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Demand forecasting application with regression and artificial intelligence methods in a construction machinery company

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Abstract

Demand forecasts are used as input to planning activities and play an important role in the management of fundamental operations. Accurate demand forecasting is an important information for many organizations. It provides information for each stage of inventory management. In this study, multiple linear regression analysis, multiple nonlinear regression analysis, artificial neural networks and support vector regression were applied in a production facility that produces spare parts of construction machinery. The aim of the study is to forecast the number of spare parts requested in the future period by the customer as close as possible. As the input variables in the developed models, the sales amounts of the past years belonging to the manifold product group, which is one of the important spare parts of the construction machinery, number of construction machines sold in the world, USD exchange rate and monthly impact rate are used as input variables. The inputs of the model are designed according to construction machinery sector. In the model, monthly impact rate enables us to create more robust model. In addition, the estimation results have high accuracy by systematic parameter design of artificial intelligence methods. The data of the 9 years (from 2010 to 2018) were used in the application. Demand forecasts were conducted for 2018 to compare actual values. In forecasts, artificial neural network and support vector regression produced better results than regression methods. In addition, it was found that support vector regression forecasting produced better results in comparison to artificial neural network.

Keywords Construction machinery sector · Demand forecasting · Support vector regression · Artificial neural networks · Multiple linear regression · Multiple nonlinear regression

Introduction

Different industries have very different focuses regarding spare parts. Much of it has to do with the attributes of the products themselves. The length of life of the supported products, the expense of the supported product and the complexity of the supply network are some of these features. Larger, longer-lived, more complicated and more expensive the product large percentage of overall revenues are derived from spare parts. The major spare parts industries are Automotive, Aviation, High Technology (primarily for manufacturing machines such as semiconductor equipment), Construction Equipment, Durable Consumer Goods and Medical Devices (Snap 2007).

Spare parts inventories need to be available at appropriate points within the supply chain, to provide after-sales services and to guarantee the desired service level. However, several aspects concur in making demand and inventory management for spare parts a complex matter: the high number

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of parts managed; the presence of intermittent or lumpy demand patterns; the high responsiveness required due to downtime cost for by customers; and the risk of stock obsolescence. Fast moving parts may not require ad hoc forecasting methods, but a large portion of spare parts are characterized by intermittent or lumpy demand, requesting special attention. Moreover, demand for spares may be related to some explanatory variables (e.g. failure occurrence, maintenance activities). (Bacchetti and Saccani 2012). While the availability of parts is critical, inventory is also costly to hold, and hence it is very important to achieve minimum costs and downtime. All that has been described so far is similar for all spare parts industries and explains the importance of spare parts demand. There are certain features that distinguish the construction machinery sector from other spare parts sectors and make the availability of spare parts important. To explain in detail; Construction machinery are used in construction works such as mining, lifting, material handling, excavation and tunnelling. Excavators, backhoe loaders, dozers and graders are examples of construction machinery. Numerous construction machines work in numerous construction projects around the world. Since the machines often work in harsh conditions and aging, deformation and breakage occur in various parts over time. For this reason, machine parts cannot perform their functions as before. This situation requires the spare parts replacement. The availability of spare parts at the desired time is important. Because, inability to supply spare parts of construction machinery purchased at high prices or rented at high prices on a daily, weekly or monthly basis will result in both high costs and waste of time. For these reasons, customers want to supply the required spare parts quickly when they need the assembly of the product group or any part within the product group. Because of all these characteristics of the sector, the companies producing the construction machinery parts have to keep the inventories at the right time and to produce the products at the right time and in the fastest way and deliver them to the customers. Otherwise, it will not be possible for enterprises to survive in today's world where competition is increasing day by day (Aktepe et al. 2019).

The fact that customers do not prefer to keep inventory, puts the production companies in difficult situations if they keep unnecessary inventory. Therefore, producer companies should analyze the market and their customers well while managing their inventories and maintain their existence under competitive conditions by making accurate sales forecasts (Amirkolaii et al. 2017). Since all organizations deal with an uncertain future, they make predictions when making decisions about the future. Demand forecasts are used as input to planning activities and play an important role in the management of basic operations. Without demand forecasts, businesses face the risk of making weak decisions about their products and target markets. Wrong decisions may have a negative impact on inventory keeping costs, customer satisfaction, supply chain management and profitability.

Demand is the amount of physical product or service that customers desire to purchase. Demand forecasting, which is a prediction approach for the level of future demand, plays an important role in business operations (Kuo et al. 2016; Yanık, 2019; Xu et al. 2020). For companies to be competitive, they need to achieve high customer service levels while keeping costs under control. Companies manage this by planning customer demand forecasts. If the company fails to plan customer demand, it either misses sales opportunities or increases inventory costs due to keeping inventories of unsold products (Persson and Wilhelmsson, 2018). Continuous monitoring of stock movements, keeping the necessary statistics, analyzing the tendency of customers to buy from the accumulated sales data and analyzing when they bought the products are the objectives of the inventory control. Keeping excessive inventories creates great risks for businesses. Because, in this case, businesses will have invested their capital in stocks. Although inventories seem to be the property of the business, they have no return unless sold. Over-supplied raw materials for a production business occupy machinery and workers in vain, creating extra costs as well as purchase costs.

Demand forecasts are used as input in production planning. Production planning and control is actually an arrangement method. Directing the product movement from raw material production to final product delivery to the entire production cycle, it achieves the targets such as maximum production, minimum inventory and fast delivery and customer satisfaction. Of course, in order to achieve these goals, customer demands must be well predicted and plans must be carried out in line with these estimates (Tanyaş and Baskak 2012). When studies conducted with demand forecasting to date are analysed time series analyzes that make mathematical calculations using sales data are the most primitive methods. Because methods based on time series analysis such as weighted moving average, exponential correction and Holt models do not take into account variables that affect demand. Regression analysis, Box-Jenkins models and methods based on artificial intelligence seem to be more successful methods in establishing relationships between historical data. In this study, besides the regression analysis that makes predictions by revealing the relationships between the variables, artificial intelligence methods that make smart decisions on the learning path by using the accumulated data while making the estimation are used and their success in the demand forecast is shown.

Demand estimation for the manifold product group, which is one of the important spare parts used in construction machinery, was first made by linear and nonlinear regression analysis. In the developed models, forecasts were not only based on past sales. In the regression models, predicted number of monthly construction machinery sales around the world, monthly USD rate adjusted for inflation and monthly impact rate were used as inputs. And the output is future demand forecast in the regression models. In addition, artificial intelligence methods such as Support Vector Regression (SVR) and Artificial Neural Network (ANN) were used for forecasting. In the artificial intelligence models, input part of training data of past sales, predicted number of monthly construction machinery sales around the world, monthly USD rate adjusted for inflation and monthly impact rate were used as inputs. The output of artificial intelligence methods is the future demand forecast. As a result of the application, successful results were achieved. SVR produced the best forecast results. The innovation of the paper exists in two points. Firstly, the inputs of the model are designed according to construction machinery sector. Among the inputs, especially, monthly impact rate enables us to create more robust model. Secondly, with systematic parameter design of artificial intelligence approaches, the estimate results produced higher accuracy.

The paper is organized as follows: In the second section the literature is review is presented, in the third section methods and models are explained, in the fourth section data sets are described, in the fifth section application and computational results are presented and concluding remarks are presented in the sixth and final section.

Literature review

In the literature, demand forecast problems have been solved by various approaches. There are various studies carried out with traditional time series modelling and Box-Jenkins method. In addition, there are also studies conducted with Winter's method in the prediction of series with trends and seasonal fluctuations. However, in most of the first studies in this field only past demand data were taken into other variables that affect demand were not taken into account. Later, in the studies conducted with regression analysis, which take into account the variables affecting the demand and other factors that affect the relationship between these variables, came to the fore. Finally, prediction studies have been carried out with artificial intelligence methods, which offer a way to make smart decisions by learning from past data and information. Artificial intelligence approaches included various advanced intelligent algorithms and functions. For example, Artificial Neural Networks (ANN) and support vector machine are advanced technologies that can predict hidden relationships between variables. With these methods the prediction model can be created with learning property and intelligent functions. In this section, we present a literature review on demand forecast models with regression analysis, artificial intelligence and other approaches. The literature review is focused on industrial applications and also studies that are conducted in the spare parts industry are also presented.

