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Forecasting Drinking Water Sales Values with Artificial Neural Networks: A Comparative Analysis with ARIMA and Winters' Methods

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Abstract: *This study aimed to forecast drinking water sales accurately for a water company dealer using the artificial neural networks method. The data used in this study is the total monthly sales number of dispenser-size water bottles of a water company's dealer in Bursa. The data consists of 85 months, from May 2017 to May 2024. In this context, an artificial neural network model was developed, and the estimations' performance was quite good. The histogram of estimation errors and normality tests showed a normal distribution. The findings show that the network can generalize. Besides this, visualizing the actual and estimated values showed that they follow the same patterns. As a result, it was concluded that monthly sales can be forecasted with the model developed using the threshold values and weights obtained from the trained network. Long-term forecasts were made and interpreted for the water company dealer using the developed model. Finally, the proposed artificial neural network was validated by comparing it with the average absolute percentage error values of alternative models, seasonal autoregressive integrated moving average, and seasonal exponential smoothing models.*

Keywords: Forecasting, Sales Forecast, Drinking Water, Artificial Neural Networks, ARIMA, Winters' Method

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1. Introduction

Companies can prepare themselves for the environment where competition and rapid change come to the fore by planning (Lancaster & Lomas, 1985: 5-14). Sales planning strategy plays a decisive role as it can result in improved customer service, reduced lost sales and product returns, and more efficient production planning (Fries & Ludwig, 2024: 253). Sales forecasting is one of the most essential areas to successful business plans and executions (Wu et al., 2023: 630). While sales refer to the amount of products sold within a certain period (Longman Dictionary, 2003: 1451), sales forecasting estimates the amount of future sales based on past sales data. It should be noted that sales forecasts have an essential and valuable place in various companies' operations. Sales are forecasted because strategies and size inventories are planned in companies (Carlberg, 2016: 24-25). Inventory planning, logistics planning, production scheduling, cash flow planning, staffing levels, and purchasing decisions depend on forecasts (Goodwin, 2018: 2).

Companies generally make sales plans using mathematical forecasting models that project demand (or sales) quantities of products into the future (Fries & Ludwig, 2024: 254). Various forecasting methods, including subjective methods, time series methods, and causal methods, exist in the related literature

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(Amariei et al., 2022: 16). In addition to these standard methods, there are also new forecast methods based on machine learning (ML) for users' needs. Of these methods, the subjective method is a judgmental technique based on an individual's intuitive guess. Subjective methods include the consumer survey method, panels of expert opinion, the Delphi method, morphological analysis, etc. The study of sales forecasts based on consumer reviews done by Zhang and Qiu (2021) is one of the recent examples of subjective studies. Methods other than the subjective method are methods in which numerical calculations are made using past data. Time series methods include popular models such as autoregressive (AR), moving averages (MA), autoregressive moving averages (ARMA), autoregressive integrated moving averages (ARIMA) models, and so on. Time series are a family of techniques that use time as a proxy variable to represent the underlying independent variables, which may not be easily obtained (Lancaster & Lomas, 1985: 102). Causal methods are a family of techniques that include correlation analysis, regression analysis, simulation, Bayesian decision analysis, decision trees, and diffusion models. Here, the correlation analysis is used to select the independent variable (or predictor variables) to be used in regression analysis (Carlberg, 2016: 68). Unlike time series, the assumption is that there is a discernible relationship between the forecasted dependent variable and a measurable independent variable in regression analysis (Lancaster & Lomas, 1985: 104). ML means using machines (computers and software) to gain meaning from data (Paluszek & Thomas, 2024: 1). ML methods in the area of forecasting include algorithms such as linear regression, logistic regression, decision tree regression, random forest method, k-nearest neighbor regression support vector machine and artificial neural networks (ANNs).

Some sales forecasting studies in the forecasting literature related to time series methods, causal methods, and ML methods are: Ayyıldız and Özkan (2011) made pharmaceutical sales forecasts using the multiple regression method, Sofyalıoğlu and Öztürk (2013) forecasted a cement company's sales values with fuzzy time series models, Babacan (2015) forecasted the total sales of an enterprise with moving averages, Merino and Ramirez-Nafarrte (2016) estimated retail sales with simulation, Özçalıcı (2017) forecasted stock prices with ANNs, Önen and Karabulut (2018) estimated airplane flight catering sales with regression models, Ecemiş (2018) forecasted sales in stainless steel sector with decision trees, Bandara et al. (2019) examined sales demand forecast in e-commerce with long short-term memory (LSTM) neural network, Pekkaya and Uysal (2020) estimated iron-steel sales with regression models, Lian et al. (2021) forecasted fuel sales with Bayesian methods, Sun et al. (2022) examined cigarette sales forecast with ANNs, Wu et al. (2023) studied avocado sales forecast with regression analysis, Yüksel (2023) forecasted sales data of a retail company with ARIMA and multiple linear regression method, Fries and Ludwig (2024) examined bakery sales forecast with ML methods, Setiyawan et al. (2024) studied the volume of aviation fuel forecast with ARIMA, and Sinap (2024) made Black Friday sales forecasts in the retail sector with the regression algorithm, one of the machine learning algorithms.

On the other hand, scientific discussions in the literature on estimating future values show that ANNs outperform time series, causal, and other ML methods. In this sense, many authors expressed this fact in different ways. For instance, Walczak and Cerpa (2001) stated that several results have shown that ANNs outperform traditional statistical techniques (e.g., linear regression or logistic regression) and other standard ML techniques for a large class of problem types. Singh and Challa (2016) stated that instead of time series techniques, researchers prefer to adopt ANN and adaptive neuro-fuzzy inference system (ANFIS), which is a kind of ANN. Lian et al. (2021) stated that AR and ARIMA models generally fail to predict the evolution of nonlinear processes accurately. Hasheminejad et al. (2022) stated that when addressing the issue of sales forecasting, time series and multivariate regression methods generally do not work when the market is constantly fluctuating. Soltaninejad et al. (2024) stated that time series and regression models often fail to capture the nonlinear relationships inherent in sales data.

Some example results showing that ANNs outperform other forecast models in the literature are as follows: Yücesan (2018) compared the accuracy of ARIMA, autoregressive integrated moving average with exogenous inputs (ARIMAX) model, and ANNs model in the sales forecasting in the white goods sector and concluded that the ANNs model outperforms ARIMA and ARIMAX models. Sönmez and Zengin (2019) compared the accuracy of the regression model and ANNs model in demand forecasting in food and beverage companies. They concluded that the ANNs model outperforms the regression model. Yurtsever (2022) compared the accuracy of the LSTM neural network model with a multivariate time series model in forecasting automobile sales and concluded that the LSTM neural network model outperforms the multivariate time series model. Han et al. (2022) compared the accuracy of Holt Winters' model and ANNs model in forecasting automobile sales and concluded that the ANNs model outperforms Holt Winters' model. Hasheminejad et al. (2022) compared the accuracy of ANFIS, ANNs, and ARIMA models and concluded that the ANFIS model performs better. Eşidir et al. (2022) compared the accuracy of the ARIMA model and the ANNs model in forecasting automobile sales and concluded that the ANNs model outperforms the ARIMA model. Soltaninejad et al. (2024) compared the accuracy of ARMA, multivariate regression, and ANN models and concluded that the ANN model performs better.

Considering the explanations above regarding the importance of sales forecasting and the valuable place of ANNs in the forecasting literature, research on sales forecasting in drinking water was conducted in this study. This study aimed to estimate and forecast drinking water sales accurately for a water company dealer in the Bursa province in Türkiye using the artificial neural networks method. The estimates were checked against the actual results. Validation was made by comparing ANN with SARIMA and Winters models.

