EVALUATION OF AUTOMOBILE DEMAND FORECAST IN TURKEY USING ARTIFICIAL NEURAL NETWORKS

2022
MASTER THESIS
INDUSTRIAL ENGINEERING

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Prepared as
Master Thesis

KARABUK
November 2022

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ABSTRACT

M. Sc. Thesis

EVALUATION OF AUTOMOBILE DEMAND FORECAST IN TURKEY USING ARTIFICIAL NEURAL NETWORKS

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November2022, 60 pages

The automotive sector is a sector that contributes greatly to the economies of countries and it is the main buyer of sectors such as iron, steel, tires, and petrochemicals as well. The sales forecast of vehicles is of enormous significance in terms of making future plans for vehicle manufacturers, dealers, and manufacturers affiliated with this sector.

The aim of this study is to make monthly sales forecasts for automatic transmission vehicles of the C segment, which are among the best-selling vehicles in Turkey. In the study, 120 monthly data between 2012 and 2021 were used. Consumer price index, producer price index, interest rate, consumer confidence index, GDP, monthly sales and dollar rates were taken as independent variables, and C segment vehicle sales numbers were taken as dependent variables. While there are two types of demand forecasting quantitative and qualitative this study is in line with the causal approach, one of the quantitative forecasting methods.

In the method, regression and artificial neural network models were established. When the accuracy rates of the two models were compared, the artificial neural networks were higher with a rate of 90%. The demand prediction of C-segment automatic transmission vehicles has been interpreted according to the results of the artificial neural networks model, which has a high success rate.

Key Words : Artificial Neural Networks, C Segment Vehicle, Demand Forecasting

Science Code : 90619

ÖZET

Yüksek Lisans Tezi

TÜRKİYE'DE OTOMOBİL TALEP TAHMİNİ YAPAY SİNİR AĞLARIYLA DEĞERLENDİRİLMESİ

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Prof. Dr. Muharrem DÜĞENCİ
Kasım 2022, 60 sayfa

Otomotiv sektörü ülkelerin ekonomisine katkı sağlayan ve demir çelik lastik petrokimya gibi sektörlerin başlıca alıcısıdır. Araçların satış tahmini, araç üreticileri Bayileri ve bu sektöre bağlı olan üreticiler açısından gelecek dönemdeki planlamaların yapılması açısından büyük önem taşımaktadır.

Bu çalışmanın amacı, Türkiye'de en çok satılan araçların arasında C segmentin otomatik şanzımanlı araçların aylık satış tahmini yapmaktır. Çalışmada 2012-2021 yılları arasındaki geçmiş aylık 120 veri kullanılmıştır. Bağımsız değişken olarak tüketici fiyat endeksi, üretici fiyat endeksi, faiz oranı, tüketici güven endeksi, GSYİH, aylık satış oranı ve dolar kuru, bağımlı değişken olarak ise C segmenti araç satış adetleri alınmıştır. Talep tahmini kantitatif ve kalitatif olmak üzere ikiye ayrılırken, bu çalışma kantitatif tahmin tekniklerinden nedensel yaklaşıma uygun düşmektedir.

Yöntemde regresyon ve yapay sinir ağları modelleri kurulmuştur, %90 oran ile yapay sinir ağları daha yüksek çıkmıştır. C segment otomatik şanzımanlı araçların talep tahmini, yüksek başarı oran gösteren yapay sinir ağları modelin sonuçlarına göre yorumlanmıştır.

Anahtar Kelimeler : Yapay Sinir Ağları, C segment Araç, Talep Tahmini
Bilim Kodu : 90619

ACKNOWLEDGMENT

First of all, I would like to give thanks to my advisor Prof. Dr. Muharrem DÜĞENCİ, for his great interest and assistance in preparation of this thesis. I am deeply indebted to my always supportive family and friends.

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ABBREVITIONS

GDP : Gross Domestic Product

ANN : Artificial Neural Network

MAPE : Mean Absolute Percentage Error

MSE : Mean Squared Error

R : Correlation Coefficient

PART 1

INTRODUCTION

The automotive industry is one that interacts with many other industries and adds a substantial amount of value to the economy. Automotive is one of the sectors that will become more important in the future when it is supported by both the production volume, the employment it creates, and technological development.

Demand forecasting is extremely important in the automotive industry, a crucial sector for the economy, in order to develop accurate plans and predictions for the future. And to software that can analyze a lot of data quickly, thanks to recent technical advancements, it is now a topic that is tackled by both academic and industry experts.