In the literature, regression models and artificial intelligence methods are used for the purpose of demand forecasting. In some of the studies in the literature ANN models were developed as in the study of Mansur and Kuncoro (2012). They used market basket analysis to understand consumers' behaviour in purchasing products. They also used ANN back propagation to prevent inventory build up and determine inventory levels for each product to be sold to customers. As a result, they found 21 rules and discovered that customers who purchase a particular product will buy similar products. They have also estimated inventory requirements and needs. Vhatkar and Dias (2016) predicted the sale of oral care products using the ANN back propagation algorithm. While reviewing forecast accuracy, they observed that artificial neural networks were a successful method of predicting sales. Silva et al. (2017) developed a simulated supply chain model in order to meet the incoming orders and predict which supply chain node the next order would be used, and used the data they produced in the simulation study as an input for ANN. They conducted two experiments with the multi-layer ANN model, which they created as a single hidden layer. In experiment 1, they predicted the capacity to send upcoming orders immediately, in experiment 2 they predicted at which node of the supply chain the reorder point would be. Thus, they aimed to increase visibility in supply chain by using ANN. Reynolds et al. (2019) planned to manage regional energy demand by identifying two optimization strategies that optimize heat generation and, in addition, control the energy requirement of buildings through the heating set point temperature. They used artificial neural networks to estimate variables such as solar energy production and indoor temperature. From these studies, it is concluded that ANN models produce high level of forecast accuracy.

Instead of classical regression models, different types of regression models are another approach for forecast studies in the literature. In this context, Guo et al. (2017) developed an uncertain linear regression model based on uncertainty theory. In their model, parameter estimators were developed with uncertainty distribution of data of experts' opinions. The application was carried out for forecasting GDP and total exports of a country. In another sample study, Merkuryeva et al. (2018) conducted their work in the pharmaceutical supply chain and developed an integrated procedure for medicinal products from a wholesaler to a distribution company in a developing market. Using the simple moving average method, they have developed alternative forecasting scenarios for basic demand calculations and have made predictions by using multiple linear regression and symbolic regression method. They showed that symbolic regression is the closest and most appropriate estimation method.

In most of the studies, there is a comparative approach. Obtaining the highest accuracy rate for demand or sales forecast has been the main purpose of the studies. One of the studies which compares regression and ANN models is carried out by Alon et al. (2001). They used the sales data which includes excess tendency and seasonality, performed demand forecasting by using methods of ANN, Winter's exponential correction, Box-Jenkins ARIMA model and multivariate regression, and compared the results. In another study, the sales data of the American retail company were collected and the demand forecasts were conducted successfully with ANN multi-layer perceptron (MLP) (Chawla et al. 2019). Frank et al. (2003) carried out statistical time series modeling and ANN, which is used to predict women's clothing sales. In their models, they used four year sales data from 1997 to 2000 and carried out an estimate for the second month of 2000. Compared to seasonal adjustment and Winters exponential correction method, the prediction carried out with ANN provided a better accuracy. Dahl and Hylleberg (2004) reviewed four alternative flexible nonlinear regression model approaches. The methods' performance is evaluated based on various measures of out of sample forecast accuracy. The flexible regression model class includes the Neural Networks, projection follow-up models and the random field regression model approach proposed by Hamilton (2001). Yücesoy (2011) carried out demand forecasting with ANN in the cleaning papers sector. Parameters based prediction model has been created by ANN. In addition, with the simple and multiple regression models, the demand forecasting for cleaning paper was conducted and the results were compared. It was determined that it predicted 61% in simple regression, 92% in multiple regression and 96% ANN. Adamowski et al. (2012) examined Multiple Linear Regression (MLR), Multiple Nonlinear Regression (MNLR), Auto Regressive Integrated Moving Average (ARIMA), ANN and Wavelet Transforms ANN (WA-ANN) for urban water demand forecasting at lead time one day in summer months. Their relative performance was compared using the coefficient of determination root mean squared error. The main variables used in the models are data of total daily precipitation, maximum daily temperature and daily water demand from 2001 to 2009 in Montreal, Canada. It has been found that WA-ANN models provide more accurate urban water demand forecasts than MLR, MNLR, ARIMA and ANN models. Rosienkiewicz (2013) conducted eight types of demand forecasting methods, including artificial intelligence and traditional methods. Additionally, a new hybrid approach is introduced which are associate regression and artificial neural network. All the estimation methods are compared. Ballı (2014), carried out a demand forecasting application using an ANN model for the delicatessen group products in the fast consuming fresh food sector. In addition, he made predictions with the average-based time series analysis methods and compared the results. One of the input variables selected in the model is seasonal effect. She explained that the seasonal effect significantly affects the sales. Sarı (2016) identified factors such as the dollar rate, the number of car parks, the number of vehicles produced and the interest rate as factors affecting the sales of engine bearings. After collecting the data on these variables, the demand forecasting study was performed using ANN, multiple regression and time series. Amirkolaii et al. (2017) developed demand forecasting models for business aircraft spare parts. They compared the results of Croston, Croston SBJ and Croston TSB, moving average, single exponential smoothening and ANN. They concluded that ANN improves demand forecasting accuracy for intermittent demands. In the study of Vijai and Sivakumar (2018), multiple regression and ANN were used to predict future water demand, and artificial neural networks were observed to yield better results in all short-term forecasts. Sönmez and Zengin (2019) used the data of a food and beverage company. They predicted the daily sales of the business. They compared the results of the two models. In the studies, that are carried out with regression and ANN models, the performance of the models were compared and it is seen that ANN models have the ability of making forecasts with lower errors and higher determination rate. Abbasimehr et al. (2020), present a forecasting method and compare the results with other techniques. The method is based on multi-layer LSTM networks. The application is carried out in furniture sector. They compared the forecast results with ARIMA, exponential smoothing, ANN, K-nearest neighbors, recurrent neural network, SVM and single layer LSTM. Application results show that the proposed method produce better results than those of compared methods. Xu et al. (2020), define demand trends in medical sector. According to demand trend vector, they cluster the hospitals. Then, they compare the forecast results of Naïve method, ARIMA, linear regression, ANN and SVR for different clusters in medical device industry.

The applications of support vector machine on demand or sales forecast is as follows: Hua and Zhang (2006) developed a hybrid Support Vector Machine (SVM) and logistic regression approach for forecasting intermittent demand of spare parts. In the approach, SVM are adapted to forecast occurrences of non-zero spare parts demand, and a hybrid method is proposed for the relationship of SVM forecast results and the occurrence of non-zero demand with explanatory variables. Real data sets of 30 different spare parts of a company in China were used. It is seen that it produces more accurate estimates compared to the existing methods in almost all delivery times. Huang et al. (2010) proposed a combined method which is a hybrid grey relational analysis and SVM approach for estimating spare parts consumption, as factors affecting spare parts consumption cannot be estimated properly. Firstly, the degree of gray relationship between impact factors and spare part consumption was calculated by gray relational analysis. Selected main influence factors were taken as the input of SVM while the output was the consumption. Later, test samples were entered into the trained model for estimation. The results show that the proposed model has better predictive accuracy and dynamic adaptability compared to the Artificial Neural Network (ANN) model. Akay et al. (2014) use the SVM to estimate the maximum oxygen consumption from submaximal data. For comparison, Estimation models have been developed using the multiple linear regression (MLR) and Multi-Layer Perceptron (MLP). In this study, Radial Based Function (RBF) was chosen as a Kernel in the SVM based model. C (which determines the relationship between error and complexity), ε parameter, (which controls the size of the "ε"-insensitive region, and the gamma, (which can be thought of as the spread of the kernel and that is the decision region), were determined using fivefold cross validation. As a result, it has been observed that the Standard Estimation Error (SEE) values of SVM base models are lower than the SEE values of MLR and MLP based models.