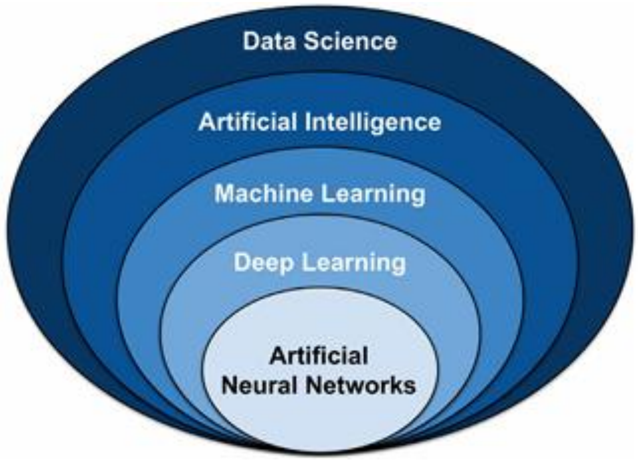
In the literature review, it was observed that sales forecasting made in different subjects such as automobile sales by Karaatlı et al. (2012), four different products sales of a company by Ataseven (2013), sales revenue by Penpece and Elma (2014), domestic car by Akyurt (2015), furniture sales by Hazır et al. (2016), dispenser size water sales by Tüzüntürk et al. (2016), automobile sales by Topal (2019), vehicle sales by Yılmaz et al. (2020), housing sales by Selçi (2021), tractor sales by Civelek (2021), cement sales by Tüzüntürk and Eteman (2023), and vented combi device sales amounts by Yakıt and Özkan (2024). It has been seen in the literature that very few studies have been conducted on water sales. Only one study was found on this subject. The small number of studies in the field indicates a gap, and the study's primary contribution is to fill this gap in the literature. This study's secondary contribution is presenting an ANN's research design to different sides of the industry by developing a drinking water model and implementing ANN-based sales forecasting. The third contribution is that the results of this study support the studies stated above, providing evidence that ANN gives better results than traditional time series methods in the stated scientific discussions. The fourth contribution is comparing the performances of different scientific approaches with ANN.

The rest of the paper is organized as follows: ANNs are theoretically explained in the second section. The data and model design are given in section three. The fourth section includes the findings. Section five covers the validation of the ANN model. The last section covers the conclusion.

2. Artificial Neural Networks

While ML is a subfield of artificial intelligence (AI) (Chopra & Khurana, 2023: 15; Kononenko & Kukar, 2007: 1), deep learning (DL) is a subfield of ML (Deng & Yu, 2014). AI is a field focused on automating intellectual tasks usually performed by humans. ML includes many methods, including DL and ANNs, for achieving this goal (Choi et al., 2020: 1). In this context, it can be said that ANN is an ML algorithm (Choi et al., 2020: 7). The umbrella of selected data science techniques is shown in Figure 1.

Figure 1. Umbrella of Select Data Science Techniques

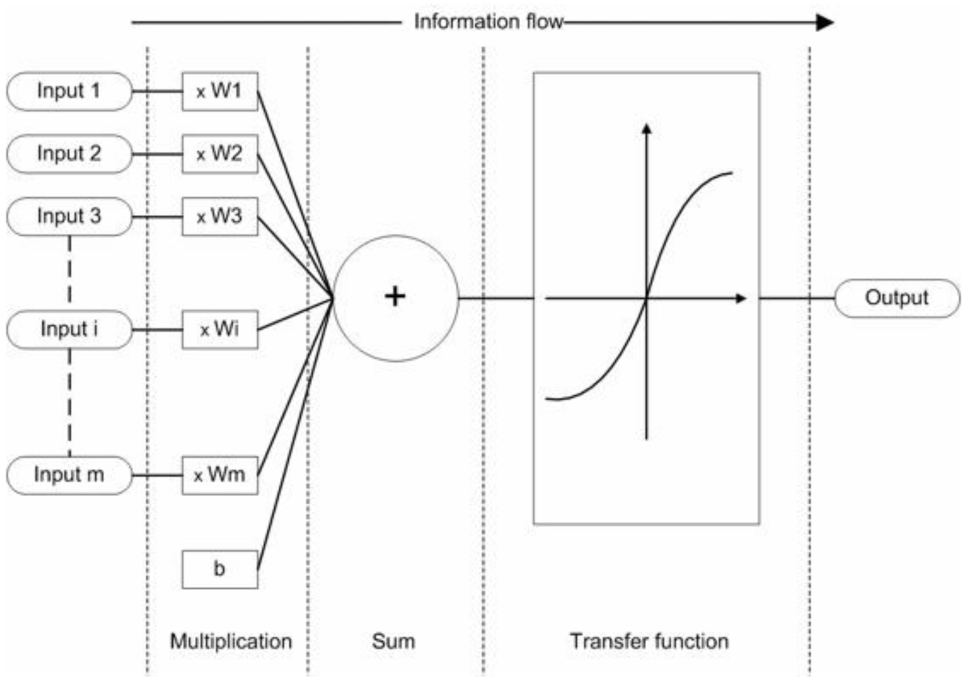


Source: Choi et al. (2020).

ANNs are machines designed to perform specific tasks by imitating the human brain (Lopez et al., 2022: 381). An ANN's basic computational entities are neurons that can take real values within the interval [-1, 1] (or [0, 1]) (Peterson & Rögnvaldsson, 1992: 115). The basic architecture of ANNS consists of three types of neuron layers: input, hidden, and output layers (Abraham, 2005: 902).

Figure 2 shows the working principle of an artificial neuron. At the entrance of the artificial neuron, the inputs are weighted, which means that every input variable is multiplied by individual weight. Then, all weighted inputs and biases are summed, and they pass through the activation function (or transfer function). In most cases, one of the functions from the step function, linear function, or non-linear (sigmod) function is chosen (Krenker et al., 2011: 5).

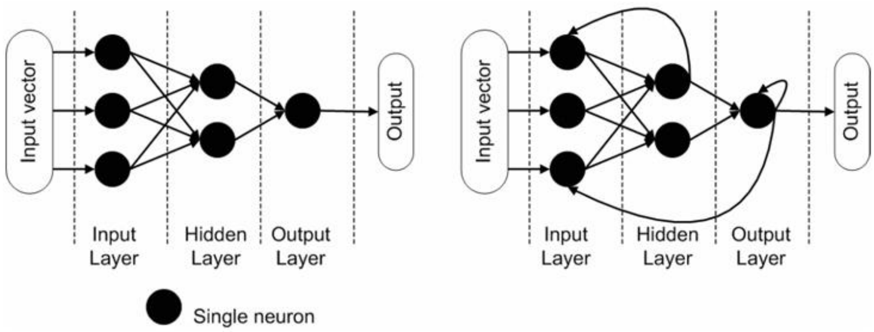
Figure 2. Working Principle of an Artificial Neuron



Source: Krenker et al. (2011: 3).

There are two different kinds of architectures in NN modeling: feed-forward and feedback (Peterson & Rögnvaldsson, 1992: 116). Figure 3 shows the architecture (topology or graph) types of ANNs.

Figure 3. Architecture (Topology or Graph) Types of ANNs



Source: Krenker et al. (2011: 6).

The feed-forward network is illustrated on the left side, and the feedback is on the right side of Figure 3. While in feed-forward networks, information flow is from input to output units in only one direction; feedback networks have feedback connections that enable information flows in both directions (Abraham, 2005: 902).

ANNs compute through a learning process (Haykin, 2008: 2). ANNs generally learn from experience rather than being explicitly programmed with rules like in conventional AI (Peterson & Rögnvaldsson, 1992: 114). The learning processes can be categorized into two main categories. These are learning with and without a teacher (Haykin, 2008: 34). In the first category, teachers know the environment. In the second category, there are two subcategories. These are reinforcement and unsupervised learning. In reinforcement learning, learning is achieved through interaction with the environment. In unsupervised learning, no teacher exists. The primary learning tasks for supervised learning are classification, regression, and forecasting. The primary learning tasks for unsupervised learning are clustering, dimension reduction, and association. The main task for reinforcement learning is decision-making.

