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Artificial intelligence based prediction models: sales forecasting application in automotive aftermarket

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Abstract. Automotive aftermarket industry is possessed of a wide product portfolio range which is in the 4th rank by its worldwide trade volume. The demand characteristic of automotive aftermarket parts is volatile and uncertain. Nevertheless, the cause-and-effect relationship of automotive aftermarket industry has not been defined obviously heretofore. These conditions bring automotive aftermarket sales forecasting into a challenging process. This paper is composed to determine the relevant external factors for automotive aftermarket sales based on expert reviews and to propose a sales forecasting model for automotive aftermarket industry. Since computational intelligence techniques yield a framework to focus on predictive analytics and prescriptive analytics, an artificial neural network model constructed for Turkey automotive aftermarket industry. Artificial intelligence is a subset of computational intelligence that focused on problems which have complex and nonlinear relationships. The data which have complex and nonlinear relationships could be modelled successfully even though incomplete data in case of implementation of appropriate model. The proposed ANN model for sales forecast is compared with multiple linear regression and revealed a higher prediction performance.

Keywords: Sales forecasting, automotive aftermarket, artificial neural network, ANN, predictive analytics

1. Introduction

Automotive industry is one of the leading sectors of the world economy, together with its sub-industries. It is the main driver of macroeconomic growth, stability and technological development in developed countries and emerging countries. The developments in automotive industry led to the emergence of several automotive brands, automotive models, business models, distribution channels and a developed automotive aftermarket industry.

World Economic Forum prepared a report to investigate the most traded goods around the world according to their trade volume in 2018. The most traded good of worldwide economy is finished automobiles with 1.35 trillion USD trade volume, automotive parts have 685 billion USD trade volume and it is in the 4th rank according to the research [45]. Automotive aftermarket industry comprises parts, accessories, maintenance items, batteries, automotive fluids and test equipment. These products are necessary to maintain useful life of automotive.

However, the demand of these products, especially the time when customers will need a product or service to solve their problems, is difficult to be foreseen. Volatility and uncertainty of automotive aftermarket demand characteristic brings automotive aftermarket sales forecasting into a challenging process. Automotive aftermarket products are to be classified into two separate groups according to complexity of its predictability. Periodic maintenance products such as filters, spark plugs, wipers tend to have predictable demand. On the other hand, the system products such

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as subcomponents of diesel systems, gasoline systems, rotating machines, brake systems and comfort electronic systems are more unpredictable since the demand is raised based on defect or breakdown of the products. Prediction of demand is crucial to decide for necessary future strategic and operational changes in the organization by considering the past and current performance. Resource allocation will be affected by future demand projections directly. Thus, accuracy of sales forecast and demand forecast is vital to determine the business strategy.

Automotive aftermarket is more unpredictable than original equipment (OE) business since the demand is based on defect or breakdown of an automotive part. OE Business is directly related to automotive production planning; it can be scheduled and be more predictable than automotive aftermarket industry.

The aim of this paper is to determine external factors that give proactive information regarding the utilization of automotive and abrasion in components for automotive aftermarket industry and to propose an accurate sales forecasting model. An artificial neural network (ANN) model is proposed and compared with multiple linear regression by means of prediction accuracy.

The remaining part of the paper is organized as follows: The literature review of prediction models is presented in Section 2 to gather information regarding both statistical models and machine learning methods. The external factors that might be relevant for automotive aftermarket sales are determined based on expert reviews in Section 3. In Section 4, the details of the proposed methodology are given. In Section 5, the proposed ANN model is compared with multiple linear regression and the paper is concluded in Section 6.

2. Literature review

Each prediction model has its own advantage and disadvantage depends on research area and industry. Some prediction models could be comfortably applied to linear and non-complex datasets. However, it could be inconvenient to consider these prediction models to handle uncertainty and variability of non-linear datasets. Prediction models are gathered in two groups as statistical models and machine learning techniques. While time series analysis and regression are implemented without any high effort, machine learning techniques need more effort to implement them. However, they have capability to address complicated and non-linear relationships. Therefore, the purpose of prediction is determinative for the selection of appropriate prediction model.

Statistical models are traditional analyses and generally used in descriptive analyses. The objective of statistical models is to use internal and structured data to describe transactions and activities based on historical data [42]. Combining different statistical methods provides ability to increase prediction quality depends on advantages of separate methods. Therefore, there are many hybrid applications in different research areas. Nieto and Benitez (2018) [30] proposed a hybrid statistical model to forecast number of passengers in air transportation for airline industry by utilizing ARIMA, GARCH and Bootstrap. Fantazzini and Toktamysova (2015) [14] applied Vector Error Correction (VEC), Vector Auto-Regressive (VAR), Bayesian Vector Auto-Regressive (BVAR) models to car sales forecasting problem as a hybrid model that is based on economic variables and Google search index. Linear regression models and ridge regression models are statistical methods which have been widely used in many instances. Choi et al. (2019) [6] combined ridge regression with the fuzzy regression model. Elfahham (2019) [12] applied regression analysis to estimate construction cost index and compared the results with neural network model.