Support vector regression (SVR), a method of machine learning that emerged from statistical learning theory, is also used in forecast models in the literature: Demren (2011) carried out mid-term electrical load demand forecast of Istanbul European Side with SVR. The inputs are past load data average air temperature calendar days and electricity price. Daily peak load values of April were estimated. For comparison, ANN were used with the same data. As a result of this study, it was revealed that the SVR algorithm is superior to ANN and is suitable for medium term load demand prediction. Li et al. (2012) state that SVR is one of the approaches to forecast the yield trend. They enhanced the SVR model with past manufacturing experience and virtual samples to estimate the yield of polarizers. They considered learning effects in the study. The results of application showed that the proposed method is effective in reducing cost thanks to highly accurate forecasts. Kargul et al. (2016) carried out heavy equipment demand forecast with support vector machine regression. They calculated the equipment monthly usage rate with support vector machine regression. They aimed to reduce costs by renting unused equipment and buying the most used ones. García et al. (2019) estimate physical quality indices in a tube extrusion process with regression models. They used nearest neighbor regression, linear regression and SVR. In their study, results show that k nearest-neighbor and SVR methods (with a linear kernel and radial basis function) produce effective results for predicting the inner and outer diameters of an extruded tube. Daş et al. (2019) analyze wind energy potential of Sinop and Adiyaman in different regions of Turkey based on the data measured by the State Directorate of Meteorology Station between 2008 and 2017. Weibull distribution function is used to determine the distribution of wind speed and wind power density. For the power density values obtained as a result of the study, a predictive model was created with the SVR. Polynomial, Normalized Polynomial, RBF and Pearson kernel models were used in SVR. It was shown that the best estimation belonged to polynomial kernel in wind power density predictive models created with 4 different kernel functions using SVR. In these studies that use SVR for forecasting, it is observed that SVR makes predictions with smaller errors is that it can overcome the local minimum and over compliance.

In the literature, fuzzy methods are also used for demand forecast. Ay (2016) has estimated the amount of sales in a factory with fuzzy linear and quadratic models. In this study, two fuzzy regression models of Tanaka, Linear and Quadratic, were used. These models were applied to past sales data for three products of the factory producing the paper bag and estimated sales ranges were obtained. By comparing the estimated values with the actual data of that year, the most suitable model was tried to be determined for the three products. Kuo et al. (2016) worked with a laptop sales data set provided by a distributor in Taiwan and made predictions with a fuzzy neural network, an integrated forecasting system that can take into account both quantitative and qualitative factors to achieve a more comprehensive result. As a result of the calculation, they said that the approach is superior to other estimation methods and can decrease customer inventory costs and increase customer satisfaction. With fuzzy modelling approach, it is possible to handle uncertain data in prediction models. In connection with this, Aengchuan and Phruksaphanrat (2018) present a fuzzy inference system and hybrid models combining fuzzy inference systems and ANN in their study. They used both uncertain supply and uncertain demand data. Application was carried out for the inventory system. According to results they achieved best cost savings from hybrid model compared to stochastic EOQ model.

Another approach to forecasting problems is developed by Qian et al. (2017). They took into account the factors affecting the consumption of equipment spare parts. By analyzing all the features of equipment spare parts, they solved the prediction problem with engineering analysis method. As a result of the application, they observed that the results of the engineering analysis method provided a good prediction accuracy. In another study that is applied in automotive sector, churn detection and prediction is carried out by Karapınar et al. (2016). They emphasize the importance of chasing technological developments and the importance of accurate predictions to be competitive in automotive industry. In addition, Xu et al. (2017) developed a multi-level unified forecasting model that includes a method combination forecasting approach and an information combination forecasting approach to predict product service requests in the context of a hierarchical service structure. They explained that the model they proposed was flexible and transferable to solve other prediction problems, especially if there are hierarchical time series.

According to literature review, demand or sales forecast is considered as a significant problem due to its strategic effect on the decisions of institutions. As an inference from literature review; it is seen that, in the field of demand or sales forecast, regression models, support vector regression, artificial intelligence approaches such as artificial neural networks and fuzzy logic methods are used. The main objective of the models is to achieve higher forecast accuracy and minimum errors. In the next section, the methods and models developed in this study are discussed.

Methods

In this study, demand estimation was carried out with linear and nonlinear regression analyses which measure the cause-effect relationship between variables, and artificial neural networks and support vector regression that make smart predictions by learning from past information. In this section, firstly the methodology developed in this study is explained and then the methods used for developing the demand forecast models are explained.

Methodology developed in this study

The stages of the demand forecast methodology is presented in Fig. 1. The forecast models are developed for the manifold product group. As a result of interviews with the sales team and managers, sector-specific variables affecting sales were determined. The data were taken from the Canias ERP system (Canias 2019) used by the enterprise. In addition, data on worldwide construction equipment sales, as well as actual sales data in the market were used. Finally, demand forecasts are conducted. In the inputs are determined as X_1 (number of construction machines sold in the world), X_2 (USD rate) and X_3 (monthly impact rate) which are critical factors for machinery spare parts industry. Linear and nonlinear regression, ANN and SVR are the methods that are used in the study. Firstly, regression models are developed. Secondly, the ANN model is developed. In order to procure the best performance ANN model, transfer functions,

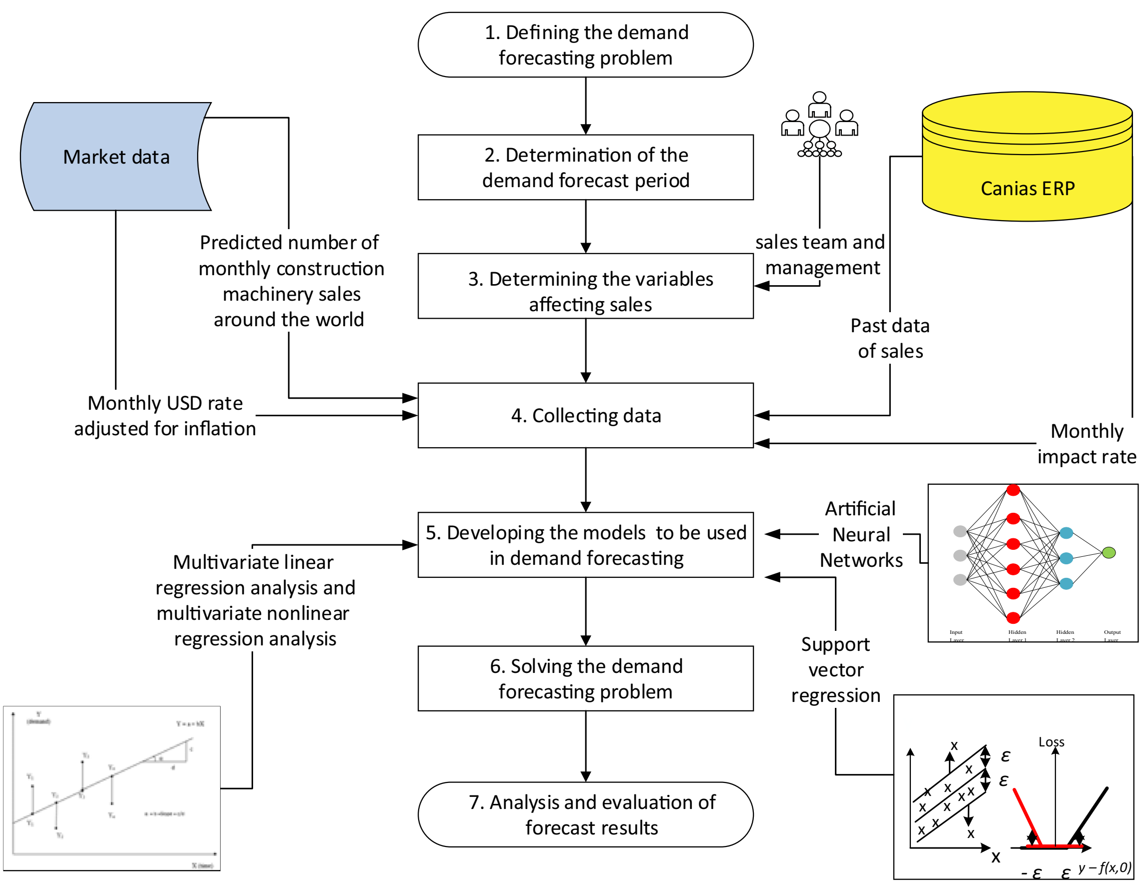

Fig. 1 Methodology

number of layers and number of neurons in each ANN layer are optimized with a systematic approach. Thirdly, SVR model is developed. And, the models are compared according to forecast accuracy rate.