3. Data and Model Design

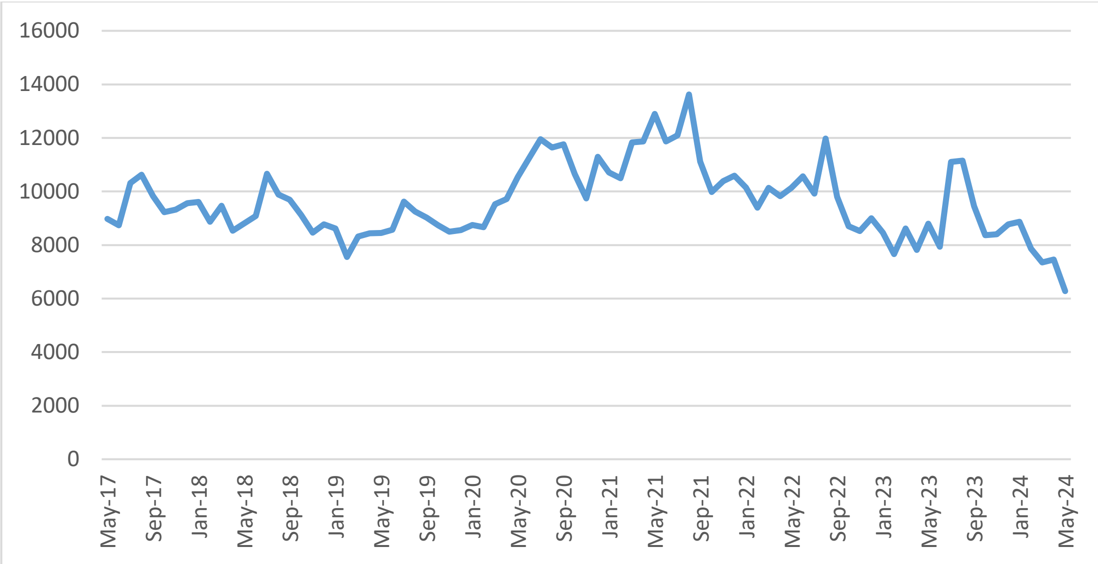
The data used in this study is the total monthly sales number of dispenser-size water bottles of a water company's dealer in the Bursa province in Türkiye. The data consists of 85 months, from May 2017 to May 2024. 80% of the data was used in training the network and 20% in testing the network. The data was standardized between -1 and +1, and the reverse standardization process was applied before using the estimated data obtained from the network. The application was implemented in the MATLAB (Matrix Laboratory) environment using the MATLAB R2021a programming language. The results obtained were visualized in the Excel program.

The appearance of the data over time is drawn with a graph, and the graph is examined first. Figure 4 shows the time series plot of sales data.

The total monthly sales number of dispenser-size water bottles is shown on the vertical axis, and the months are displayed on the horizontal axis in Figure 4.

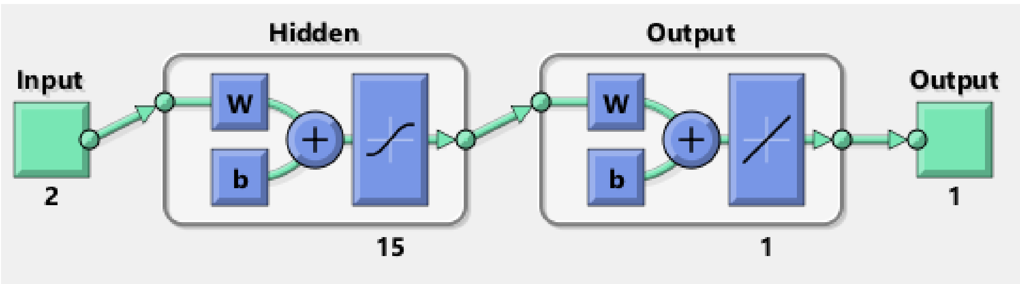
When the sales graph in Figure 4 is examined, it is seen that sales increase in the summer months and decrease in the winter months. This indicates that there is a monthly seasonal fluctuation in the data set. Again, when the graph is examined, although there is no regular increase or decrease (trend) in sales, there is a variability in annual sales averages. This indicates that there is a yearly seasonal fluctuation in the data set. It is seen that sales change monthly, and more sales are made, especially in the summer months, while sales are at a minimum level in the winter months. Therefore, the month dummy variable (M_{ti}) can be included in the model to capture these seasonal fluctuations by the network.

Figure 4. Time Series Plot of Sales Data



On the other hand, it is understood from the data set that there are fluctuations in the company's customer portfolio on an annual basis. The model can also include the year dummy variable (Yti) to capture these annual fluctuations by the network. According to the examinations and gathered information from Figure 5, actual sales can be written as a function of month and year variables, and a model can be established as follows: $S_t = f(M_{ti}, Y_{ti})$. M_{ti} is a dummy variable for month i at time t ($i = 1,2,3, \dots ,12$). And, Y_{ti} is a dummy variable for year i at time t ($i = 1,2,3, \dots ,8$). Figure 6 shows the network architecture for the current study.

Figure 5. Network Architecture (Topology or Structure)



The network in Figure 5 consists of 3 layers: input, hidden, and output. According to the working principle of artificial neural networks, there are artificial neurons in the input layer as many as the number of independent variables in the designed model. Since the designed model has two independent variables, this layer has two artificial neurons. These cells are responsible for transferring the observation values of the independent variables to the cells in the hidden layer by multiplying them with the relevant weights. The number of cells to be used in the hidden layer varies depending on the designer and the content of the problem. Although there is no definitive method for determining the optimal value of cells in the hidden layer, the number of cells is generally decided by trial and error. Using insufficient cells may cause the hidden patterns in the data not to be captured, and using more cells than necessary may cause the network to memorize the data and lose its ability to generalize. Therefore, data separation for testing is essential in practice. The current study decided to have 15 cells in this layer by trial and error. In the output layer, cells are used as many as the number of predicted variables, again due to the working principle of artificial neural networks. In the current study, one cell was used because only sales figures were estimated.

The summation function was used as the combining function. The hyperbolic tangent sigmoid (tensing) function was used in the hidden layer, and the linear (purely) function was used in the output layer. The network has 16 threshold values (bias), including 15 cells in the hidden layer and one cell in the output layer. There is a 2x15 size weight matrix in which the data transferred from the two artificial neurons in the input layer to each of the 15 cells in the hidden layer are multiplied, and a 15x1 size weight matrix. During the training phase of the network, these threshold values and weights are systematically changed and fixed at the point where the estimation errors are minimal.

4. Findings

In ANN, training the network consists of determining the weights and threshold values to minimize the error in the estimations obtained. Although there are many training algorithms in the literature, the Bayesian regularization backpropagation algorithm was used in the current study. Here, the weights and threshold values in the network are updated to increase the performance of the estimations according to Levenberg-Marquardt's optimization. Mean square error (MSE) was used to measure estimation performance. In this algorithm, training stops based on adaptive weight minimization. Therefore, unlike other backpropagation algorithms, in this learning algorithm, the data set is divided into two parts, training and testing, instead of being divided into three parts: training-validation-testing. The data set allocated for testing is not introduced to the network during training. The network is run by introducing test data to the trained network. The performance value obtained with test data is essential for the network designer as it shows whether the network does not memorize the training data and can generalize. In practice, 80% of the data is randomly allocated for training the network and 20% for testing the trained network. It is desired that the performances of the estimations obtained with the data allocated for training and testing are close to each other. Otherwise, the network: It is understood that he memorized the data set in the training set but could not generalize. The threshold values and weights determined in the trained network are given in Table 1 and Table 2, respectively.