Machine learning methods allow to achieve more accurate forecasts compared to statistical models especially for complex and nonlinear data. It emerged as research area of computer science and applied to different industries. The data which have complex and nonlinear relationships could be modelled successfully even though incomplete data in case of implementation of appropriate model. Modelling and forecasting time series are among the most active areas of research in order to meet the needs of industries. Sales price, sales quantity, cost of sales, production planning, cash flow, personnel capacity planning, sales general and administrative costs, investments, energy loading etc. are general forecasting topics in the industries. Ghorbel et al. (2015) [16] applied reinforcement learning which is one of machine learning methods to solve a stock shortage problem. Reward and punishment is used as signals for positive and negative behavior to manage spare parts procurement by reinforcement learning. Tang et al. (2019) [36] applied weighted support vector machine (WSVM) that is a machine learning method to stock turning points. Sun et al.(2008)

[35] applied novel neural network technique to fashion sales forecasting in retailing as extreme learning machine. Hybrid machine learning models provide more accurate results. Therefore, Chou and Tran (2018) [7] proposed a hybrid time series forecasting model for energy consumption of a residential building by using machine learning techniques; the support vector machine, ANN, decision tree algorithms. Bianchi et al. (2018) [3] applied recurrent neural networks to forecast short term loading problems. Pal and Kar (2019) [31] hybridized forecasting method on weight adjustment of neural networks with back-propagation learning using general type-2 fuzzy sets in order to forecast closing price index of Shenzhen stock exchange, closing price index of Shanghai stock exchange, Canadian lynx data. Jain et al. (2020) [21] proposed a model that gathers K-Means clustering and fuzzy logic to predict the electricity demand of an Indian city and they compared the performance different methods such as regression, ANN, LSTM, Arima, and fuzzy logic.

Artificial intelligence (AI) is able to figure out complex relationships among data, behavioral patterns, rules governing a process, classification schemes and able to extract useful knowledge from these data [13]. AI is an operating system which has capability to achieve complex human brain activities such as perception, cogitation, learning, evaluation, decision making and problem solving. While achieving the activities, the computer algorithms are used to describe the circumstances of the system, to diagnose the reasons behind which cause the effect, to predict the future and optimize the best alternative for a specific objective and supported by machine learning. The computer algorithms are constructed on artificial neurons that are mathematical functions inspired by a nerve cell. Since AI has ability to analyze complex relationship and knowledge, time series could be converted to an input decision process easily.

ANNs have capability to learn the complex nonlinear relationships [33]. Neural networks could be named as flexible nonlinear models since they have ability to analyze relations that are available in the data [46]. The most important characteristic of an ANN is learning from its external environment [18]. Successful ANN applications have been implemented for forecasting problems in different research areas. Wang et al. (2018) [43] applied ANNs to airline industry in order to forecast the number of passengers. Bedi and Toshniwal (2019) [1] applied deep learning approach to forecast electricity demand and Wang et al. (2019) [44] proposed a deep neural network model for production forecasting. Gheyas and Smith (2011) [15] constructed Generalized Regression Neural Network model based on dynamic nonlinear weighting system for time series forecasting. ANN is able to be applied to financial time series. Mammadli (2017) [27] proposed an ANN forecasting method to establish profitable trading strategy. Chung et. Al. (2016) [8] proposed a cerebellar model neural network (CMNN) to predict the financial distress of Taiwan companies. Sagheer and Kotb (2019) [34] applied deep learning approach to predict petroleum production. Loureiro et al. (2019) [26] proposed a deep neural network model to forecast sales of fashion retail and compared the results with other sales predictions models. Kocadagli and Asikgil (2014) [23] implemented Monte Carlo algorithm to train the Bayesian Neural Network to predict sales of a finance magazine.

3. Relevant external factors of automotive aftermarket

Since uncertainty and volatility of the demand is high and it depends on many factors, the prediction is a problematic process for the organizations in automotive aftermarket. The creation of aftermarket demand is a dependent activity and the demand of an automotive part is triggered based on repair requirement [24]. The breakdown of a product is directly related to utilization rate of automotive. Increasing utilization rate of automotive will cause abrasion in automotive components and automotive aftermarket demand will be triggered mainly based on the abrasion.

Demand forecasting in automotive aftermarket should consider external factors which affect automotive aftermarket such as economic environment, automotive industry, and utilization rate of car. In addition, internal company key performance indicators might be included in demand forecasting process. Accuracy of sales or demand forecast is decisive to define long-term strategy of industry and take necessary actions.

External factors that might be relevant to the automotive aftermarket and give proactive information regarding the utilization of automotive and abrasion in components are gathered in five categories; economic environment in Table 1, vehicle park in Table 2, transportation indicators in Table 3, automotive industry price and trade index in Table 4 and Google search index in Table 5. The economic growth of automotive aftermarket industry is derived

Table 1
External factors that are grouped under the economic environment category