Regression analysis models

Dependent variables in regression analysis are variables that are tried to be understood or estimated. Independent variables are the variables that are thought to have an effect on the dependent variable that is tried to be estimated Predictions can be made by measuring the relationships between variables with regression analysis. In order to express the relationship between variables mathematically in regression analysis, it is necessary to show the variable data set with dots in a scatter diagram. For example, if the points in the scatter gram are centered on a line, it would be more appropriate to use a linear function. If bends have occurred at points, a curvilinear function should be used. It can also be determined how many degrees the functions are according to the number of bending points. A twist point requires the use of a second order function and two twist points require the use of a third order function.

In the linear regression model, X represents independent variables (input data) and Y dependent variables (output data). In this study, the multiple regression equation (Eq. 1) is created as follows:

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 \tag{1}$$

a_0: Constant value,

a_1: Weighting coefficient of the number of construction machinery sold worldwide,

a_2: Weight coefficient of the dollar rate variable,

a_3: Weight coefficient of the monthly impact rate variable,

X_1: Number of construction machines sold in the world,

X_2: USD rate,

X_3: Monthly impact rate,

Y: Monthly demand forecast.

In nonlinear regression analysis, the relationship between variables is curvilinear. In the model, X represents independent variables (input data) and Y dependent variables (output data). In this study, the multiple nonlinear regression equation (Eq. 2) is created as follows.

$$Y = a_0 + b_1X_1 + b_2X_2^2 + b_3X_3^3 + \cdots + b_nX_n^n \tag{2}$$

Artificial neural network (ANN) model

Artificial neural networks are designed to simulate the way the human brain analyzes and processes information. With them we solve problems that are difficult or impossible by human calculation or statistical calculation methods. ANN can produce better results when the number of data is large because it is self-learning. ANN is a technology that enables computers to learn events. Usually, examples are used to learn the relationships between the inputs and outputs of events. The artificial neural network exists anywhere in the thousands-millions of artificial cells arranged in a series of layers. Technically, the task of the artificial neural network is to convert the various data received by the input layer from the outside world into information that can be used as output by processing and learning by the network (Öztemel 2016).

In this study, the ANN model was developed with Matlab software (MATLAB 2019). For modeling ANN, back propagation algorithm is used. While estimating weights, tangent hyperbolic, sigmoid and linear functions were used as activation functions. The results were more successful with the sigmoid function. Matlab also has many back propagation functions as training functions. Some of these are “trainbfg”, “trainbr”, “traincgf”, “traingdm”, “traingdx”, “trainlm”, “trainoss” and “trainrp”. After systematic trial and error approach, “trainrp” was observed as best functioning training method.

Support vector machine and support vector regression models

Support Vector Machine (SVM) is the machine learning algorithm used for classification and regression analysis. The generalized portrait method developed by Vapnik and Chervonenkis (1964) for pattern recognition forms the basis of SVM. SVM has reached its current form with the studies of Vapnik and Chervonenkis (1974), Vapnik (1979), Boser Guyon and Vapnik (1992), Cortes and Vapnik (1995), Osuna et al. (1997) and (Smola and Schölkopf 2004). The basic idea of SVM is to determine the hyper plane that will make the most appropriate distinction between different sample types (Vapnik 2000).

The basic logic of the Support Vector regression (SVR) is to try to determine the regression function that will minimize the expected risk error instead of minimizing the training error within the scope of statistical learning theory. Similar point of Gaussian, Laplace and Huber loss functions is that they do not have sparseness feature which is expected to increase the number of support vectors (Cherkassky and Ma 2002). Therefore, the ε-insensitive loss function in Fig. 2 has been proposed by Vapnik (1995) to ensure margin formation in SVR (Alves et al. 2017).

The defined ε-insensitive loss function allows data to remain within the margin by tolerating data with an error value in the range $[-\varepsilon, \varepsilon]$ in the regression model (Girma 2009). The ε-insensitive loss function is expressed mathematically as follows in Eq. 3 (Müller et al. 1997).

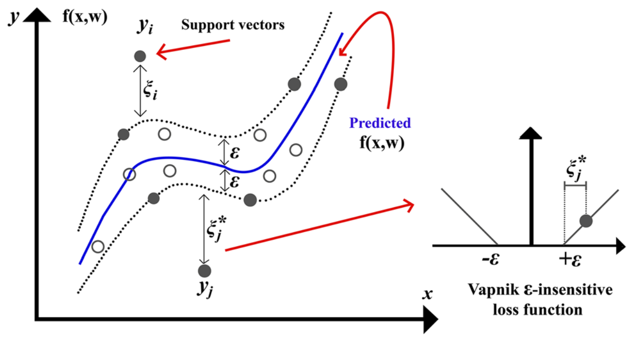

Fig. 2 Vapnik loss function (Huang et al., 2006; Alves et al., 2017)

$$L_\varepsilon(y) = \begin{cases} 0 & if\,|y - f(x)| \le \varepsilon \\ |y - f(x)| - \varepsilon & otherwise \end{cases} \quad (3)$$

In linear cases, the function f is expressed as in Eq. 4 below (Vapnik 1995). Convex optimization problem is expressed with Eq. 5 (Cortes and Vapnik 1995):

$$\mathrm{f(x) = w^*x + b\ w \in R^D,} \quad \mathrm{b \in R} \quad (4)$$

$$\min \frac{1}{2}\left\|w^2\right\| y_i - \left(w * x_i + b\right) \le \varepsilon \left(w * x_i + b\right) - y_i \le \varepsilon \quad (5)$$

The optimization equation for support vector regression in nonlinear cases is specified in Eqs. (6) and (7) (Smola and Schölkopf 2004).

$$\max \frac{1}{2} \sum_{i=1}^{N} \sum_{J=1}^{N} (a_i^+ - a_i^-) * \left(a_j^+ - a_j^-\right) * k\left(X_i, X_j\right) - \varepsilon \sum_{i=1}^{N} \left(a_i^+ - a_i^-\right) - \sum_{i=1}^{N} y_i\left(a_i^+ - a_i^-\right) \quad (6)$$

$$\sum_{i=1}^{N} \left(a_i^+ - a_i^-\right) = 0 \quad 0 \le a_i^+ - a_i^- \le c \quad (7)$$

It is essential to determine the kernel function and optimum parameters of this function to be used for a regression process to be performed with SVM. The most commonly used kernel functions in the literature are polynomial, normalized polynomial, radial based, Pearson VII (PUK) function. The parameters for each kernel function by user need to be determined. In this study, to determine the validity of the obtained model, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Relative Absolute Error (RAE) and Root Relative Square Error (RRSE) analyzes were performed. The optimum parameters of the used kernel functions were determined by the grid search algorithm.

Data sets

In this study the data are collected from various sources. These are management information system of the company at which the application is carried out, research from sectoral databases and the statistical institute. After literature review, interviews conducted with the managers and sales department experts, 4 variables affecting the demand of manifold product group are determined as follows: i.Past data of sales, ii.Predicted number of monthly construction machinery sales around the world, iii. Monthly USD rate adjusted for inflation and iv. Monthly impact rate.

For the monthly sales volumes variable, monthly sales numbers of the manifold product group were queried from the ERP database and a summary table was created.