Table 1. Threshold Values

Number of Neurons	Biases	
	Hidden Layer	Output Layer
1	0.230183369630119	0.213010170150065
2	-0.705105136979617	
3	1.064152194377780	
4	-1.442552844585920	
5	-0.043633427492776	
6	-0.577119016534988	
7	0.379386773021642	
8	0.043633427492780	
9	0.043633427492776	
10	0.320610004412630	
11	-0.666889283323622	
12	0.043633427492775	
13	0.043633427492775	
14	-1.060661902428450	
15	0.043633427492774	

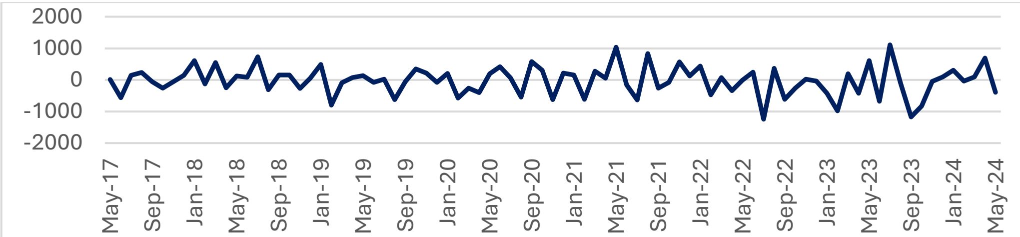
Sales can be forecasted as far into the future as desired using the threshold values above and the weights below.

Table 2. The Input and Layer Weights

	Input Weights		Layer Weights
Number of Neurons	M_{it}	Y_{it}	
1	1.877098535043440	0.075712852950394	-1.952480085627230
2	-0.457580950433186	2.364331958352460	-2.063991918527810
3	-0.308651618990065	-1.136783367370740	-1.451066491638290
4	1.375350487992050	-1.466427756936280	-0.905302557663977
5	-0.337018211873942	0.120275189800491	-0.482498853660896
6	1.380773844214220	1.536008294011160	-0.853930945607393
7	0.210582538840764	-3.745917727352300	-1.322014543475600
8	0.337018211873944	-0.120275189800489	0.482498853660902
9	0.337018211873942	-0.120275189800490	0.482498853660901
10	-0.323447200195947	0.461794148317008	-0.700458326621897
11	-3.924656867450720	-0.395908181402316	-1.645856987719070
12	0.337018211873943	-0.120275189800490	0.482498853660901
13	0.337018211873944	-0.120275189800492	0.482498853660905
14	-1.110006779957150	1.360441048357170	1.081685237914590
15	0.337018211873944	-0.120275189800490	0.482498853660910

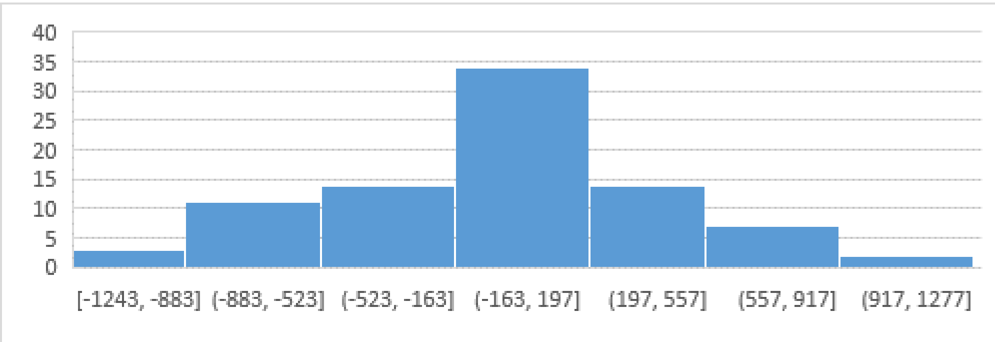
The estimation errors obtained from the training are shown in Figure 6. As can be seen in the figure, the errors are randomly distributed around zero.

Figure 6. The Estimation Errors



To assume that the network can generalize, it is desired that the errors are normally distributed. The histogram of errors is given in Figure 7.

Figure 7. The Histogram of Errors



In Figure 7, the errors in the estimates obtained appear to be by the normal distribution. In addition to this, normality tests (KS, AD, RJ, and SW) were also performed in Minitab 17, and the same result was achieved (p-values ≥ α=0.05).

The difference between observation and estimation values needs to be examined to evaluate the performance of estimates. Although it is necessary to use the MSE measure for the training algorithm to work during the network training, it isn't easy to interpret because it is squared values. Therefore, to compare the performance of training and test data sets, the table containing the mean absolute error (MAE) and mean percentage error (MPE) values are given below in Table 3.

Table 3. Performances of Estimations for Training and Test Data Sets

	Train	Test	All
MSE	218.673	150.954	206.722
MAE	358	292	346
MPE	0.037066941	0.032995913	0.03634852

According to the MAE values, the estimations deviate from the observation values by an average of 358 units for the training data set and an average of 292 units for the test data set. According to MPE values, the estimations deviate from the observation values by an average of 3.7% for the training data set and 3.3% on average for the test data set. Although these figures show that more successful results were obtained in the test data set compared to the training data set, the estimation performances are the same. This indicates that the network has generalization ability.

By using the threshold values and weights obtained from the trained network, monthly sales amounts were forecasted until December 2026. The total monthly sales number of dispenser-size water bottles forecasted values are given in Table 4.

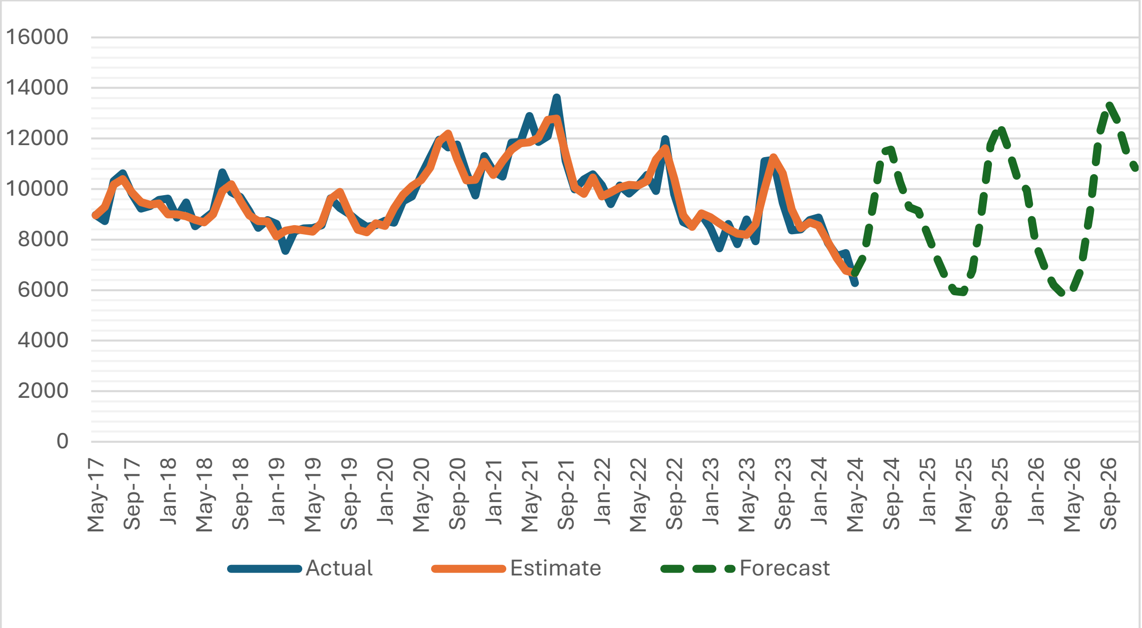
Table 4. Sales Forecasts

NO	DATE	FORECAST	NO	DATE	FORECAST	NO	DATE	FORECAST
1	Jun-24	7.380	11	Apr-25	5.957	21	Feb-26	6.894
2	Jul-24	9.337	12	May-25	5.924	22	Mar-26	6.194
3	Aug-24	11.455	13	Jun-25	6.768	23	Apr-26	5.832
4	Sep-24	11.557	14	Jul-25	9.002	24	May-26	5.932
5	Oct-24	10.274	15	Aug-25	11.744	25	Jun-26	6.812
6	Nov-24	9.272	16	Sep-25	12.562	26	Jul-26	9.053
7	Dec-24	9.133	17	Oct-25	11.567	27	Aug-26	12.080
8	Jan-25	8.256	18	Nov-25	10.419	28	Sep-26	13.416
9	Feb-25	7.333	19	Dec-25	9.967	29	Oct-26	12.714
10	Mar-25	6.501	20	Jan-26	7.821	30	Nov-26	11.507
						31	Dec-26	10.838

The total monthly sales number of dispenser-size water bottles actual, estimated, and forecasted values are given in Figure 8. Here, the total monthly sales number of dispenser-size water bottles is shown on the vertical axis, and the months are displayed on the horizontal axis.

