnesses determined during the quality control and electrical testing steps in the production process using logistic regression analysis.

Keywords: Machine learning, Artificial neural networks, Logistic regression analysis, Determination of risk factors

***Corresponding author:** Ondokuz Mayıs University, Department of Industrial Engineering, Faculty of Engineering, 55139, Samsun, Türkiye
E mail: nacimurat@omu.edu.tr (N. MURAT)
Gülşah KURNAZ https://orcid.org/0000-0002-1341-1517
Naci MURAT https://orcid.org/0000-0003-2655-2367

Received: May 12, 2023
Accepted: July 25, 2023
Published: October 15, 2023

Cite as: Kurnaz G, Murat N. 2023. Determination of harness production time and defective product formation risk factors with artificial neural network. BSJ Eng Sci, 6(4): 325-329.

1. Introduction

Computers and computer systems having critical role among the indispensable elements of our life have had limited capabilities such as to be able to make calculation or transfer data in the past. Nowadays, it has the ability to be able to operate and interpret its decision mechanism on existing or future situations by using large amounts of data (Alpaydın, 2010). On the other hand, the rapid digitization of the world and the increase in internet usage, which offers instant access to information and news, have increased total data (Pacci et al., 2023). In parallel with these developments in technology, the amount of numerical information produced in enterprises is increasing. It is seen that databases have reached the level of being able to store larger amounts of data and it is easier to access the data (Leech et al., 2004). This has revealed the presence of large data concept with high capacity and capacity increasingly a wide range of data (Bayır, 2006). Each day, the storage of increasing data and reaching the data have started to be difficult for businesses. For this reason, the enterprises are required to provide sustainable competitive advantage that makes it possible to provide products or services with a higher value added value. It is not always possible to work with experts who are accurate, realistic, and have sufficient knowledge and foresight in making strategic decisions that determine the future of enterprises in order to ensure the highest efficiency (Kotsiantis, 2007). Strategic decision-making and predictions are able to save the workforce and cost when performing the computer. In addition, it provides many gains such as being able to be objective and the information needed is easily copied and replicate (Kurt et al., 2017). Machine learning is defined as a method that uses AI, statistics and mathematics to make strategic decisions, predict, and use knowledge from experience. Artificial intelligence benefiting from statistics and mathematics; The machine learning described as a method that uses the information obtained from strategic decision-making, prediction, and experiences (Jackson, 2002; Karabulut and Alpar, 2011). Inspired by the human brain, which incorporates the ability to discover or produce new information, artificial neural networks (ANNs) are a simulation of the biological nervous system that can perform complex calculations by creating relationships and performing them automatically (Beale et al., 2010). Artificial neural networks are a branch of computer science developed for systems that are difficult or impossible to program (Öztemel, 2003). Artificial neural networks are called structures consisting of many interconnected nodes, which are expressed as simple nerves and mostly function in parallel (Elmas, 2003). Artificial neural networks are usually a structure consisting of the input layer, hidden layers and output layer (Öğücü, 2006; Buduk, 2013). In artificial neural networks, each of the neurons is connected by synaptic weight to other neurons in the previous layer (Kalogirou, 2000). The artificial nerve cell, expressed as the smallest unit of an artificial neural network, consists of five main parts: inputs, weights, joining function, activation function and output (Gürsoy, 2012). Methods used in machine learning such as classification, clustering and estimation are among the basic functions of artificial neural networks (Chiang et al., 2004; Küçüksille, 2009).

In this study, it is aimed to estimate the production times of cable sets produced in a company operating in the aviation and defense industry of our country through artificial neural networks.

2. Materials and Methods

2.1. Materials

In a company that has been operating in the aerospace and defense industry for many years, approximately 650 different types of harness are produced in "IPC/EIA J-STD-001C Requirements for Soldered Electrical and Electronic Assemblies" and "IPC/WHHA-A-620 Requirements and Acceptance for Cable and Wire" Harness Assemblies standards. In order to produce these cable sets, a tender for the purchase of labor services has been opened.

This study was completed between August 2016 and November 2018 and the projected production times of the cable tools (harness) delivered for the tender were determined with the help of machine learning algorithms. For this purpose, it was determined that the cable module, cable pin, cable label, cable back-ring, cable macaroon and cable terminal were both used jointly and went through similar integration processes during the production of 187 of the 650 types of cable set produced in the company (Figure 1).

Figure 1. Materials commonly used in cable set production.