While collecting data on the number of construction equipment sold in the world, the estimated number of construction equipment sold worldwide between 2010 and 2018 was reached by the world's giant construction equipment brands such as Caterpillar, Komatsu, Kawasaki and Hitachi. These figures, which are on an annual basis, have been converted into a monthly basis according to the monthly sales numbers of the product group.

While calculating the dollar exchange rate, monthly buying and selling data of the USD between 2010 and 2018 were collected and the arithmetic average was calculated. Considering that the past value of the Turkish lira is not the same as its present value and the purchasing power of all years is not the same, the dollar rate data has been updated according to inflation.

Finally, in order to take advantage of the sensitivity of monthly changes in customer demands, a monthly impact rate variable was developed to estimate the demand. It has been calculated how much less or more monthly sales are compared to the annual average sales.

The enterprise actively uses the Canias ERP software system (Canias 2019) in all production and management processes. The data used in the application was obtained from the ERP database.

Past data of sales

Monthly sales quantities are the most important variable to predict future demand. 75 products were selected for Manifold product group and monthly sales quantity for each of them was obtained from ERP system. Monthly sales volume data are shown in Table 1 (Yanık 2019).

Predicted number of monthly construction machinery sales around the world

It is clear that the number of construction machines sold in the world will affect the demand. Because spare parts are required for wearing parts during the use of construction machinery in various jobs. In other words, there will be an accurate ratio between the number of machines sold that year and the number of spare parts required. For this reason, the estimated sales data of the construction machines sold every year in the world between 2010 and 2018 were reached from the studies of Philips (2019) and STATISTA (2019) and these data are shown in Table 2. The data obtained are the sales data of the construction machines of brands such as Caterpillar, Komatsu, Kawasaki, Hitachi in accordance with the brands produced by the company. The data belong to major markets such as Europe, North America, Japan, China and India. Since the data show the number of machines sold on an annual basis, it is considered that how much of the monthly sales represents the percentage of the total annual sales (Yanık 2019).

In order to convert the data in Table 2 to the monthly base, it is thought that the annual number of machines sold in the world can be converted into monthly sales according to a predicted percentage Table 3 (Yanık, 2019). The transactions performed are shown in Eqs. (8) and (9).

Table 1 Past data of sales (units)

Years	Months											
	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
2010	756	545	720	710	805	650	834	712	910	696	562	603
2011	805	650	1120	847	1428	935	1421	1555	1192	903	658	913
2012	862	749	1240	915	1126	841	1413	1012	850	704	852	876
2013	732	890	1466	751	1202	891	1357	1036	612	995	829	884
2014	819	752	805	945	1339	884	926	848	1117	791	1114	983
2015	606	953	462	427	851	670	694	590	273	699	807	739
2016	606	484	414	761	849	643	1104	874	598	755	926	462
2017	910	400	968	971	1039	1714	802	1248	667	669	868	965
2018	836	561	1456	833	1277	597	1436	406	1186	649	670	966

Table 2 Forecast of number of construction machinery sales around the world (in 1000 s of units sold)

Regions	Years								
	2010	2011	2012	2013	2014	2015	2016	2017	2018
Europe	100.99	123.71	118.90	111.86	124.78	125.71	130.50	132.67	131.25
North America	90.60	124.22	146.83	158.10	171.31	177.94	186.03	175.69	160.61
Japane	37.06	47.09	64.86	90.83	84.23	80.00	73.83	71.62	71.65
China	401.48	435.07	290.21	273.72	209.76	131.35	137.82	147.43	156.99
India	42.81	54.05	50.80	42.71	36.81	38.55	46.41	54.18	59.28
Total	672.94	784.13	671.59	677.21	626.89	553.55	574.59	581.59	579.78

Table 3 Predicted number of monthly construction machinery sales around the world (units)

Years	Months											
	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
2010	59,831	43,132	56,982	56,191	63,709	51,442	66,004	56,349	72,019	55,083	44,478	47,723
2011	50,795	41,014	70,671	53,445	90,105	58,997	89,663	98,119	75,214	56,978	41,519	57,609
2012	50,604	43,970	72,795	53,715	66,102	49,371	82,951	59,410	49,900	41,329	50,017	51,426
2013	42,569	51,758	85,255	43,674	69,902	51,816	78,916	60,248	35,591	57,864	48,210	51,409
2014	45,343	41,634	44,568	52,319	74,133	48,942	51,267	46,949	61,842	43,793	61,676	54,423
2015	43,167	67,885	32,910	30,416	60,619	47,726	49,436	42,027	19,447	49,792	57,485	52,641
2016	41,081	32,810	28,065	51,588	57,554	43,589	74,840	59,249	40,539	51,182	62,774	31,319
2017	47,166	20,732	50,172	50,327	53,852	88,837	41,568	64,684	34,571	34,675	44,989	50,016
2018	44,578	29,914	77,638	44,418	68,093	31,834	76,572	21,649	63,241	34,607	35,726	51,510

$$(MSV * 100) / TNPY = RP \tag{8}$$

$$TNMS * (RP / 100) = WMS \tag{9}$$

MSV: Monthly sales volume,
TNPY: Total number of demands per year,
RP: Representative percentage,
TNMS: Total number of construction machinery sold worldwide,
WMS: Worldwide estimated number of construction machinery sales converted to monthly base.

Monthly USD exchange rate adjusted for inflation

The USD rate indicates the value of an American dollar against the Turkish Lira. There are two main reasons why the dollar exchange rate affects sales. First: Since the raw materials that make up the products such as casting and steel are purchased at the dollar rate, when the dollar rate rises, raw materials are supplied more expensively. This may cause a decrease in sales volume as it increases the sales price. Because price is an important criterion for customers. The opposite can also be considered. If raw material prices are low, more affordable product prices can be offered to customers. Second: Although the company operates abroad as a majority, it makes a substantial portion of its sales domestically. In products sold domestically, the dollar rate is an important factor affecting sales. Because when the exchange rate is high, the decrease in sales will be inevitable as the purchasing power will decrease. Likewise, when the exchange rate falls, its purchasing power will also increase. In this case, the products requested by the customers can be requested with stocks and this leads to an increase in sales. Therefore, the dollar rate is an important variable affecting sales. While calculating the dollar rate, monthly buying and selling data of the USD between 2010 and 2018 were collected and the arithmetic mean was calculated. It is thought that it would be wrong to use the dollar rate data in ANN model exactly as it would not be the same as the past value of the Turkish Lira in the past. Therefore, using dollar exchange rate in the whole year, of which data were gathered from Turkish Statistics Institute (TUIK 2019), the consumer price index (CPI) based inflation was calculated in 2018 and was converted into Turkish Lira using the monthly value. Thus, the purchasing power for all years has been expressed in a common way. Monthly USD rate data are shown in Table 4 (Muhasebe News 2019; Yanık 2019).

Considering that the value of money is not the same in different periods, the values in all years were converted to the values of 2018 by using the inflation calculator. 2018 Turkish Lira values are shown in Table 5 (Yanık 2019).

Monthly impact rate

When fluctuations in sales data are observed, it is observed that customer demands change monthly in a shorter period of time than seasonal effects. Therefore, in order to benefit from the sensitivity of the monthly demand change and to predict the demand, the monthly impact rate variable was developed. Monthly sales are calculated as the percentage below or above the annual average sales and their monthly impact on sales is determined as variable. These are shown in Eqs. (10) and (11).

$$ADI = \left[(MD * 100) / AD\right] - 100 \tag{10}$$

$$MIR = ADI + 100 \tag{11}$$

The explanations in the formulas are as follows:
ADI: Decrease or increase in percentage compared to average, MD: Monthly demand, AD: Average demand,
MIR: Monthly impact rate.