Visualizing the actual and estimated values showed that they follow the same sales patterns, which implies that the estimations are pretty good. When we look at the forecasts for the next 31 months, it is observed that sales vary between 6000 and 12000 dispenser-size water bottles, and there is seasonal fluctuation. Although there is a positive trend in the forecast period, it should be noted that the company could not increase its sales compared to the actual data period. Still, it would be better to increase its sales to compete.

Figure 8. Actual, Estimated and Forecasted Values Plot



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5. Validation of the ANN Forecasting Model

The literature shows that the ANN, ARIMA, and Winters models are generally compared to validate the most appropriate model. Akıncılar et al. (2011), Irmak et al. (2012), Çuhadar (2013), Benli and Yıldız (2014), Karahan (2015), Ertuğrul and Bekin (2016), Oruç and Eroğlu (2017), Demir et al. (2018), Çuhadar et al. (2019), Özkan et al. (2020), Çuhadar (2020a), Çuhadar (2020b), Nebati et al. (2021), Han et al. (2022), Eşidir et al. (2022), Yüksel (2023), and Ölçenoğlu and Borat (2023) are some of the recent related sample studies.

Since the monthly sales data of dispenser-sized water bottles contain seasonality, comparing the seasonal exponential smoothing (Winters) model and the ARIMA model with ANN would be appropriate.

5.1. Winters' Triple Exponential Smoothing

In this method, the time series is asserted to have level, trend, and seasonal components. Winters proposes two models that include these components: additive and multiplicative. These are (1) the additive seasonality model and (2) the multiplicative seasonality model (Akgül, 2003a: 135). The additive model is:

$$L_t = \alpha\left(Y_t - S_{t-p}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{1}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \tag{2}$$

$$S_t = \delta(Y_t - L_t) + (1-\delta)S_{t-p} \tag{3}$$

Where α is the weight for the level, γ is the weight for the trend, and δ is the weight for the seasonal component. These three smoothing constants range between 0 and 1. The parameters α, γ, and δ can be chosen to minimize MAPE (Makridakis et al., 1997: 169). Here, L_t is the level at time t, T_t is the trend at time t, and S_t is the seasonal component at time t. And Y_t is the data value at time t and p is the seasonal period. The fitted values are estimated with the following equation:

$$\widehat{Y_t} = L_{t-1} + T_{t-1} + S_{t-p} \tag{4}$$

The multiplicative model is:

$$L_t = \alpha\left(Y_t/S_{t-p}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{5}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \tag{6}$$

$$S_t = \delta(Y_t/L_t) + (1-\delta)S_{t-p} \tag{7}$$

The fitted values are estimated with the following equation:

$$\widehat{Y_t} = (L_{t-1} + T_{t-1})S_{t-p} \tag{8}$$

The seasonal period (p) is taken as 12 for the monthly data (Akgül, 2003a: 138). So, for both additive and multiplicative estimations, the seasonal length was taken as 12 in this study. The smoothing constants (weights) were determined by selecting the model that best fits among the alternatives according to mean squared deviation (MSD), mean absolute deviation MAD, and MAPE statistics. For additive and multiplicative estimations, the following weights were used: For level is 0.2, for trend is 0.2, and for seasonal is 0.2. All Winters' model estimations were performed in MINITAB 17. Table 5 shows the accuracy comparisons of Winters' models.

Table 5. Accuracy Comparisons of Winters' Models

Alternative Forecasting Models	MAPE Statistics (%)	MAD	MSD
Winters Multiplicative Seasonal	5.949	570	618126
Winters Additive Seasonal	6.054	577	606004

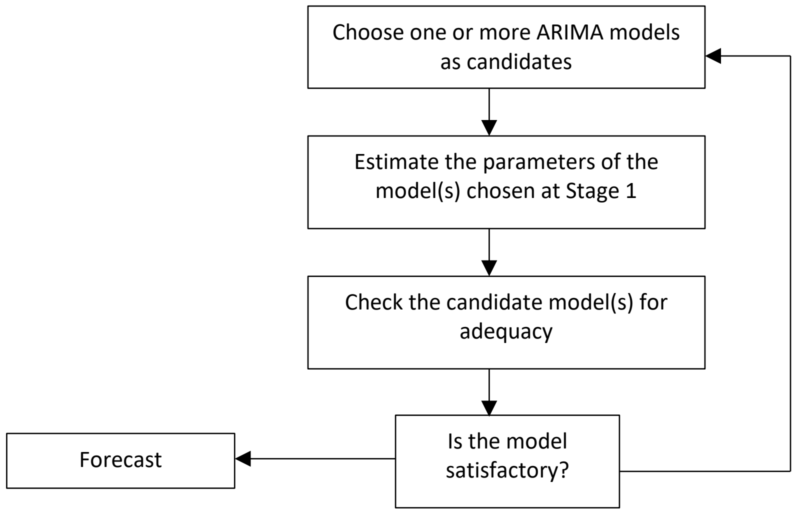
Because two of the three accuracy measures (MAPE and MAD) for the multiplicative seasonal model are less than the additive model, the multiplicative model outperforms the additive model. According to these measures, the multiplicative model fits the data better.

5.2. ARIMA

ARIMA models are applied to time series analysis and forecasting (Makridakis et al., 1997: 312). An ARIMA model is an algebraic statement showing how a time series variable relates to its past values (Pankratz, 1983: 16). The ARIMA (p, d, q) model's basic processes include the auto-regressive, integrated, and moving average processes (Yaffee & McGee, 2000: 108). p is the order of the autoregressive (AR) process, and q is the moving average (MA) order (Brockwell & Davis, 2002: 84). And, d is the order of integration (I).

To develop a suitable estimation form in ARIMA models, an attempt is made to find a appropriate model suitable for the time series at hand, or in other words, a model that will be compatible with the time series data (Akgül, 2003b: 3). The stages of this iterative approach are summarized with the Figure 9:

Figure 9. Stages of the Box-Jenkins Iterative Approach



Source: Pankratz (1983: 17).

ARIMA models are suitable for non-stationary series, and there are also models suitable for stationary series, such as moving averages (MA), autoregressive (AR), and autoregressive moving averages (ARMA) models (Akgül, 2003b: 4). ARIMA (p, 0, 0) process means a purely AR(p) stationary process and ARIMA (0, 0, p) process means a purely MA(q) stationary process (Gujarati, 2003: 840). If a time series order of integration is 1 which is shown as I(1) then this means the first difference of the time series is stationary. So, we have to difference a time series d times to make it stationary. The concept of stationarity refers to the situation where there is no systematic change in the mean and variance of the time series (Akgül, 2003b: 5). Augmented Dickey-Fuller (ADF) and Phillips Perron tests are the formal unit root tests that are generally used in the determination of whether the time series is stationary or nonstationary.

An autoregressive model of order p, that is, ARIMA (p, 0, 0) can be written as follows:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \tag{9}$$

Here, y_t depends on y_{t-1}, y_{t-2}.....y_{t-p} and the value of the auto regressive coefficients ϕ's .

A moving average model of order q, that is ARIMA (0, 0, q) can be written as follows:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{10}$$

Here, y_t depends on the error term ε_t and the previous error terms, with coefficients θ's.

An ARMA model of first order, that is ARIMA (p, 0, q) can be written as follows:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{11}$$

Akaike's information criteria (AIC) is useful for determining the order of an ARIMA model.