Economic Environment	Frequency	Source	Explanation
Consumer price index	M	TURKSTAT	Measures the average price changes of the goods and services
Producer price index	M	TURKSTAT	Measures the average price changes of purchasing costs of producers
Consumer confidence index	M	TURKSTAT	Measures thoughts of consumers regarding the economy in the near future
EUR/TRY Exchange Rate	D	CBRT	Monthly average of daily CBRT EUR/TRY exchange rate
EUR/USD Exchange Rate	D	CBRT	Monthly average of daily CBRT EUR/TRY exchange rate
Economic confidence index	M	TURKSTAT	Expectations of both consumers and producers regarding general economic situation
Retail trade confidence index	M	TURKSTAT	Measures economic situation of real trade in consideration of orders, stocks, expenditures and general business situation and next 3 months' volume of output, total employment and export orders, past 3 months' orders
Expected financial situation	M	TURKSTAT	A questionnaire that measures financial situation expectation of citizens
Expected economic situation	M	TURKSTAT	A questionnaire that measures general economic situation expectation of citizens
Number of people unemployed (expectation)	M	TURKSTAT	Rate of unemployed population to civilian labor force
Saving probability of consumers (next 12 months)	M	TURKSTAT	Showing consumers' tendency to save money over the next 12 month-period
Number of new company establishments	M	TOBB	Number of new company establishments in Turkey
Number of company liquidation	M	TOBB	Number of company liquidations in Turkey
Number of new company establishments - motor vehicles and motorcycles repair sector	M	TOBB	Number of new company establishments in Turkey motor vehicles and motorcycles repair sector
Number of company liquidation - motor vehicles and motorcycles repair sector	M	TOBB	Number of company liquidations in Turkey motor vehicles and motorcycles repair sector

Table 2
External factors that are grouped under the vehicle park category

Vehicle Park	Frequency	Source	Explanation
Gasoline type vehicles	M	TURKSTAT	Number of gasoline type vehicles
Diesel type vehicles	M	TURKSTAT	Number of diesel type vehicles
LPG gasoline type vehicles	M	TURKSTAT	Number of LPG type vehicles

Table 3
External factors that are grouped under the transportation indicators category

Transportation Indicators	Frequency	Source	Explanation
Number of vehicles passing through bridges and highways	M	GDH	Number of vehicles passing through tolled bridges and highways
Freight and passenger transportation	Y	GDH	Transportation and the circulation on roads by million kilometers
Gas consumption	M	PETDER	Monthly gasoline consumption amount of motor vehicles
LPG consumption	M	PETDER	Monthly LPG consumption amount of motor vehicles
Distribution of household consumption expenditures – Transportation	Y	TURKSTAT	Share of household consumption for the purpose of transportation

from two main factors; vehicle park and utilization rate of automotive. The vehicle park represents number of vehicles in the country therefore, increasing number of vehicles leads to automotive aftermarket potential. Additionally, rising utilization of vehicles causes abrasion in automotive components of exist-

Table 4
External factors that are grouped under the automotive industry price and trade index category

Automotive Industry Price and Trade Index	Frequency	Source	Explanation
Spare parts and accessories prices	M	TURKSTAT	Monthly average price of spare parts and accessories in Turkey
Brent – Europe	M	EIA	Crude oil prices (Brent - Europe)
Gas prices	M	TURKSTAT	Monthly average price of gasoline in Turkey
Liquid petroleum gas (LPG) prices	M	TURKSTAT	Monthly average price of liquid petroleum gas (LPG) in Turkey
Motor oil prices	M	TURKSTAT	Monthly average price of motor oil in Turkey
Maintenance and repairs equipment and service for vehicle prices	M	TURKSTAT	Monthly average price of maintenance and repairs equipment and service for vehicle in Turkey
Trade turnover index of motor vehicles and motorcycles repair sector	M	TURKSTAT	Trade turnover index of the sector in Turkey
Trade turnover index of motor vehicles and motorcycles repair sector	M	TURKSTAT	Trade turnover index of the sector in Turkey
Trade turnover index of sale of motor vehicles	M	TURKSTAT	Trade turnover index of sale of motor vehicles in Turkey
Trade turnover index of maintenance and repair of motor vehicles	M	TURKSTAT	Trade turnover index of maintenance and repair of motor vehicles in Turkey
Trade turnover index of sale of motor vehicle parts and accessories	M	TURKSTAT	Trade turnover index of sale of motor vehicle parts and accessories in Turkey
Trade turnover index of sale, maintenance and repair of motorcycles and related parts and accessories	M	TOBB	Trade turnover index of sale, maintenance and repair of motorcycles and related parts and accessories in Turkey

Table 5
External factors that are grouped under the Google Search Index category

Google Search Index	Frequency	Source	Explanation
Google search Index of the company	D	Google Trends	The number queries by the company name
Google search Index of the competitor 1	D	Google Trends	The number queries by the name of company's competitor number 1
Google search Index of the competitor 2	D	Google Trends	The number queries by the name of company's competitor number 2
Google search Index of the competitor 3	D	Google Trends	The number queries by the name of company's competitor number 3
Google search Index of the competitor 4	D	Google Trends	The number queries by the name of company's competitor number 4
Google search Index of "Automotive Aftermarket Part''	D	Google Trends	The number queries by Automotive Aftermarket Part
Google search index of "Automotive Aftermarket Part" & "Company Name''	D	Google Trends	The number queries by input signal Automotive Aftermarket Part and Company Name

ing vehicle park. Utilization of vehicles could be modelled by transportation indicators, automotive industry price and trade index. Since general economic environment directly affects purchasing power of household and probability of saving, economic environment is to be considered in the automotive aftermarket sales forecasting model. Google Search Index is included to feed the model as proactive signals regarding consumers' purchase decision.