In this study, the competence level of the personnel who produce cable set connector type, cable set label type, and cable set label type was determined as independent risk factors that affected the formation of defective cable sets detected during quality-control and test processes after the production of cable sets. Therefore, the type of cable set connector, the cable set label type, the level of competence of the personnel who produce the cable set are as independent variable; whether there is a defect in the products during the quality control and testing processes of the cable sets is determined as dependent variable. The risk factors that affect the formation of defective products are shown in Figure 2.

Figure 2. Risk factors that affect defective product formation.

2.2. Method

Modeling has been established for the analysis to be carried out to determine the cable tool production time, risk factors affecting defective products and defective/defective cable sets. Artificial neural networks, which are formed by the combination of nerve cells expressed as basic units by forming parallel bonds within various layers, obtain information from the learning process just like in the human brain (Haykin, 1994; Tiryaki et al., 2015).

Although artificial neural networks usually consist of an input layer, hidden layers and an output layer, basically each neuron binds to other neurons in the previous layers with the help of their synaptic weight (Kalogirou, 2000). The structure of the artificial neural network is shown in Figure 3.

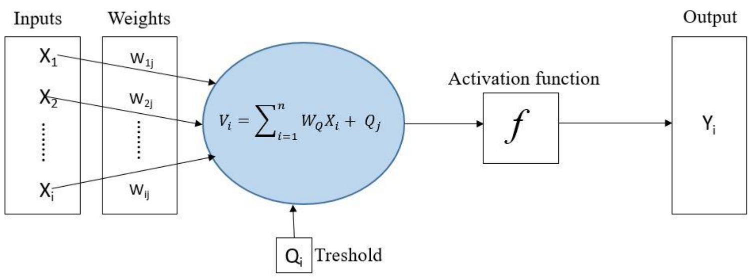

Figure 3. Structure of artificial neural network (Elmas, 2003).

In the structure of the artificial neural network shown in Figure 3, the inputs expressed with Xi transmit the information obtained from the environment to the nerve. The weights expressed by Wi determine the effect of inputs taken by the artificial nerve on the nerve. The large weight value refers to the strong binding of the corresponding input to the artificial nerve, while the small weight value refers to the weak attachment of the corresponding input to the artificial nerve (Elmas, 2003). The aggregation process indicated by Vi in the nerve is added to the activity function by adding the total of the weights to the threshold value obtained from the sum of their product (Qj) with the inputs to which they belong. The result of the aggregation function is then passed through the activity function expressed by f(activity) and forwarded to the output. The activity function allows the output of the collection function to change when time is involved.

2.2.1. Modeling with artificial neural network

Since back propagation algorithm is the most frequently used algorithm for solving prediction problems with artificial neural network model in the literature, multilayer feedforward back propagation machine learning algorithm was also used in this study. In this study, 7 independent variables were determined that the projected production periods can affect the production time in order to be estimated. These variables represent the input number of the artificial neural network model (Figure 4). The output layer was determined as production times in the tender.

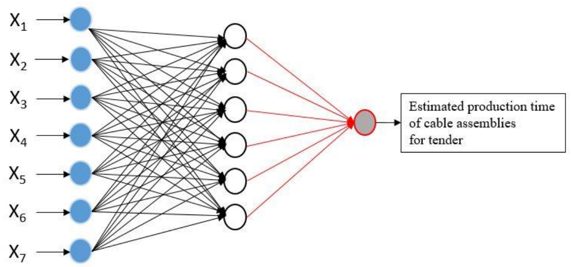

Figure 4. The artificial neural network architecture of the model.

In the study, Knime 3.6.2 program was used in the analysis of the artificial neural network model. Normalization was applied to these values in order to keep the impact of input variables in very low or very large value in the formation of the artificial neural network. The most critical stage of the neural network is the training of the network. For this, the partitioning operator in the Knime 3.6.2 program was used in order to divide 70% of the 415 datasets for training (290 units) and 30% (125 units) for testing.

3. Results and Discussion

Evaluation results of the models created for the detection of defective or flawless cable sets detected in quality control and test steps using machine learning algorithms are included.

3.1. Evaluation of the Artificial Neural Network Model

Mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and R2 values were examined as performance criteria after the application of the artificial neural network model created to determine cable tool production times (Table 1).