In addition to the above ARIMA models, seasonality can also be captured by adding seasonal terms in the ARIMA models. This type of models is called seasonal ARIMA or seasonal autoregressive integrated moving average (SARIMA) models. The ARIMA notation can be extended to handle seasonal aspects with the following form (Makridakis et al., 1997: 346): ARIMA (p, d, q) (P, D, Q)$_s$. Here, (p, d, q) is the non-seasonal part of the model and (P, D, Q)$_s$ is the seasonal part of the model. The stages (choosing models, estimating parameters, checking models and forecast stages in Figure 9) applied for non-seasonal models are also applied for seasonal models (Akgül, 2003b: 201).

Unit root tests should first be performed for sales time series data before running ARIMA models. Unit root tests were performed in Eviews 12. Table 6 shows the results of the ADF and PP (Phillips-Perron) unit root tests.

Table 6. ADF and PP Unit Root Tests' Results

			t Statistics	p-value
ADF	Intercept	Level	-2.7235	0.0743
		1st Difference	-10.7557	0.0001
	Trend + Intercept	Level	-2.7255	0.2293
		1st Difference	-10.8021	0.0000
	None	Level	-0.6776	0.4206
		1st Difference	-10.8099	0.0000
PP	Intercept	Level	-2.7235	0.0743
		1st Difference	-11.3508	0.0001
	Trend + Intercept	Level	-2.7255	0.2293
		1st Difference	-11.8043	0.0000
	None	Level	-0.6649	0.4262
		1st Difference	-11.3942	0.0000

All test results for all three situations ((i) intercept, (ii) trend and intercept, and (iii) none) show that the null hypothesis is not rejected at level (p-value $\geq \alpha$ =0.05), which means that the sales data has a unit root (or non-stationary). But, when the first difference of the sales data is taken, the null hypothesis is rejected (p-value $< \alpha$=0.05), which means that the sales data are stationary. ARIMA or its extension, SARIMA, is employed in such a situation. Since the existing data on drinking water sales includes seasonality, the SARIMA model was thought to be meaningful and the model shown in Table 7 was finally obtained among the alternative models. SARIMA model estimations were performed in MINITAB 17. Table 7 below shows the SARIMA model estimation results.

Table 7. SARIMA (1, 0, 0) $(0, 1, 1)_{12}$ Model Estimation Results

	Coefficients	t Statistics	p-value
AR (1)	0.8767	12.58	0.0000
SMA (1)	0.7759	5.96	0.0000
Original Series	85		
After differencing	77		
Sum Square (SS)	40992126		
Mean Square (MS)	577354	-0.6776	0.4206

Here, the difference equals one (D=1), and the seasonality is twelve (S=12). Because the constant term is not significant, it was omitted from the equation. The p-values show that all the coefficients are statistically significant (p-value $< \alpha$ =0.05).

5.3. Comparisons of Models with MAPE

The mean absolute percentage error (MAPE) statistic is usually used in this comparison. The MAPE is a useful indicator that gives relative information (Makridakis et al., 1997: 173). It is calculated with the following formula (Akgül, 2003a: 151):

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|y_t - \hat{y_t}|}{y_t}}{n} \times 100 \tag{12}$$

Where y_t is the actual value at time t, $\hat{y_t}$ is the estimated value at time t, and n is the number of estimated periods. Among the MAPE values to be calculated for alternative models, the model with the lower value is selected as the most suitable model.

The estimated values and residuals were obtained with MINITAB for the SARMA and Winters' models to calculate the MAPE values. Then, the MAPE statistics were computed using EXCEL for all alternative models. Table 7 shows these statistics.

Table 7. Accuracy Comparisons of Forecasting Models

Alternative Forecasting Models	MAPE Statistics (%)
ANN	3.634
SARIMA (1,0,0) $(0,1,1)_{12}$	5.787
Winters Multiplicative Seasonal	5.949

According to the MAPE values in Table 7, the lower value is 3.634, which indicates that the most suitable forecasting model is the ANN model.

6. Conclusion

Due to future uncertainties in the economic and business world, estimations to determine the future behavior of the series are extremely important (Akgül, 2003: xii). Forecasting plays a crucial role in business, industry, government, and institutional planning because many important decisions depend on the anticipated future values of certain variables (Pankratz, 1983: 3). Especially sales forecasts are essential for companies in the scope of this study. Businesses benefit from sales forecasts when taking action in many aspects, such as inventory, logistics, production, cash flow planning, personnel, and purchasing decisions. In addition, much literature proves that ANNs perform better than other forecasting techniques, such as time series, causal, and other ML methods. Combining these two valuable pieces of information, this study investigated sales forecasting in drinking water for a water company dealer in Bursa using ANNs. The data used in this study is the total monthly sales number of dispenser-size water bottles of a water company's dealer in Bursa. The data consists of 85 months, from May 2017 to May 2024. The usual approach is to draw the time series plot data to detect whether the data follow a stationary, trend, or seasonality pattern and then use this information to develop the model. Monthly and yearly seasonal fluctuations were detected visually, and according to this information gathered, the ANN model was developed. With the application of some procedures, the network model that consists of 3 layers (input, hidden, and output) was designed with the following characteristics: (i) The input layer has two artificial neurons, (ii) the hidden layer has 15 cells, and one cell was used for the output layer. Then, the ANN model was developed according to these structures and the network architecture. Network training was performed, and the estimations performed quite well. The histogram of estimation errors and normality tests (KS, AD, RJ, and SW) showed a normal distribution. The findings of this ANN analysis suggest that the network can be generalized. Besides this, visualizing the actual and estimated values showed that they follow the same patterns. In conclusion, monthly sales can be forecasted using the model developed using threshold values and weights obtained from the trained network. Besides the above analysis, the proposed ANN model was validated by comparing it with the estimated alternative models (SARIMA and Winters models) using MAPE statistics. In this comparison, the ANN model provided a slightly better fit than SARIMA and Winters' models.

The following managerial inferences can be made for the dealer company: The company's dealer can use future forecasts for stock planning and making plans, such as the number of employees and the number of water distribution vehicles. Depending on Lancaster and Lomas's (1985) statements, short-term forecasts will be helpful in production planning and control, cash requirements, and seasonal fluctuations. The medium-term forecasts will help achieve the expected sales, money spent on selling efforts, and capital requirements. The long-term forecasts will be helpful for financial planning requirements, plant expansion, and management succession. With the help of the current study's 31-month forecasts, the dealer company may benefit from the opportunities provided by all three forecast periods. On the other hand, the long-term forecast values and the graph showed that dealer sales vary between 6000 and 12000 dispenser-size water bottles, and there are still seasonal fluctuations. Although there was a positive trend during the forecast period, it was observed that there was no increase in sales when the dealer's estimated sales were compared with the current data period. The suggestion for the company's dealer is to benefit from the forecasted values and increase sales to compete in the market with competitors for the latter market actions.

The study is limited to the water company and only covers one dealer. In the future, it can be done for the water company's total sales, including all its dealers. In addition, being a case study for other companies in the water sector may encourage companies to make sales forecasts and plans using scientific methods. In addition, another product can be determined in the future, and its sales forecast can be made using the specified methods.

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References

Abraham, A. (2005). Handbook of measuring system design. In P. H. Sydenham & R. Thorn (Eds.), *Artificial neural networks* (pp. 901-908). John Wiley & Sons.

Akgül, I. (2003a). *Geleneksel zaman serisi yöntemleri*. DER Yayınları.

Akgül, I. (2003a). *Zaman serilerinin analizi ve ARIMA modelleri*. DER Yayınları.

Akıncılar, A., Temiz, İ., & Şahin, E. (2011). An application of exchange rate forecasting in Turkey. *Gazi University Journal of Science, 24*(4), 817-828.

Akyurt, İ. Z. (2015). Talep tahminin yapay sinir ağlarıyla modellenmesi: Yerli otomobil örneği. *Ekonometri ve İstatistik, 23,* 147-157.