All industries strive to generate products and services that will satisfy consumer demand and make them available on the market. Demand forecasting is the process of estimating, with the help of factors, how much customers will demand in the future in terms of products and services. The two primary categories of estimation techniques are quantitative and qualitative. The varieties of qualitative methods depend on the concepts of the individual, whereas quantitative methods are utilized when there is enough numerical evidence to support a mathematical model.

In this study, artificial neural networks, one of the qualitative methodologies, are used to estimate the sales of c segment automatic transmission vehicles, one of the most popular car classes in Turkey. Macro indicators were prioritized while choosing the factors that influence vehicle sales. In this context, data from the Turkish Statistical Institute include the consumer price index, producer price index, interest rate, consumer confidence index, and GDP. The Automotive Distributors Association's (odd) monthly vehicle sales rate and the investing source's dollar rate were chosen as independent variables. Then, regression models and artificial neural networks were developed, and comparisons between the two models were made.

The thesis study is divided into six parts, the second part of the study is a literature review on demand forecasting in the automotive sector. The third part discusses the global and Turkish automotive industries' production and sales figures. Demand forecasting and its methodologies are discussed in the fourth part. The statistical values of the data are provided, the findings of a model that was developed using artificial neural networks and regression are presented in the fifth part. In the last part, the results of the models are interpreted, and suggestions are given.

PART 2

LITERATURE REVIEW

In this part, sales forecasting studies in the automotive sector are researched. The methods used for estimation and the parameters in the model are examined.

Granger analysis, statistical unit root, and weak exogeneity were used in this study to identify dynamic relationships between vehicle sales (both small and big vehicle segments) and economic indices (Consumer price index, Unemployment rate, Gasoline Prices, Housing Starts). offered a set of causality and cointegration tests as part of a structural connection identification technique. Comparisons of prediction accuracy reveal that the VECM model performs better than other traditional and cutting-edge time series approaches.[7].

On the basis of the principles of multi-criteria decision making (MADM), the performance of the Box-Jenkins and Artificial Neural Network (ANN) approaches was assessed. For a product family in the automotive industry, these two approaches are used, and the results are then compared and examined. The findings demonstrate that the Box-Jenkins technique (Arima) provides much superior estimates.[8].

In order to make decision-making during inventory and transportation management easier, this study suggests a way to forecast auto aftermarket components. Four steps make up the method: graphical analysis, trends and seasonal adjustment, forecasting using a chosen ARMA model, white noise, and optimal test. This approach can accurately forecast future demand based on previous sales data. The sales statistics of a 4s shop in Shanghai are used to show how easy this approach is to utilize [9].

In order to integrate demand estimates based on historical data with applications from industry experts, this study intends to develop a hybrid approach. Date, Interest rate, GDP, Inflation, and US/MXN are the factors taken into consideration while

forecasting demand. Time series neural networks and fuzzy logic are used to integrate the data[10].

In order to make forward-looking demand forecasting considering monthly local automobile sales series, a feed forward artificial neural network model, trained with a back propagation algorithm, was applied using monthly local automobile sales values in the January 2011 - September 2015 data period[11].

The aim of this study is to contribute to the determination of some policies related to the automotive sector by predicting new automobile sales amounts by using artificial neural networks. Monthly data between January 2007 and June-2011 were used in the study[12].

A model has been developed to anticipate new automobile sales in Taiwan . established a sales forecasting system utilizing artificial neural networks that includes numerous aspects such as current auto sales volume, consistency indicator, leading indicator, wholesale price index and revenue. based on previous month's sales data[13].

Artificial neural networks (ANN) and Holt Winters' exponential correction approach were used to anticipate automobile sales. The dependent variables in the study include the exchange rate, consumer confidence index, GDP, and real sector confidence index. [14].

To analyze the nonlinear, complicated, and time-varying aspects related with EV stock and sales, this study developed a new time-varying gray Bernoulli model. The suggested model is for EV stock and sales forecasting, as empirical data reveal.It excels in predictive capacity, confirming its significant potential as a promising tool [15].

For forecasting automotive sales, an 8-layer Deep Neural Network (DSA) model is presented. Between 2011 and 2018, 90 data points were gathered and evaluated on a monthly basis. The model's inputs include numerous economic data such as the

exchange rate, GDP, consumer confidence index, and consumer price index. Forecasts for vehicle sales were developed based on the model's production. [16].