While calculating the monthly impact rate, decreasing or increasing values were found compared to the average sales. Then, since negative values will cause errors in artificial neural networks, all values are converted to positive

Table 4 Monthly USD rate exchange data (Turkish Liras)

Years	Months											
	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
2010	1.47	1.51	1.53	1.49	1.54	1.56	1.54	1.51	1.49	1.42	1.43	1.52
2011	1.56	1.59	1.58	1.52	1.57	1.60	1.65	1.75	1.79	1.83	1.80	1.86
2012	1.84	1.76	1.78	1.78	1.80	1.82	1.81	1.79	1.80	1.80	1.79	1.78
2013	1.77	1.77	1.81	1.80	1.82	1.90	1.93	1.96	2.02	1.99	2.02	2.06
2014	2.22	2.22	2.22	2.13	2.09	2.12	2.12	2.16	2.21	2.26	2.23	2.29
2015	2.33	2.46	2.59	2.65	2.64	2.70	2.69	2.85	3.01	2.93	2.88	2.92
2016	3.00	2.94	2.89	2.84	2.93	2.92	2.95	2.96	2.96	3.07	3.28	3.49
2017	3.74	3.67	3.67	3.65	3.57	3.52	3.56	3.51	3.47	3.67	3.88	3.85
2018	3.77	3.78	3.88	4.05	4.41	4.63	4.75	5.80	6.34	5.85	5.38	5.30

Table 5 Monthly USD exchange rate adjusted for inflation (Turkish Liras)

Years	Months											
	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
2010	2.80	2.85	2.90	2.86	3.01	3.16	3.14	3.13	3.26	3.13	3.11	3.29
2011	2.82	2.88	2.88	2.79	2.86	3.04	3.16	3.41	3.67	3.74	3.57	3.65
2012	3.02	2.88	2.94	2.95	3.03	3.18	3.18	3.21	3.39	3.41	3.33	3.30
2013	2.70	2.72	2.78	2.81	2.88	3.06	3.12	3.24	3.53	3.50	3.51	3.55
2014	3.15	3.15	3.15	3.04	3.02	3.13	3.14	3.26	3.54	3.65	3.55	3.64
2015	3.08	3.25	3.41	3.51	3.53	3.72	3.72	4.02	4.46	4.40	4.23	4.27
2016	3.61	3.57	3.55	3.52	3.67	3.74	3.75	3.87	4.10	4.30	4.51	4.70
2017	4.13	4.05	4.05	4.05	4.01	4.06	4.13	4.14	4.31	4.59	4.72	4.63
2018	3.77	3.78	3.88	4.05	4.41	4.63	4.75	5.80	6.34	5.85	5.38	5.30

by adding 100. Monthly sales effect ratios calculated for manifold product group are shown in Table 6 (Yanık 2019).

Computational results and analysis

Demand forecasting application was carried out in a company that operates in the construction machinery sector and manufactures spare parts for world big machinery brands such as Caterpillar, Komatsu, Kawasaki and Hitachi. The company manufactures many spare parts used in construction machinery such as dozers, loaders and graders. The opinions of the managers and the sales department were taken in determining the factors affecting the sales of the construction equipment parts. Manifold product group was chosen as the product group for demand forecast. Manifold is one of the components of the air intake and exhaust system of the construction machines. Manifold product group is the most produced product group of the enterprise. Therefore, it is the product group that occupies the machines and workers the most. There are a total of 75 products in the manifold product group selected for estimation. The application of demand forecast models are presented below.

Estimation application with multivariate linear regression analysis

When conducting linear multivariate regression analysis, enter method was used, in which all prediction variables were added to the model. Since there are few variables, the enter method has been found appropriate. Multiple regression analysis was performed using IBM SPSS Statistics 21 software. The weight coefficients obtained as a result of the linear regression analysis are shown in the linear regression equation is shown in Eq. (12).

$$Y = -200.03 + 0.018\,X_1 + 50.990\,X_2 - 0.668\,X_3 \tag{12}$$

Demand forecasts for 2018 are shown in Table 7. Demand forecasting by linear regression analysis showed a success rate of 92.36%.

Estimation application with multivariate nonlinear regression analysis

Multiple nonlinear regression analysis was performed using IBM SPSS Statistics 21 software (SPSS 2019). The nonlinear regression equation is shown in Eq. (13). The non-linear equation is attained by finding the best fitting

Table 6 Monthly Impact Rate Values

Years	Months											
	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
2010	107	77	102	100	114	92	118	100	128	98	79	85
2011	78	63	108	82	138	90	137	150	115	87	64	88
2012	90	79	130	96	118	88	148	106	89	74	89	92
2013	75	92	151	77	124	92	140	107	63	103	85	91
2014	87	80	85	100	142	94	98	90	118	84	118	104
2015	94	147	71	66	131	103	107	91	42	108	125	114
2016	86	69	59	108	120	91	156	124	85	107	131	65
2017	97	43	104	104	111	183	86	133	71	72	93	103
2018	92	62	161	92	141	66	158	45	131	72	74	107

Table 7 Multivariate linear regression analysis estimation results

Months	Estimation values	Actual values	MAPE	Forecast accuracy (%)	Deviation (pieces)
Jan	733	836	0.1232	87.68	103
Feb	490	561	0.1266	87.34	71
Mar	1288	1456	0.1154	88.46	168
Apr	745	833	0.1056	89.44	88
May	1156	1277	0.0948	90.52	121
June	565	597	0.0536	94.64	32
July	1314	1436	0.0850	91.50	122
Aug	455	406	0.1207	87.93	49
Sep	1174	1186	0.0101	98.99	12
Oct	673	649	0.0370	96.30	24
Nov	668	670	0.0030	99.70	2
Dec	926	966	0.0414	95.86	40
Averages			0.0764	92.36	69.33

polynomial degree among alternatives produced with SPSS software non-linear regression and curve estimation properties.

$$Y = -200 + 0.01901\,X_1 + 0.8\,X_2^3 + 0.875\,X_3 \qquad (13)$$

Demand forecasts for 2018 with non-linear model are shown in Table 8 and it was 94.66% successful, which is a better forecast than linear regression.

It is seen that nonlinear regression performance is higher than linear regression model. Linear regression was first used to understand whether the data fit a general linear curve type. However, it was seen from the prediction success that the model provides a better fit in nonlinear structure. In addition, since change in demand on a monthly basis is significant for our research problem, a better estimation result was obtained by making estimates with nonlinear regression.

Demand forecasting application with artificial neural networks method

The network architecture is shown in Fig. 3. While creating the ANN architecture, the rule called Geometric pyramid was used to determine the cell numbers in the hidden layers. Trials to find the best artificial neural network architecture are shown in Table 9.

Of the 108 data between 2010 and 2018, 96 data between 2010 and 2017 were used for the training of the network, while 12 data in 2018 were selected for testing. The ANN

Table 8 Multivariate nonlinear regression analysis estimation results

Months	Estimation values	Actual values	MAPE	Forecast accuracy (%)	Deviation (pieces)
Jan	772	836	0.0769	92.31	64
Feb	466	561	0.1691	83.09	95
Mar	1464	1456	0.0053	99.47	8
Apr	778	833	0.0658	93.42	55
May	1286	1277	0.0074	99.26	9
June	542	597	0.0919	90.81	55
July	1481	1436	0.0311	96.89	45
Aug	407	406	0.0019	99.81	1
Sep	1321	1186	0.1136	88.64	135
Oct	681	649	0.0490	95.10	32
Nov	669	670	0.0019	99.81	1
Dec	992	966	0.0270	97.30	26
Averages			0.0534	94.66	43.83