Amariei, O., Hamat, C., & Amariei, D. (2022). Analysis of the quality of the sales forecast. *Studia Universitatis Babeş-Bolyai Engineering*, *67*(1), 16-26. https://doi.org/10.24193/subbeng.2022.1.2

Ataseven, B. (2013). Yapay sinir ağları ile öngörü modellemesi. *Öneri Dergisi, 10*(39), 101-115. https://doi.org/10.14783/od.v10i39.1012000311

Ayyıldız, H., & Özkan, K. (2011). Türkiye ilaç endüstrisinde satış tahmini araştırması. *Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 6*(1), 71-102.

Babacan, A. (2015). İşletmelerde toplam satış (finansal) tahminlemesi: Bir kobi uygulaması. *Bingöl Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 5*(10), 49-62.

Bandara, K., Shi, P., Bergmeir, C., Hewamalage, H., Tran, Q., Seaman, B. (2019). Sales demand forecast in e-commerce using a long short-term memory neural network methodology. In T. Gedeon, K. Wong, & M. Lee, (Eds.), *Neural information processing*. Springer. https://doi.org/10.1007/978-3-030-36718-3_39

Benli, Y. K., & Yıldız, A. (2014). Altın fiyatlarının zaman serisi yöntemleri ve yapay sinir ağları ile öngörüsü. *Dumlupınar Üniversitesi Sosyal Bilimler Dergisi, 42*, 213-224.

Brockwell, P. J., & Davis, R. A. (2002). *Introduction to time series and forecasting*. Springer.

Carlberg, C. (2016). *Microsoft Excel sales forecasting for dummies*. John Wiley & Sons.

Choi, R. Y., Coyner, A. S., Kalpathy-Cramer, J., Chiang, M. F., & Campbell, J. P. (2020). Introduction to machine learning, neural networks, and deep learning. *Translational Vision Science Technology, 9*(2), 1-14. https://doi.org/10.1167/tvst.9.2.14.

Chopra, D., & Khurana, R. (2023). *Introduction to machine learning with Python*. Bentham Science Publishers.

Civelek, Ç. (2021). Yapay sinir ağları kullanarak Türkiye tractor satış adedinin tahmin edilmesi. *Avrupa Bilim ve Teknoloji Dergisi, 31*(Ek Sayı 1), 375-381. https://doi.org/10.31590/ejosat.1000964

Çuhadar, M. (2013). Türkiye'ye yönelik dış turizm talebinin MLP, RBF ve TDNN yapay sinir ağı mimarileri ile modellenmesi ve tahmini: Karşılaştırmalı bir analiz. *Journal of Yaşar University, 8*(31), 5274-5295. https://doi.org/10.19168/JYU.54484

Çuhadar, M. (2019). TÜFE bazlı reel efektif döviz kurunun alternatif yaklaşımlarla modellenmesi ve tahminlenmesi. *Süleyman Demirel Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 34*(2), 78-103.

Çuhadar, M. (2020a). A comparative study on modeling and forecasting tourism revenues: The case of Turkey. *Advances in Hospitality and Tourism Research, 8*(2), 235-255. https://doi.org/10.30519/ahtr.765394

Çuhadar, M. (2020b). Modeling and forecasting inbound tourism demand to Croatia using artificial neural networks: A comparative study. *Journal of Tourism and Services, 21*(11), 55-70. https://doi.org/10.29036/jots.v11i21.171

Demir, İ., Genç, T., & Karaboğa, H. A. (2018). Türkiye Cumhuriyet Merkez Bankası altın rezervinin Holt-Winters üstel düzleme yöntemi ve yapay sinir ağları ile incelenmesi. *Uluslararası Ekonomi, İşletme ve Politika Dergisi, 2*(1), 131-146. https://doi.org/10.29216/ueip.411814

Deng, L., & Yu, D. (2014). Deep learning: Methods and applications. *Foundations and Trends in Signal Processing, 7*(3–4), 197-387. https://doi.org/10.1561/2000000039

Ecemiş, O. (2018). Model ağaç yöntemiyle satış tahmini: Paslanmaz çelik sektöründe bir uygulama. *Akademik Sosyal Araştırmalar Dergisi, 6*(84), 336-350. http://dx.doi.org/10.16992/ASOS.14538

Ertuğrul, İ., & Bekin, A. (2016). Türkiye'de bazı temel gıda fiyatları için yapay sinir ağları ve zaman serisi tahmin modellerinin karşılaştırılması. *Kafkas Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 7*(13), 253-280.

Eşidir, K. A., Gür, Y. E., Yoğunlu, A. & Çubuk, M. (2022). Yapay sinir ağları ve ARIMA modelleri ile Türkiye'de aylık sıfır km otomobil satiş adetlerinin tahmin edilmesi. *Pamukkale Üniversitesi İşletme Araştırmaları Dergisi, 9*(2), 260-277. https://doi.org/10.47097/piar.1132101

Fries, M., & Ludwig, T. (2024). Why are the sales forecast so low? Socio-technical challenges of using machine learning for forecasting sales in a bakery. *Computer Supported Cooperative Work, 33*, 253-293. https://doi.org/10.1007/s10606-022-09458-z

Goodwin, P. (2018). *Profit from your forecasting software: A best practice guide for sales forecasters*. John Wiley & Sons.

Gujarati, D. N. (2003). *Basic econometrics*. McGraw Hill.

Han, G., Sönmez, E. F., Avcı, S., & Aladağ, Z. (2022). Uygun normalizasyon tekniği ve yapay sinir ağları analizi ile otomobil satış tahminlemesi. *İşletme Ekonomi ve Yöneylem Araştırmaları Dergisi, 5*(1), 19-46. https://doi.org/10.33416/baybem.1001149

Hasheminejad, A. A., Shabaab, M., & Javadinararb, N. (2022). Developing cluster-based adaptive fuzzy inference system tuned by particle swarm optimization to forest annual automotive sales: A case study in Iran market. *International Journal of Fuzzy Systems, 24*(6), 2719-2728. https://doi.org/10.1007/s40815-022-01263-6

Haykin, S. (2008). *Neural networks and learning machines*. Pearson.

Hazır, E., Koç, K. H., & Esnaf Ş. (2015, Nisan). *Türkiye mobilya satış değerlerinin örnek bir yapay zeka uygulaması ile tahmini.* 3. Muğla Mobilya Kongresi.

Irmak, S., Köksal, C. D., & Asilkan, Ö. (2012). Hastanelerin gelecekteki hasta yoğunluklarının veri madenciliği yöntemleri ile tahmin edilmesi. *Uluslararası Alanya İşletme Fakültesi Dergisi, 4*(1), 101-114.

Karaatlı, M., Helvacıoğlu, Ö. C., Ömürbek, N., & Tokgöz, G. (2012). Yapay sinir ağları yöntemi ile otomobil satış tahmini. *Uluslararası Yönetim İktisat ve İşletme Dergisi, 8(*17), 87-100. https://doi.org/10.11122/ijmeb.2012.8.17.290

Karahan, M. (2015). Yapay sinir ağları metodu ile ihracat miktarlarının tahmini: ARIMA ve YSA metodunun karşılaştırmalı analizi. *Ege Akademik Bakış, 15*(2), 165-172.

Kononenko, I., & Kukar, M. (2007). *Machine learning and data mining introduction to principles and algorithms*. Horwood Publishing.

Krenker, A., Bester, J., & Kos, A. (2011). Artificial neural networks – methodological advances and biomedical applications. In K. Suzuki (Ed.), *Introduction to the artificial neural networks* (pp. 3-18). InTech.

Lancaster, G. A., & Lomas, R. A. (1985). *Forecasting for sales and materials management*. Macmillan Publishers.

Lian, H., Liu, B., & Li, P. (2021). A fuel sales forecast method based on variational bayesian structural time series. *Journal of High-Speed Networks, 27*(1), 45-66. https://doi.org/10.3233/JHS-210651

Longman dictionary of contemporary English. (2003). Pearson Longman.

Lopez, O. A. M., Lopez, A. M., & Crossa, J. (2022). *Multivariate statistical machine learning methods for genomic prediction*. Springer. https://doi.org/10.1007/978-3-030-89010-0

Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1997). *Forecasting: Methods and applications*. John Wiley and Sons.