The source of datasets such as economic environment in Table 1, vehicle park in Table 2, transportation indicators in Table 3, automotive industry price, trade index in Table 4 and Google search index in Table 5 is shown in respective tables as Turkish Statistical Institute (TURKSTAT) [41], Central Bank of the Republic of Turkey (CBRT) [37], Turkish Oil Industry Association (PETDER) [32], Republic of Turkey General Directorate of Highways (GDH) [22], Google Trends [40], U.S. Energy Information Administration (EIA) [11], Turkey Union of Chambers and Commodity Exchanges (TOBB) [38]. The explanation of the external factors in the tables are gathered from the periodic reports of the institutions. The frequency of the reports is also indicated in the tables as daily (D), monthly (M) or yearly (Y). Since we aim to foresee monthly automotive aftermarket sales of a company, daily and yearly data are converted to monthly for this study.

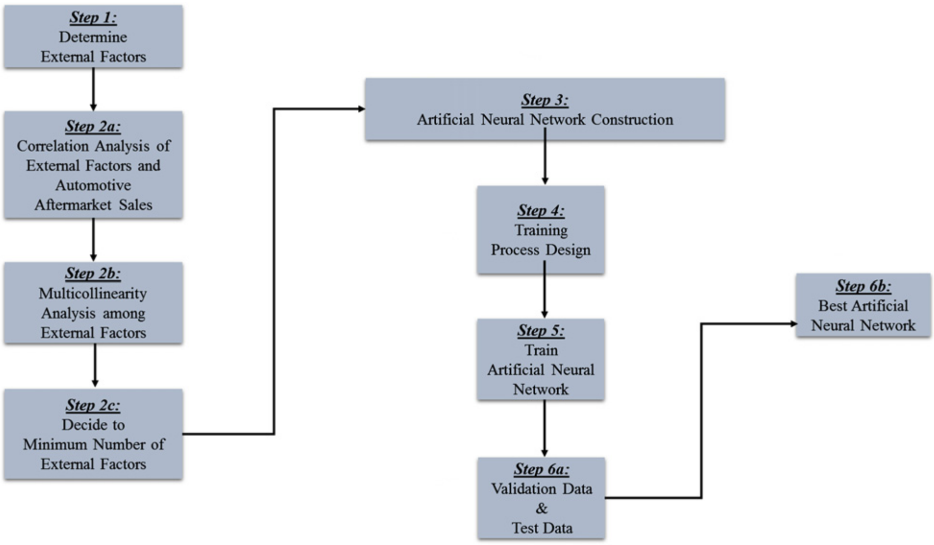

Fig. 1. Artificial neural network based automotive aftermarket sales forecast model.

Google Trends is a website that provides information about search queries in Google Search at a given period and region. Increasing number of internet users and preference of Google as a search engine allow to obtain information regarding the link between behaviors in online platforms and purchasing decision of customers [14]. Therefore, Google Search Index could be included into the model while estimating the sales based on external factors. The search queries that are considered in the model are shown in Table 5.

4. Methodology

Computational intelligence techniques provide a framework to focus on predictive analytics and prescriptive analytics. AI is a subset of computational intelligence and it is focused on problems which have complex and nonlinear relationships [10]. Combining different type of methods give opportunity to increase prediction quality by utilizing advantages of these different methods. Therefore, a statistical based ANN model as a hybrid model is proposed for automotive aftermarket in order to get accurate sales forecasts. The code of the ANN model is programmed in MATLAB R2011 software. The model applied to automotive aftermarket sales forecast process is illustrated summarized in Fig. 1.

Forty external factors will be gathered under five categories as economic environment, vehicle park, transportation indicators, automotive industry price and trade index and Google search index as a result of expert reviews in Step 1. The correlation analysis will be applied in order to evaluate the strength of relevance among the actual automotive aftermarket sales and external factors is Step 2a. After correlation analysis of external factors and automotive aftermarket sales, multicollinearity analysis will be applied to determine linear relationship among external factors in Step 2b. The decision of minimum number of external factors will be given in Step 2c. based on statistical analysis. In Step 3, the ANN structure will be constructed by considering the determined external factors, activation function types, number of hidden layers and number of neurons that are located in the hidden layers. The Back-propagation training algorithm will be applied in this article as an application of feed-forward networks. Levenberg-Marquardt algorithm based ANN training process is applied to minimize error and the weights of neurons are updated during training process in Step 4. Initial weights of the neural network are randomly generated. The weights are adjusted to minimize error and the error is calculated with the new weights in Step 5. The validation phase is necessary to estimate the network performance and decide when the training is to be stopped. The test phase is planned to estimate the expected performance in the future. The validation and test phase will be planned in Step 6. After validation and test phases, the ANN performance will be in a condition that could be evaluated in Step 6.