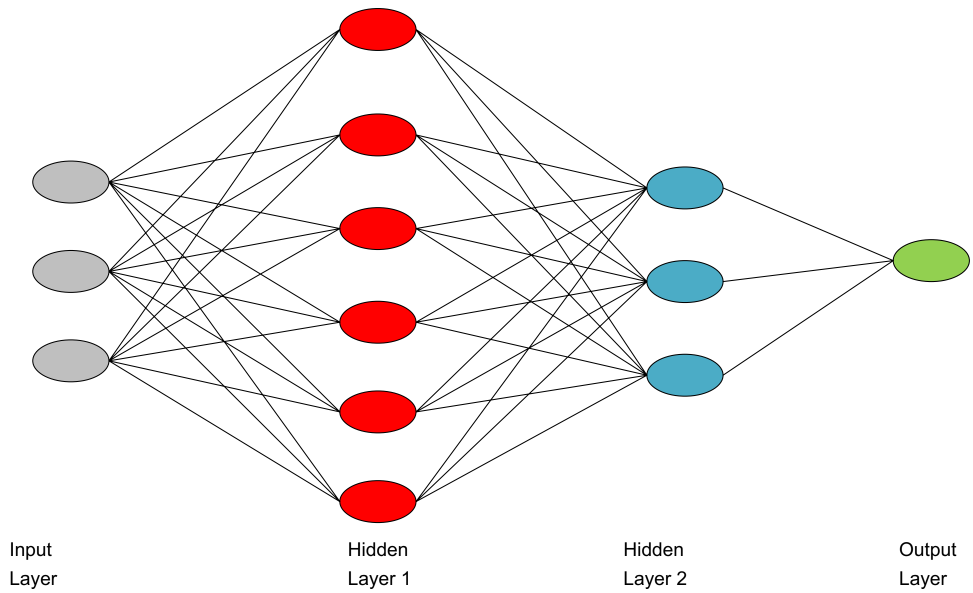

Fig. 3 Network architecture

Table 9 Trial and error results for best architecture

Number of hidden layers	Activation function	Number of neurons in layers	Training function	Learning rate	MAPE	R^2
1	logsig	1	trainlm	0.5	0.07794	0.95520
	logsig	2	trainlm	0.6	0.06651	0.94810
	logsig	3	trainoss	0.7	0.10056	0.93996
	purelin	6	trainbfg	0.8	0.09366	0.92692
	tansig	8	trainlm	0.9	0.17505	0.50514
	tansig	10	trainrp	0.6	0.07527	0.94754
	logsig	10	traincgf	0.7	0.09545	0.84036
	logsig	12	trainlm	0.8	0.09475	0.91707
	logsig	15	trainbr	0.6	0.09521	0.89173
	logsig	15	trainlm	0.7	0.11352	0.57003
2	tansig	1–1	trainlm	0.5	0.06448	0.96218
	purelin	3–3	trainlm	0.6	0.12641	0.78486
	purelin	5–5	trainbfg	0.7	0.13080	0.79473
	logsig	5–4	trainbfg	0.8	0.12673	0.85568
	logsig	**6–3**	**trainrp**	**0.7**	**0.04990**	**0.97890**
	logsig	10–5	trainoss	0.9	0.12919	0.85534
	tansig	10–8	trainrp	0.7	0.08734	0.95748
	logsig	10–10	trainrp	0.8	0.07954	0.91453
	logsig	15–10	trainrp	0.6	0.06969	0.95350
	logsig	15–15	trainlm	0.7	0.11701	0.86562

The bold values indicate the best architecture and the best performance values for the artificial neural network model

model architecture consists of 1 input layer, 2 hidden layers and 1 output layer. There are 3 neurons in the input layer, 6 neurons in the first hidden layer, 3 neurons in the second hidden layer and 1 neuron in the output layer (3X6X3X1).

The performance graph showing how the training validation and test sets in each iteration change as a result of the training of the network is shown in Fig. 4. The regression graph is also shown in Fig. 5.

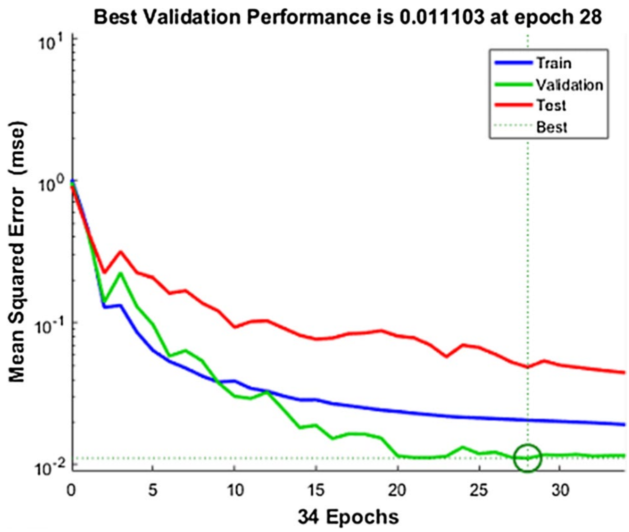

Fig. 4 ANN performance graph

Table 10 ANN estimation results of test data

Months	Estimation values	Actual values	MAPE	Forecast accuracy (%)	Deviation (pieces)
Jan	827	836	0.0108	98.92	9
Feb	596	561	0.0624	93.76	35
Mar	1431	1456	0.0172	98.28	25
Apr	832	833	0.0012	99.88	1
May	1375	1277	0.0767	92.33	98
June	525	597	0.1206	87.94	72
July	1521	1436	0.0592	94.08	85
Aug	458	406	0.1281	87.19	52
Sep	1158	1186	0.0236	97.64	28
Oct	634	649	0.0231	97.69	15
Nov	635	670	0.0522	94.78	35
Dec	940	966	0.0269	97.31	26
Averages			0.0502	94.98	40,08

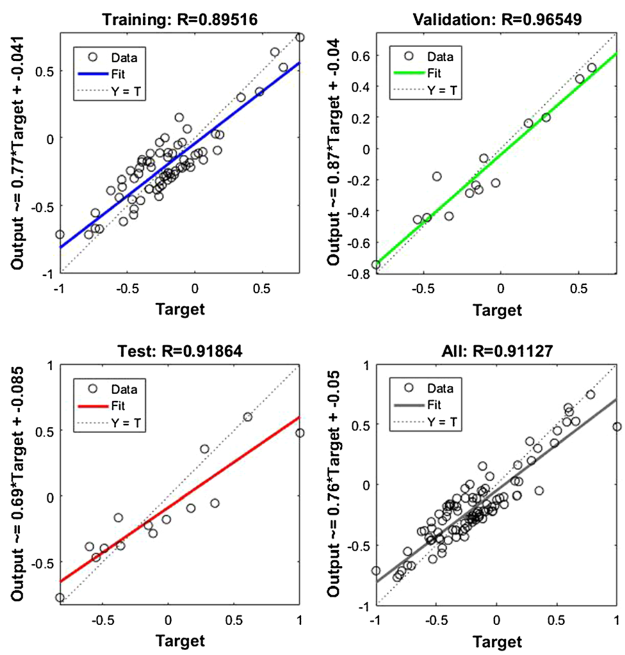

Fig. 5 Regression graph

The estimation results, which are the main target of the study, are shown in Table 10. Comma values are rounded to the nearest number to be an integer. Figure 6 shows the comparison results between the actual and the forecast. With the model developed, the sales of future times can be estimated by using past data. For example, the estimates of year 2020 can be carried out by using data up to year 2019. The estimates in most of the months are close to real values. However, in some months (especially in summer) the deviation is high. To research the reason of this situation (maybe a seasonal effect) is considered as a future study. The application results of demand forecasting can be used as input in production planning, financial planning, labor planning and decision making.

Differently from linear and nonlinear regression models, in Artificial Neural Networks (ANN), inputs, outputs, weights, training, learning and transfer functions are used for determining complex relationships between independent and dependent variables. Neural networks are much more advanced technology than regression due to its features such as learning using examples, the availability of multiple training algorithms and transfer functions, and the ability to generate information about unseen examples. Because of these reasons, better results can be achieved with ANN technology.

Application of support vector regression (SVR)

SVR training set is constructed from three inputs which are machinery sales in the world, exchange rate of USD and monthly impact rate. It has one output which is sales forecast of spare parts. In the model, while the data of 2010–2017 were used as training data, 2018 data were used as test data. Implementation of SVR was built in WEKA software (WEKA 2019). Experiments have been carried out to determine the best kernel function and results are shown in Table 11.

As seen in the table above, Polynomial Kernel that works with minimum error was chosen as the kernel function. The optimum parameters of the used kernel functions were determined by the grid search algorithm. Polynomial kernel function is shown in Eq. (14) (Daş et al. 2019).