Merino, M., & Ramirez-Nafarrate, A. (2016). Estimation of retail sales under competitive location in Mexico. *Journal of Business Research, 69*(2), 445-451. https://doi.org/10.1016/j.jbusres.2015.06.050

Nebati, E. E., Taş, M., & Ertaş, G. (2021). Türkiye'de elektrik tüketiminde talep tahmini: Zaman serisi ve regresyon analizi ile karşılaştırma. *Avrupa Bilim ve Teknoloji Dergisi, 31*(Ek Sayı 1), 348-357. https://doi.org/10.31590/ejosat.998277

Oruç, K. O., & Eroğlu, Ş. Ç. (2017). Isparta ili için doğal gaz talep tahmini. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 22*(1), 31-42.

Ölçenoğlu, A., & Borat, O. (2023). Holt-Winters ve Box-Jenkins modellerini kullanarak su tüketimi tahmini: İstanbul örneği. *Teknoloji ve Uygulamalı Bilimler Dergisi, 6*(2), 81-96. https://doi.org/ 10.56809/icujtas.1330019

Önen, V., & Karabulut, N. (2018). Havayolu uçak içi ikram satış tahmin modeli bir havayolu uygulaması. *Avrupa Sosyal ve Ekonomi Araştırmaları Dergisi, 5*(3), 100-121.

Özçalıcı, M. (2017). Aşırı öğrenme makineleri ile hisse senedi fiyat tahmini. *Hacettepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 35*(1), 67-88. https://doi.org/10.17065/huniibf.303305

Özkan, E., Güler, E., & Aladağ, Z. (2020). Elektrik enerjisi tüketim verileri için uygun tahmin yöntemi seçimi. *Journal of Industrial Engineering, 31*(2), 198-214. https://doi.org/10.46465/endustrimuhendisligi.708830

Paluszek, M., & Thomas, S. (2024). *MATLAB Machine learning recipes: A problem solution approach.* Apress Media.

Pankratz, A. (1983). *Forecasting with univariate Box-Jenkins Models: Concepts and cases.* John Wiley & Sons.

Penpece, D., & Elma, O. E. (2014). Predicting sales revenue by using artificial neural network in grocery retailing industry: A case study in Turkey. *International Journal of Trade, Economics and Finance, 5*(5), 435-440. https://doi.org/10.7763/IJTEF.2014.V5.411

Pekkaya, M., & Uysal, Z. (2020). Demir çelik işletmelerinde pandemi dönemi satış değerlendirmesi ve satış modellemesi. *Uluslararası Yönetim İktisat ve İşletme Dergisi, Özel Sayı*, 69-83. https://doi.org/10.17130/ijmeb.837159

Peterson, C., & Rögnvaldsson, T. (1992). *An introduction to artificial neural networks.* CERN Summer School of Computing Yellow Report 92-02.

Selçi, B. Y. (2021). Prediction using artificial neural network of Turkey's housing sales value. *Ekoist: Journal of Econometrics and Statistics, 35*, 19-32. https://doi.org/10.26650/ekoist.2021.35.180033

Setiyawan, A. P., Wibowo, W., & Atok, R. M. (2024). Forecast sales volume of aviation fuel in Jakarta using ARIMA method to support inventory control. *Indonesian Journal of Multidisciplinary Science, 3*(4), 355-361. https://doi.org/10.55324/ijoms.v3i4.804

Sinap, V. (2024). Perakende sektöründe makine öğrenemsi algoritmalarının karşılaştırmalı performans analizi: Black friday satış tahminlemesi. *Selçuk Üniversitesi Sosyal Bilimler Meslek Yüksek Okulu Dergisi, 27*(1), 65-90. https://doi.org/10.29249/selcuksbmyd.1401822

Singh, L. P., & Challa, R. T. (2016). Integrated forecasting using the discrete wavelet theory and artificial intelligence techniques to reduce the bullwhip effect in a supply chain. *Global Journal of Flexible Systems Management, 17*(2), 157-169. https://doi.org/10.1007/s40171-015-0115-z

Sofyalıoğlu, Ç., & Öztürk, Ş. (2013). Bir çimento fabrikası için dönemsel satış miktarlarının tahmininde bulanık zaman serisi modellerinin karşılaştırılması. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 18*(3), 161-186.

Soltaninejad, M., Aghazadeh, R. Shaghaghi, S., & Zarei, M. (2024). Using machine learning techniques to forecast Mehrams company's sales: A case study. *Journal of Business and Management Studies, 6*(1), 42-53. https://doi.org/10.32996/jbms.2024.6.2.4

Sönmez, O., & Zengin, K. (2019). Yiyecek ve içecek işletmelerinde talep tahmini: Yapay sinir ağları ve regresyon yöntemleriyle bir karşılaştırma. *Avrupa Bilim ve Teknoloji Dergisi, Özel Sayı*, 302-308. https://doi.org/10.31590/ejosat.638104

Sun, Z., Li, X., Zhang, H., Ikbal, M. A. & Farooqi, A. R. (2022). A GA-BP Neural network for nonlinear time series forecasting and its application in cigarette sales forecast. *Nonlinear Engineering, 11*, 223-231. https://doi.org/10.1515/nleng-2022-0025

Topal, İ. (2019). Çevrimiçi tüketici bütünleşmesi ve arama motoru verileri kullanılarak yapay sinir ağları ile otomobil satış tahmini. *Nevşehir Hacı Bektaş Veli Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 9*(2), 534-551.

Tüzüntürk, S., & Eteman, F. S. (2023). Türkiye iç piyasasında ulusal çimento talebinin yapay sinir ağları ile tahmini. *Maliye ve Finans Yazıları, 37*(120), 131-154. https://doi.org/10.33203/mfy.1297367

Tüzüntürk, S., Eteman, F. S., & Sezen, H. K. (2016). Yapay sinir ağı yöntemi ile damacana su satış miktarlarının tahmini. *Akademik Bakış Dergisi, 56*, 129-145.

Walczak, S., & Cerpa, N. (2001). Encyclopedia of physical science and technology. In R. A. Meyers (Ed.), *Artificial neural networks* (pp. 631-645). Academic Press. https://doi.org/10.1016/B0-12-227410-5/00837-1

Wu, D., Xu, Z., & Bach, S. (2023). Using Google trends to predict and forecast avocado sales. *Journal of Marketing Analytics, 11*, 629-641. https://doi.org/10.1057/s41270-023-00232-8

Yaffee, R., & McGee, M. (2000). *Introduction to time series analysis and forecasting*. Academic Press.

Yakıt, O., & Özkan, Y. (2024). Bacalı kombi satış miktarlarının tahmininde yapay sinir ağının kullanılması ve tedarik zinciri yöntemi içerisindeki önemi. *Gümüşhane Üniversitesi Sosyal Bilimler Dergisi, 15*(1), 237-253.

Yılmaz, A., Kaya, U., & Şaykol, E. (2020). An ANFIS based vehicle sales forecasting model utilizing feature clustering and genetic algorithms. *Journal of Aeronautics and Space Technologies, 13*(1), 139-154.

Yurtsever, M. (2022). LSTM Yöntemi ile ekonomik göstergeler kullanılarak otomobil satış tahmini. *Nevşehir Hacı Bektaş Veli Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 12*(3), 1481-1492. https://doi.org/10.30783/nevsosbilen.987093

Yücesan, M. (2018). YSA, ARIMA ve ARIMAX yöntemleriyle satış tahmini: Beyaz eşya sektöründe bir uygulama. *İşletme Araştırmaları Dergisi, 10*(1), 689-706. https://doi.org/10.20491/isarder.2018.414

Yüksel, B. (2023). Zaman serilerinde talep tahmini. *Yönetim Bilişim Sistemleri Ansiklopedisi, 11*(2), 10-28.

Zhang, G., & Qui, H. (2021). Competitive product identification and sales forecast based on consumer reviews. *Mathematical Problems in Engineering, Article ID 2370692,* 1-15. https://doi.org/10.1155/2021/2370692