Step 1: Determine external factors that might be relevant for automotive aftermarket sales

Table 6
Correlation analysis of external factors and automotive aftermarket sales

	Correlations			Correlations	
	Pearson correlation	*P* value (2-tailed)		Pearson correlation	*P* value (2-tailed)
Consumer Price Index	,916**	0,000	Brent - Europe	-,450**	0,000
Producer Price Index	,912**	0,000	Gas Prices	,753**	0,000
Consumer Confidence Index	-,251**	0,007	Liquid petroleum gas (LPG) Prices	,647**	0,000
EUR/TRY Exchange Rate	,905**	0,000	Motor Oil Prices	,865**	0,000
EUR/USD Exchange Rate	-,630**	0,000	Maintenance and repairs equipment and service for vehicle Prices	,921**	0,000
Economic Confidence Index	-0,161	0,084	Gas Consumption	,428**	0,000
Retail Trade Confidence Index	0,066	0,482	LPG Consumption	,547**	0,000
Expected financial situation	-,213*	0,022	Number of road motor vehicles (LPG)	,803**	0,000
Expected economic situation	-,195*	0,036	Number of vehicles passing through bridges and highways	,849**	0,000
Number of people unemployed expectation	-,260**	0,005	Freight and passenger transportation and the circulation on the state roads, provincial roads and motorways	,873**	0,000
Saving probability of consumers (next 12 months)	-0,164	0,078	Trade turnover index of motor vehicles and motorcycles repair sector	,931**	0,000
Distribution of household consumption expenditures – Transportation	,672**	0,000	Trade turnover index of motor vehicles and motorcycles repair sector	,899**	0,000
Google Search Index of the Company	,894**	0,000	Trade turnover index of Sale of motor vehicles	,857**	0,000
Google Search Index of the Competitor 1	,820**	0,000	Trade turnover index of Maintenance and repair of motor vehicles	,942**	0,000
Google Search Index of the Competitor 2	,505**	0,000	Trade turnover index of Sale of motor vehicle parts and accessories	,951**	0,000
Google Search Index of the Competitor 3	-0,057	0,545	Trade turnover index of Sale, maintenance and repair of motorcycles and related parts and accessories	,798**	0,000
Google Search Index of the Competitor 4	-,309**	0,001	Number of New Company Establishments	,703**	0,000
Google Search Index of "Automotive Aftermarket Part"	,943**	0,000	Number of Company Liquidation	-0,037	0,692
Google Search Index of "Automotive Aftermarket Part" & "Company Name''	,638**	0,000	Number of New Company Establishments - motor vehicles and motorcycles repair sector	,646**	0,000
Spare parts and accessories Prices	,903**	0,000	Number of Company Liquidation - motor vehicles and motorcycles repair sector	-,266**	0,004

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Determination of external factors that give proactive information regarding the utilization of automotive and abrasion in components is the most significant problem of sales forecast in automotive aftermarket such as vehicle park, consumer price index, gas consumption rate, exchange rates, oil price and Google search index etc.

Step 2: Decision of minimum number of external factors by correlation analysis and automotive aftermarket sales together with multicollinearity analysis among external factors.

Correlation analysis is a methodology that measures strength of the correlation among two variables. It is applied to evaluate the strength of a relationship between actual sales and external environment. The correlation analysis is illustrated in Table 6. External factors that have a significantly high Pearson's coefficient are kept and the external factors that have not strong correlation are eliminated.

After the correlation analysis of external factors and automotive aftermarket sales, multicollinearity analysis is applied to eliminate external factors

Table 7
Multicollinearity analysis of external factors

Model	Unstandardized coefficients		Standardized coefficients			Collinearity statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1 (Constant)	-67244,026	13973,617		-4,812	,000		
EUR/TRY	1645,177	1817,691	,121	,905	,367	,057	17,465
EUR/USD	20290,812	8747,726	,193	2,320	,022	,149	6,703
Consumer Confidence Index	230,299	115,500	,098	1,994	,049	,426	2,348
Google Search Index of the Company	275,808	57,659	,364	4,783	,000	,177	5,644
Brent - Europe	-148,173	41,450	-,320	-3,575	,001	,128	7,808
Gas Prices Liquid petroleum gas (LPG) Prices Motor Oil Prices	3474,303	990,267	,513	3,508	,001	,048	20,805
Benzin (m3)	,011	,013	,033	,839	,404	,668	1,497
Wholesale and retail trade; repair of motor vehicles and motorcycles (Number of New Company Establishments) / (Number of Company Liquidation)	-1009,471	3302,198	-,012	-,306	,760	,636	1,573

Dependent Variable: Actual Turnover.

that are highly linearly related among each other. The result of multicollinearity is shown in Table 7. Multicollinearity analysis contributes to determine minimum number of external factors. Variance inflation factor (VIF) in Equation (1) is a ratio that measures the variance value of an estimated figure of a regression model in the presence of collinearity among the independent variables in a multiple regression model [28]. Increasing VIF means that the predictors of the model are correlated. In this application, the highest variance inflation factor is assumed as 20 and different combination of external factors are analyzed during multicollinearity analysis.

$$VIF_i = \frac{1}{1 - R_i^2} \tag{1}$$

Step 3: Construction of ANN structure

The number of external inputs, the number of hidden layers and neurons in the hidden layers are defined and constructed in this step. The decision of activation function type is also given in this step. The equation describes the feed forward equation corresponding to the inputs () and outputs () of a three-layer feed forward Multilayer perceptron model in matrix form [17]. The ANN structure directly affects the performance of back propagation neural network by the number of hidden layer and nodes in the hidden layer [5].

Supervised Learning is applied in this model and Levenberg – Marquardt training algorithm is performed. The efficiency of the model will be evaluated according to Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Running Sum of Forecast Error (RFSE).