The elements influencing the demand price for used cars are identified in this study. The study focuses on the urban cores in the TR83 Region. The information was gathered from businesses that dealt in used cars between February and April 2015. The study utilized a semi-logarithmic regression model [17].

The selling price of used cars was estimated using decision trees. A genetic algorithm was used to select variables. On one of the Turkish e-commerce sites, 252645 adverts for the sale of automobiles were scanned. For each car, there are 139 versions. Models with 5, 10, 15, and 20 chosen variables, respectively, were examined using genetic algorithms [18].

The relationship between Turkey's imported automotive and light commercial vehicle retail sales and foreign exchange rates was investigated in this study. Monthly data from 2015 August to 2020 August were utilized. The variables' descriptive statistics were obtained, and regression analysis, unit root analysis for stationarity testing, VAR analysis, Johansen cointegration test, and Vector Error Correction Model were used [19].

In this study, artificial neural networks were used to estimate tractor sales. The following variables were chosen as independent variables: Gross domestic product (GDP), dollar price, agricultural input price index, real sector confidence index, transportation and communication expenditures, consumer expenditures, and automobile loans. The feedforward backpropagation artificial neural network method was used to conduct tests in 2 and 3 layers, and the results showed that the LOGSIG transfer function for a 3-layered artificial neural network with 2 neurons in the first layer and 4 neurons in the second layer produced the best estimation [20].

In this study, a method for predicting future automobile sales in the Saipa group, one of the top automakers in Iran, is suggested. It incorporates two artificial intelligence algorithms. GA is paired with Anfis as the fundamental method. The findings of the

circuit are adjusted using GA. Additionally, yearly data from 1990 to 2016 is used to anticipate sales. As a result, the following factors were selected as useful variables: per capita income, inflation rate, housing, Importation, Currency Rate (USD), loan interest rate and automobile import tariffs. The model was then put up against the ANN model, a well-known prediction model[21].

A prediction model was established for end-of-life vehicles in Brazil. Data on vehicles were obtained from Brazilian sectoral platforms. The model was established using ARIMA and ANN formulas. As a result of the estimation, 5.2 million end-of-life vehicles will be produced in 2030[22].

In this study, the sales forecast for an Indian automaker is covered. The prediction for this company's car sales has been found to be more significantly impacted by the inflation rate, fuel prices, and sales from the previous month. The Fuzzy Neural Back Propagation Algorithm is used to train the model. This result's output is contrasted with the results of other statistical methods[23].

In this research The conditional logit and nested logit models were used to predict the demand for automobiles in the US market based on market-level data on volumes, pricing, and vehicle attributes in 2010 and 2013 [24].

The amount of vehicles manufactured between 2006 and 2016 was chosen as the dependent data for the Iranian automobile demand forecast. As independent data, the monthly gold, rubber, and iron ore prices, as well as the monthly commodity metals price index and the Stock index, were determined. The model artifcal neural network (ANN) and artificial neuro fuzzy system (ANFIS) technique with the lowest MAPE value was evaluated[25].

PART 3

AUTOMOTIVE SECTOR

The automotive industry is defined as a business division that produces vehicles (including tractors, passenger cars, buses, minibuses, and vans) as well as the parts utilized in their production. [1].

The automobile sector has a big influence on the country's economy because of the extra value it produces. Turkey is the only country in the region with an advanced automotive industry. The industry's structure is intimately related to those of the marketing, dealer, service, fuel, financing, insurance, and related businesses, all of which help completed goods, sub-industries, and raw materials reach customers. This sector also makes the most contributions to the expansion of the defense sector. The automobile industry is the main consumer of fundamental industrial sectors such iron-steel, petrochemistry, rubber, textile, glass, and electric electronics, and it significantly contributes to the technical development of these sectors. All types of motor vehicles are required for the construction, transportation, tourism, and agricultural industries.

In conclusion, the automotive industry is crucial to the growth of the nation's raw material manufacturing and military sectors, assuring social and economic development, growing employment, raising national income, and reaching a large geographic region. Together with the related sub-sector, the automotive major industry contributes to the nation's economic and social growth [1].