Table 1. Artificial neural network model predictive performance criteria and values

Criterion	Value
R^2	0.852
MAE (Mean Absolute Error)	0.013
MSE (Mean Squared Error)	0.001
RMSE (Root Mean Squared Error)	0.036

The relationship between the estimated values reached after the application of the artificial neural network model and the actual values is shown in Figure 5. When evaluated, this graph shows that the actual values are estimated with high accuracy.

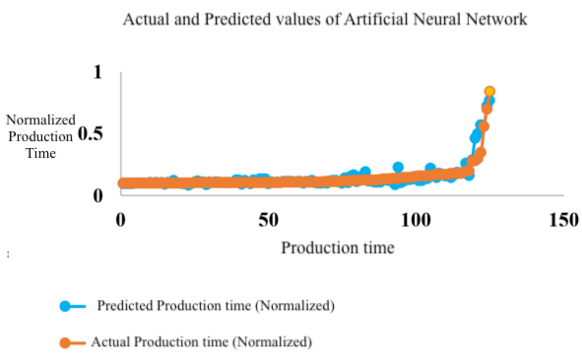

Figure 5. Relationship between predicted values and actual values according to ANN.

Multiple linear regression (MLR) models have been created to test the strength of the artificial neural network model created to estimate cable tool production times. After the implementation of this model, the performance criteria for the model are R^2, MAE, MSE, and RMSE values are included in Table 2.

Table 2. Multiple linear regression model forecast performance criteria and values

Criterion	Value
R^2	0.745
MAE (Mean Absolute Error)	0.013
MSE (Mean Squared Error)	0.002
RMSE (Root Mean Squared Error)	0.048

The estimated values obtained by the application of the multiple linear regression model and the actual values are shown in Figure 6.

A comparison of the results of the artificial neural network and multiple linear regression model for estimating cable tool production times according to performance criteria is shown in Table 3.

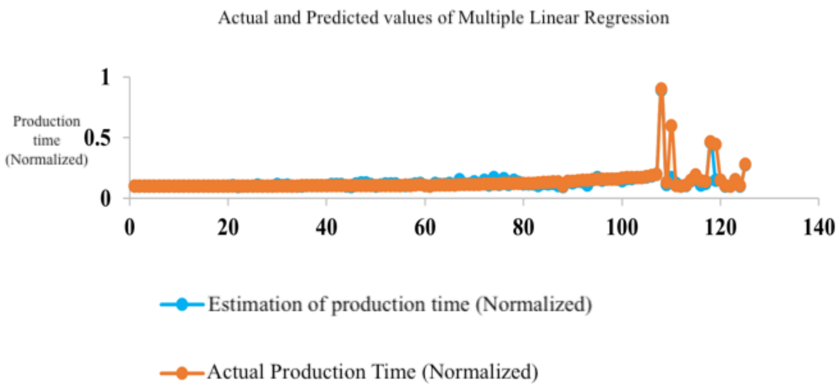

Figure 6. The relationship between predicted values and actual values in a multiple linear regression model.

Table 3. Comparative model performance criteria values

Methods	R^2	MAE	MSE	RMSE
ANN	0.852	0.013	0.001	0.036
MLR	0.745	0.013	0.002	0.048

In Table 3, the mean square error (MSE) value is evaluated as a performance measure in the forecast methods. With the artificial neural network model with the smallest MSE value, it is estimated with higher accuracy to the actual values.

Considering the results of the artificial neural network model, it is understood that 85.2% of the changes in the projected production times of the cable sets produced and delivered between August 2016 and November 2018, which are considered dependent variables, were explained by amount of work order, number of cable set modules, number of cable set pins, number of cable set labels, number of cable tool backs, number of cable set macarons and number of cable set terminals which are independent variables. According to the results of the multiple linear regression model, 74.5% of the changes in the dependent variable can be explained by the independent variables.

Considering all these criteria, it was concluded that the estimation values with the artificial neural network offer closer to the actual values.

4. Conclusion

Thanks to the technological developments today, large data sets are recorded on databases and these data can be inferred about future possible situations. Machinery learning techniques, which have the ability to learn the existing data and to control systems by basic, and the machine learning techniques that have the ability to predict future events with acquired experiences. For this reason, all organizations have to carry out studies to prevent and improve their results by predicting the uncertain situations that they may be affected in the future. In this study, the artificial neural network model was created in order to predict the production periods that are produced in a company operating in the Aeronautics and Defense Industry. Then, artificial neural network results and multiple linear regression model results were compared in order to measure the predictive power of the model.