After the correlation and multicollinearity analyses among external factors, minimum number of external factors that are input of the ANN is decided as 8. The external factors are EUR/TRY, EUR/USD, Consumer Confidence Index, Google Search Index of the Company, Brent – Europe, average of Gas Prices-Liquid petroleum gas (LPG) Prices - Motor Oil Prices, gas consumption (), ratio of number of new company establishments and number of company liquidation in the sector of motor vehicles and motorcycles repair.

While constructing the ANN structure, number of hidden layers is assumed as 1 and number of neurons in the hidden layer is 15. Hyperbolic Tangent Activation Function (tansig) is applied in hidden layers and Linear Activation Function (purelin) is implemented as activation function of the output layer. The nonlinear activation functions that are available in hidden layer and output layer yield to solve complex nonlinear problems [25]. Hyperbolic Tangent Activation Function Equation (2) will be applied in the model in order to handle nonlinearity of the model. Hyperbolic Tangent Activation Function is a continuous function that produces outputs in scale of [-1,+1]. The advantage is that its derivative is steeper than other activation functions and it contributes to be more efficient since it has a wider range for faster learning and grading [39].

$$f(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{2}$$

Step 4: Training process design

Back propagation is a widely applied for training a neural network and Levenberg-Marquardt algorithm based ANN training process could be applied to minimize error by adjusting the synaptic weights. Levenberg-Marquardt algorithm could be formulized as shown between Equations (3) and (6) [17].

When μ=0 or near to zero, Equation (3) becomes the Gauss Newton algorithm and is given by

$$x_{k+1} = x_k - \left[\left[J^T J + \mu I\right]^{-1} J^T R\right] \qquad (3)$$

x_{k+1} represents the update equation at time, $t+1$
x_k is the vector consisting of $x1, x2......xn$
μ is combination coefficient and is always positive
I is Identity matrix
R is a vector that is the difference the expected outputs of the neural network and the actual outputs
ΔX is the error in the X estimation and is given by

$$\Delta X = \left[J^T J + \mu I\right]^{-1} J^T R \qquad (4)$$

J is the Jacobian matrix of the objective function and is given by

$$J(x) = \frac{\partial R}{\partial X}\begin{bmatrix} \frac{\partial r_1}{\partial x_1} & \frac{\partial r_1}{\partial x_2} & \cdots & \frac{\partial r_1}{\partial x_n} \\ \frac{\partial r_2}{\partial x_1} & \frac{\partial r_2}{\partial x_2} & \cdots & \frac{\partial r_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial r_m}{\partial x_1} & \frac{\partial r_m}{\partial x_2} & \cdots & \frac{\partial r_m}{\partial x_n} \end{bmatrix} \qquad (5)$$

When μ»0.

Equation (3) becomes the steepest descent algorithm and is given by

$$x_{k+1} = x_k - \alpha_k \left[J^T R\right] \qquad (6)$$

Where, α_k is the learning rate (step length) and is given by $\alpha_k = 1/\mu$.

In order to adjust weights, Equation (7) is updated. The training process is programmed in MATLAB R2011a software. Figures 2–5 are plotted in MATLAB R2011a software.

Step 5: Evaluate the error of initial weights that are randomly defined and update the adjust weights after that valuate the error with the new weights

$$f(x) = \frac{1}{2}\sum_{i=1}^{m}(r_j)^2 \qquad (7)$$

$$r_j = \left(Actual\ Output_j - Expected\ Output_j\right) \qquad (8)$$

For a given input, the expected outputs of the neural network are checked against the actual outputs.

The training process of the proposed model is shown in Fig. 2. The Mu graph represents the change in the training parameter of the Levenberg-Marquardt method. The Mu value is used to control the weights of the neurons during training. If MATLAB gives the message "Maximum MU reached'', it means that additional training will not improve learning

Step 6: Validation and test the dataset and model.

The validation phase is necessary to estimate the network performance and to decide when the training is stopped. The test phase is planned to estimate the expected performance in the future. The errors are operated 6 times before leaving the process thus the validation check is reported as 6. The best validation performance of the model is reported at epoch 11. It is repeated 6 times and the process is stopped at epoch 17.

The ANN performance is evaluated in consideration of Mean Absolute Deviation (MAD) in Equation (9), Mean Absolute Percentage Error (MAPE) in Equation (10), Root Mean Square Error (RMSE) in Equation (11), Running Sum of Forecast Error (RFSE) in Equation (12). The results are illustrated in Table 8. The test set is utilized for evaluating of the error of model. Mean Absolute Deviation of the test

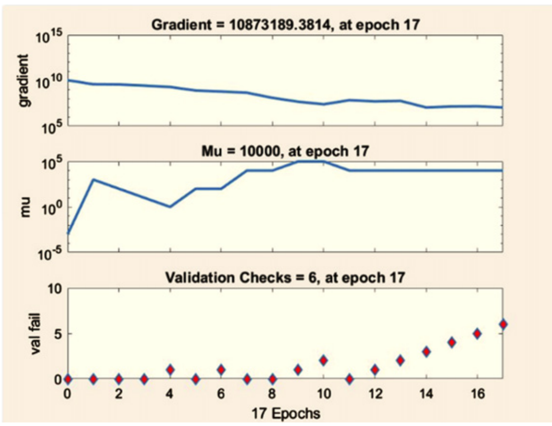

Fig. 2. The training process for the artificial neural network model.