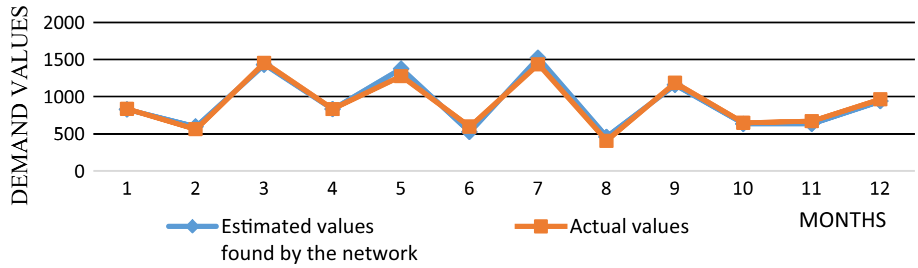

Fig. 6 Comparison of actual values and estimated values by ANN

Table 11 Test results

Kernel function	MAE	RMSE	RAE (%)	RRSE (%)
Normalized Poly Kernel	280	356	96	103
Poly Kernel	38	40	13	11
PUK	142	163	48	47
RBF Kernel	197	251	64	72

Table 12 Comparison of actual and predicted values by SVR

Months	Predicted values by SVR	Actual values	MAPE	Forecast accuracy (%)	Deviation (pieces)
Jan	810	836	0.0311	96.89	26
Feb	542	561	0.0339	96.61	19
Mar	1403	1456	0.0364	96.36	53
Apr	802	833	0.0372	96.28	31
May	1227	1277	0.0392	96.08	50
June	571	597	0.0436	95.64	26
July	1379	1436	0.0397	96.03	57
Aug	380	406	0.0640	93.60	26
Sep	1127	1186	0.0497	95.03	59
Oct	615	649	0.0524	94.76	34
Nov	635	670	0.0522	94.78	35
Dec	923	966	0.0445	95.55	43
Averages			0.0437	95.63	38.25

$$K(x, y) = ((x * y) + 1)^d \tag{14}$$

The prediction values of kernel function are compared with the actual values in table Table 12 and actual & predicted graph is drawn in Fig. 7.

The error percentage between the estimated values by SVR test and actual values is 4.37%.

Comparison of estimation results

As a result of models developed, linear regression analysis was 92.36% successful in the estimates, the nonlinear regression analysis was successful at 94.66%, Artificial Neural Network (ANN), achieved a success of 94.98%, while the SVR method was slightly more successful than ANN and achieved a success of 95.63%. In this study, it has been shown how artificial intelligence technologies are successful in estimation problems where the data are not linear and there are multiple variables that affect demand.

ANN model consists of 1 input layer, 2 hidden layers and 1 output layer. Training function, activation function, number of hidden layer and number of neurons in hidden layer were found by systematic trial and error based experiments. There are 6 neurons in the first hidden layer and 3 in the second hidden layer. While "trainrp" is used as training function, "logsig" is used as activation function. The ANN model found better predictive values than linear and nonlinear regression.

As a result of the tests applied in the SVR model, the best kernel function was found polynomial kernel. The parameters of the polynomial kernel are optimized with grid search method. SVR's forecast gave the highest accuracy and lowest deviation compared to other methods. In Fig. 8, it can be seen which method estimates the sales values better.

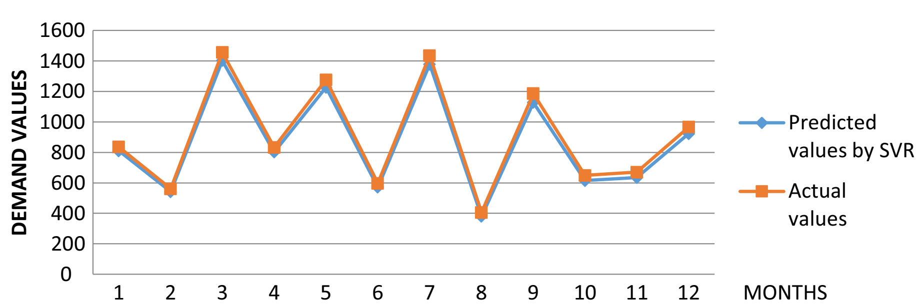

Fig. 7 Comparison of actual values and estimated values by SVR

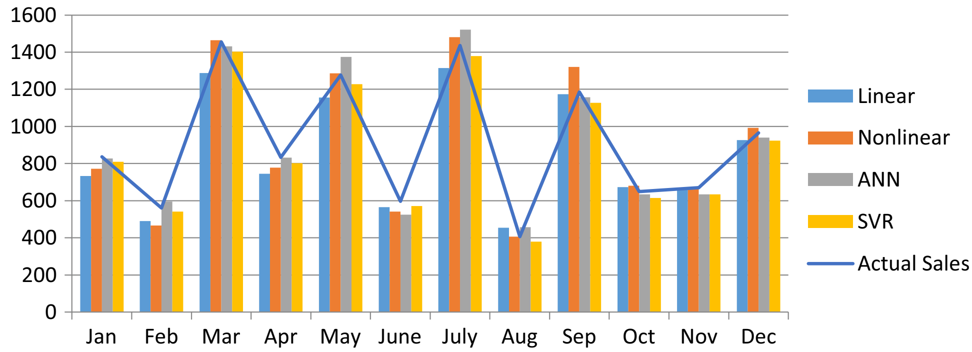

Fig. 8 Comparison of the results of the methods

Table 13 Average of deviations in units

Months	Linear regression	Nonlinear regression	ANN	SVR
Jan	103	64	9	26
Feb	71	95	35	19
Mar	168	8	25	53
Apr	88	55	1	31
May	121	9	98	50
June	32	55	72	26
July	122	45	85	57
Aug	49	1	52	26
Sep	12	135	28	59
Oct	24	32	15	34
Nov	2	1	35	35
Dec	40	26	26	43
Average	69.33	43.83	40.08	38.25

In forecasts, ANN and support vector regression (SVR) give better results than other methods. In addition, it was found that support vector regression forecasting is better compared to ANN. The arithmetic average of the deviations of number of sales according to the models is given in Table 13.

Conclusion and Discussions

When a company orders raw materials to its suppliers, it considers the previous sales of the products for forecasting. However, traditional methods are used to determine the size of the batch for the order and important factors affecting the sales of the product are ignored. This causes some purchase orders to be more or less than necessary. In this case, various costs arise from transportation costs to storage costs, machine preparation costs to labour costs.

In this study, it is aimed to predict the monthly sales of the manifold product group, which is one of the important parts of construction machinery in a company operating in the construction machinery sector. Since the company is producing spare parts, its product range is quite high. A wide variety of parts make it difficult to make efficient production planning. Therefore, the business needs to know the timing and quantities of the demands for the products it produces. If these are well known, production planning is much easier and inventory costs can be reduced. Linear regression, nonlinear regression, ANN and SVR models are developed for the objective of obtaining accurate sales forecasts. The application was carried out in one of the biggest companies in construction machinery sector in Turkey. Monthly sales data were collected between 2010 and 2018 for the manifold product group, which is a part of the air intake and exhaust system of construction machinery. Factors affecting sales are determined as a result of literature review, negotiations with managers and sales expert team. Demand forecasts have been conducted for the selected product group using the sales data of 9 years, estimated monthly machinery sales in the world, USD rate and monthly impact rate.

The estimates are used as input for production planning and inventory management. With highly accurate demand forecasting study, job forecasts are now achieved effectively such as increasing or decreasing the number of machines and determining the amount of workforce.

With this study, it can be said that artificial intelligence methods are more successful than linear and nonlinear regression models for demand forecasts. In future study, with the additional inputs, listening to the voice of the customer, accuracy of demand forecast of spare parts can be improved. In addition, other machine learning algorithms can be used. As a result, it is quite pleasing to obtain models that can produce results close to actual values, especially for demand forecast of spare parts.

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