According to the estimation result of ANN, 85.2% success was determined by 0.001 MSE value. As a result of the estimation made with the multi-linear regression model, 74.5% success was determined with 0.002 MSE value. As a result of the applications performed, it was concluded that the artificial neural network model generated by machine learning algorithms is more successful.

Author Contributions

The percentage of the author(s) contributions is presented below. All authors reviewed and approved the final version of the manuscript.

	G.K.	N.M.
C	50	50
D	50	50
S	50	50
DCP	50	50
DAI	50	50
L	50	50
W	50	50
CR	50	50
SR	50	50
PM	50	50
FA	50	50

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

Acknowledgements

It was produced from the thesis titled "Determination of harness production time and defective product formation risk factors with machine learning algorithms" at Ondokuz Mayis University Thesis no: 571508. https://tez.yok.gov.tr/UlusalTezMerkezi/tezSorguSonucYeni.jsp.

References

Alpaydın E. 2010. Introduction to machine learning (Second edition). MIT Press, London, UK, pp: 537.

Bayır F. 2006. An application on artificial neural networks and predictive modeling. Master Thesis, Istanbul University Institute of Social Sciences, Department of Business Administration, İstanbul, Türkiye, pp: 122.

Beale MH, HaganMT, Demuth HB. 2010. Neural network toolbox 7 user's guide. The MathWorks Inc., Natick, Massachusetts, US, pp: 424.

Burduk A. 2013. Artificial neural networks as tools for controlling production systems and ensuring their stability. 12th International Conference on Information Systems and Industrial Management (CISIM), Computer Information Systems and Industrial Management, 25-27 October, 2013, Krakow, Poland, pp: 487-498.

Chiang YM, Chang LC, Chang FJ. 2004. Comparison of static-feedforward and dynamic-feedback neural networks for rainfall–runoff modeling. J Hydrol, 209: 297-311.

Elmas Ç. 2003. Artificial neural networks theory, architecture, education, practice (first edition). Seçkin Publishing, Ankara, Türkiye, pp: 192.

Gürsoy A. 2012. Estimation of tire mold cost with artificial neural networks approach. Master Thesis, Kocaeli University Institute of Science and Technology, Department of Industrial Engineering, Kocaeli, Türkiye, pp: 102.

Haykin S. 1994. Neural netwroks: A comprehensive foundation (First edition). Macmillan College Publishing, New York, Us, pp: 696.

Jackson J. 2002. Data mining: A conceptual overview. Communication of the Association for Information System Magazine, 8(1): 267-296.

Kalogirou SA. 2000. Applications of artifical neural-networks for energy systems. Appl Energy, 67(1): 17-35.

Karabulut E, Alpar R. 2011. Logistic regression, applied multivariate statistical methods. Detay Publishing, Ankara, Türkiye, pp: 876.

Kotsiantis SB. 2007. Supervised machine learning: A review of classification techniques. Informatica, 31(3): 249-268.

Küçüksille E. 2009. Evaluation of portfolio performance using data mining process and an application in the ISE stock market. PhD Thesis, Süleyman Demirel University, Institute of Social Sciences, Department of Business Administration, Isparta, Türkiye, pp: 128.

Kurt R, Karayılmazlar S, İmren E, Çabuk Y. 2017. Predictive modeling with artificial neural networks: The case of Turkish paper-cardboard industry. J Bartın Fac Forestry, 19(2): 99-106.

Leech HL, Barrett KC, Morgan GA. 2004. Spss for intermediate statistics: use and interpretation (Second edition). Lawrance Erlbaum Associates Publishers, 240, Manwah New Jersey.

Öğücü MO. 2006. System recognition with artificial neural networks. Master Thesis, Istanbul Technical University, Institute of Science and Technology, Department of Control and Automation Engineering, İstanbul, Türkiye, pp: 85.

Öztemel E. 2003. Artificial neural network (first edition). Papatya Publishing, İstanbul, Türkiye, pp: 232.

Pacci S, Safli ME, Odabas MS, Dengiz O. 2023. Variation of USLE-K soil erodibility factor and its estimation with artificial neural network approach in semi-humid environmental condition. Brazilian Arch Biol Technol, 66: e23220481.

Tiryaki S, Bardak S, Bardak T. 2015. Experimental investigation and prediction of bonding strength of oriental beech (Fagus orientalis Lipsky) bonded with polyvinyl acetate adhesive. J Adhesion Sci Technol, 29(23): 2521-2536.