Table 8
Forecast accuracy of the ANN model

	Training set	Validation set	Test set
MAD	2283,36	2828,10	1544,17
MAPE	14,30	24,47	8,26
RMSE	2841,19	3709,45	2400,78
RFSE	–17755,78	14251,82	-13657,69

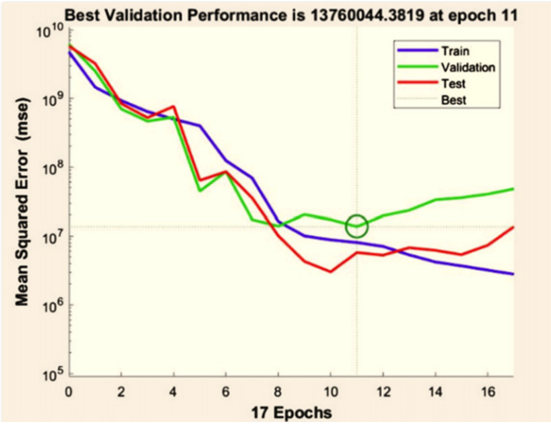

Fig. 3. Best validation performance in artificial neural network model.

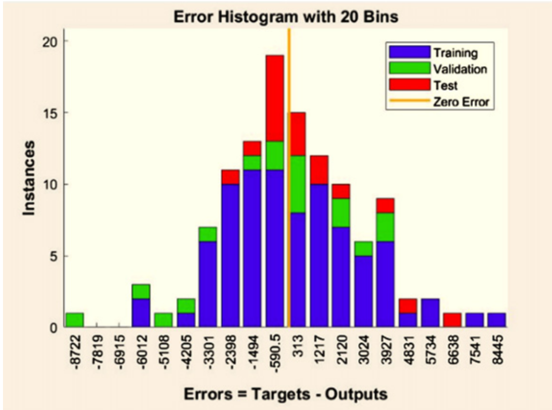

Fig. 4. Error histogram of training, validation and test dataset of artificial neural network model.

set is 1544,1. Mean Absolute Percentage Error of the test set is 8,26%. Root Mean Square Error of the test set is 2400,78. Running Sum of Forecast Error of the test set is –13657,69.

$$\mathrm{MAD} = \frac{\sum |(y_i\ measured - -y_i\ model)|}{n} \tag{9}$$

$$MAPE = \frac{100\%}{n} \sum \left| \frac{(y_i\ measured - y_i model)}{(y_i\ model)} \right| \tag{10}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum (y_i\ measured - -y_i\ model)^2} \tag{11}$$

$$\mathrm{RFSE} = \sum (y_i\ measured - -y_i\ model) \tag{12}$$

Training, validation, and test dataset is plotted separately in Fig. 3. Training process of the ANN is pursued until error of the validation vectors are reduced.

The error histogram with 20 bins that represents errors in the training, validation, and test dataset of ANN is shown in Fig. 4. The number of samples that are taken into consideration is appeared from length of vertical bar. The zero error is illustrated with a yellow line in the middle of the histogram. The total error from neural network ranges from left bin -8772 to right bin 8445.

The accuracy of the trained ANN model is shown in Fig. 5 for training, validation, and test dataset. The accuracy of the model is measured by the value of R-squared.

If it is approximated to 1, it R means that the model prediction is very close to the actual dataset. Otherwise, the forecast accuracy of the proposed model is not sufficient.

5. Comparison with multiple linear regression method

A multiple regression model is created to compare forecast results of ANN with a linear model. Same external factors used to train the ANN are applied into the multiple linear regression model that is shown in Equation (13). The external factors are Consumer Confidence Index, EUR/TRY, EUR/USD, Google Search Index of the Company, Brent – Europe, Average of Gas Prices-Liquid petroleum gas (LPG) Prices - Motor Oil Prices, Gas consumption (m^3). Ratio of number of new company establishments and number of company liquidation in the sector of motor vehicles and motorcycles repair.

Multiple Linear Regression model equation is as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_m x_{im} + \varepsilon_i \tag{13}$$

x_1: EUR/TRY
x_2: EUR/USD
x_3: Consumer Confidence Index
x_4: Google Search Index of the Company
x_5: Brent – Europe
x_6: Average of Gas Prices-Liquid petroleum gas (LPG) Prices - Motor Oil Prices
x_7: Gas consumption (m^3)
x_8: Ratio of number of new company establishments and number of company liquidation in the sector of motor vehicles and motorcycles repair

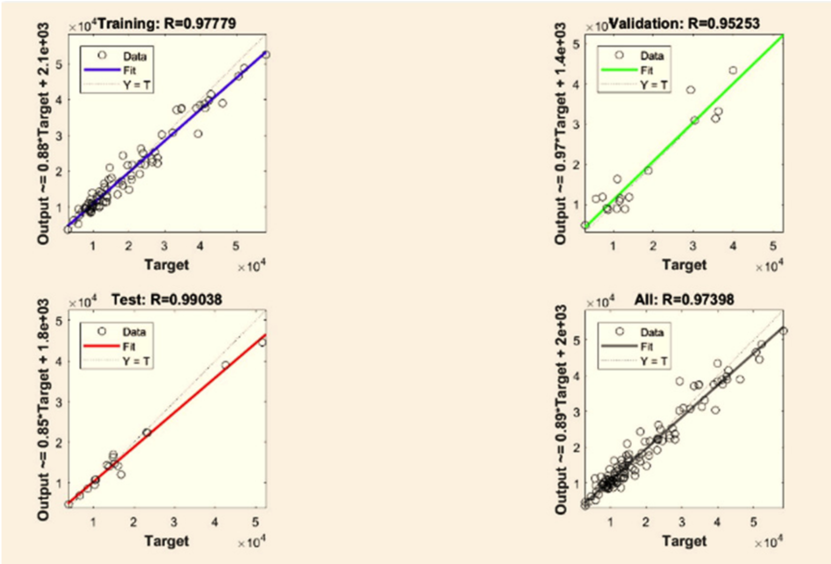

Fig. 5. The accuracy of the trained artificial neural network model.

Table 9
The multiple regression statics

Regression statistics	
Multiple R	0,943415
R Square	0,890032
Adjusted R Square	0,88181
Standard Error	4283,11
Observations	116

Table 10
Forecast accuracy of the multiple regression model

	Multiple regression model
MAD	2970,14
MAPE	19,52
RMSE	4111,54
RFSE	0,00

$$y_i = -67244,026 + 1645,177x_{i1} + 20290,812x_{i2} + 230,299x_{i3} + 275,808 - 148,173x_{i5} + 3474,303x_{i6} + 0,011x_{i7} - 1009,471x_{i8} + \varepsilon_i \quad (14)$$

R Square equals 0.89, which is not a poor fit. 89% of the variation in automotive aftermarket turnover is explained by the independent variables Consumer Confidence Index, EUR/TRY, EUR/USD, Google Search Index of the Company, Brent – Europe, average of Gas Prices-Liquid petroleum gas (LPG) Prices - Motor Oil Prices, gas consumption (m^3), ratio of number of new company establishments and number of company liquidation in the sector of motor vehicles and motorcycles repair. If R Square gets closer to 1, the regression line is to be fitted the data better.

Multiple R is the correlation coefficient of the model is 0.94 and it explains strength degree of the linear relationship.

Number of observations are shown in the Table 9 as 116 that are observed between 01.2009 and 05.2018.

The adjusted R-squared is a modified version of R-squared that adjusts for predictors that are not significant in a regression model [4]. Compared to a model with additional input variables, a lower adjusted R-squared indicates that the additional input variables are not adding value to the model [4].

Mean Absolute Percentage Error of the linear regression model is 19,52%. These results demonstrate that the Multiple Linear Regression model does not provide enough support to predict the automotive aftermarket sales. It indicates that the ANN is more accurate than the multiple regression model.

6. Conclusion

Main problem of forecasting in automotive aftermarket is to define proper external factors that give proactive information regarding the utilization of automotive and abrasion in components. The most important topic is to handle complexity of the model by defining the external factors that give an idea regarding external environment of the problem that needs to be solved [2]. Defining the cause-and-effect relationship between factors would be supportive to manage ambiguity. ANN has the capability to understand complex interrelationships and derive actions from that understanding. After the literature review that researches applications in different industries, it was decided to propose an ANN that could be successfully applied to automotive aftermarket to obtain accurate forecasts. In this context, an ANN model is constructed for Turkey automotive aftermarket industry. The ANN model is trained by considering 116 samples. Levenberg-Marquardt training algorithm is applied to the model. In this study, different performance measures have been adopted to evaluate the accuracy of the ANN model that is proposed, such as Mean Absolute Deviation (MAD) in Equation (9), Mean Absolute Percentage Error (MAPE) in Equation (10), Root Mean Square Error (RMSE) in Equation (11), Running Sum of Forecast Error (RFSE) in Equation (12). Since evaluating of forecast error as percentage is more straightforward, Mean Absolute Percentage Error (MAPE) that is calculated as the average of the unsigned percentage error is considered. Mean Absolute Percentage Error of the model is 8,26% and it is a successful result despite of significant uncertainty and variability of automotive aftermarket industry. On the other hand, the Multiple Linear Regression compared to ANN shows a worse performance than ANN. Mean Absolute Percentage Error of the linear regression model is 19,52%. The ANN model is more accurate than the multiple regression model.

The training process of the ANN model that offered in the paper is in progress to achieve the most accurate sales forecast.

In order to increase forecast accuracy of the offered ANN model, the training of the model could be done under different type of ANN structures.

- Adjustment of number of hidden layers
- Adjustment of number of neurons in the hidden layer
- Apply different type of activation functions

Adjustment of number of hidden layers could increase accuracy of the model. Cybenko (1989) [9] showed that a single hidden layer could be sufficient to solve nonlinear problems. However, some problems require more than one hidden layer, additional layers can be helpful for complex datasets such as time-series or computer vision [19].

Adjustment of number of neurons in the hidden layer could contribute to increase accuracy of the model. While modelling the hidden layers of ANN with a few neurons can cause under-fitting, modelling with higher number of neurons in the hidden layers can give higher accuracy but it can cause several problems such as over-fitting or long training time [20].

Activation function significantly affects converge and the convergence speed of the neural network [29]. Hyperbolic Tangent Activation Function is applied in the model in order to handle nonlinearity of the model. However, applying different type of activation functions can contribute to increase accuracy of the model.

To achieve higher accuracy, the results of the different type of ANN structures can be compared with each other.

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Conflict of interest

The authors declare that they have no conflict of interest.

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