3.1. DEVELOPMENT OF THE AUTOMOTIVE SECTOR IN THE WORLD

The automobile industry was established in Europe under the direction of Germany and France, and it grew and became more powerful in America (USA). The activities of the automotive industry, which have a history spanning more than a century, began with the production of automobiles. During the First World War, production of

commercial vehicles was also carried out, and the overall production was continuously changing and evolving with an emphasis on the automobile.

The conversion of steam energy into effective mechanical energy by James Watt in 1769 also gave rise to automobiles that operated on the principle of "self-propulsion". The steam-powered cars produced by the Frenchman Nicolas-Joseph Cugnot in 1770 and 1771 can be considered the first models to operate on the principle of self-propulsion. However, the fact that steam engines were not very efficient and that horse carts traveled faster than steam vehicles prevented the widespread use of steam vehicles [26].

Steam vehicle production efforts continued into the early nineteenth century. Englishman Richard Trevithick produced a steam-powered car in 1801, but it was too heavy, making it impractical. In 1805, American Oliver Evans produced a steam-powered vehicle, which was mostly used in ports. In 1829, Sir Goldsword Guyney built a steam-powered vehicle capable of speeding up to 25 km. And in the 19th century, the search for vehicle motion mechanisms led to the development of electric mechanisms that were faster than gasoline engines. In 1835, Sibrandus Stratingh succeeded in producing the first electric vehicle powered by electricity [2]. Etienne Lenoir discovered the internal combustion engine in Paris in 1860, and four years later, production of stationary internal combustion engines began at the Gasmotorenfabrik Deutz AG factory in Cologne. Otto, one of the founders of this plant, first produced the four-cylinder petrol engine in 1876.

In 1893, cars with internal combustion engines began to be produced in the USA, and their production and use gradually increased. The number of car brands in the world increased from 8 in 1880 to 50 in 1885 and 500 in 1890. Looking at production figures, the 1000% increase in 1890, and especially in 1890, when increasing production was on an upward trend, explains How fast is the sector developing [2].

After the 20th century, it continued to develop by advancing faster. Henry Ford developed new cars that were suitable for use in both the city and the countryside, with low maintenance and repair costs. These vehicles are called the "Model T". Henry Ford

established his first factory in 1913 in order to realize the entire production process. The price of the cars he produced at that time was $500. While the automotive sector continued its development, it also contributed to the iron and steel industry with which it cooperates and has had an impact on its development. With this situation in place, the automobile sector became the most important and significant industry in the United States after the 1920s [3].

More than 15 million Model T's were produced from 1908 to 1927. When the Model T which showed great commercial success produced 10 millionth production, 9 out of 10 vehicles found worldwide were Ford brands. Model T is also the first type to be produced simultaneously in the world. It has been produced in Canada and Argentina since 1911, in Germany and Argentina since 1925 and later in France, Spain, Denmark, Belgium, Brazil, Mexico and Japan. These features have made Ford Model T and Henry Ford the most sensational of automotive sensation [26].

Volkswagen firm emerged in Germany in 1926 with the slogan "automobile for everyone". Fiat was established in Italy in 1885 and Renault in France in 1944. After 1950 the Japanese joined the automotive industry. Until 1980, automotive manufacturers were producing in their own country and factories. However, after 1980 the producers expanded their production and spread them to other regions outside their own countries. In the 2000s and especially after the 2008 global economic crisis, Ford and GM reduced their work in the automotive sector and decided to shrink. The reason for this is the negative factors and regressions in the automotive industry. As a result of these bad events, both companies started to lose money and they had to stop their production in some countries and regions to reduce these losses [3].

3.2. DEVELOPMENT OF THE AUTOMOTIVE SECTOR IN TURKEY

The industrial revolution that began a long time ago in Europe was discussed at the beginning of the establishment of the republic in Turkey. However, as the other elements required for industrialization were not sufficient, the country tried to make the most of the opportunities available until the 1950s and the country began to take the leading role in industrialization.

The first assembly line was established in 1954 to produce jeeps and pickup trucks for the armed services following the production of a few vehicle prototypes in the 1950s of the previous century. In 1955, assembly lines began building trucks and buses. Three years later, assembly lines for automobiles (Tofaş-Fiat, Oyak-Renault, and Otosan-Ford) began operating. In 1966, the automotive industry began producing its own models, and Otosan was the company that produced the Anadol at that time. Two prominent automakers, Tofaş and Oyak Renault, began their manufacturing lines in 1971 with Italian and French licenses[4].

Despite all the negatives in the Turkish auto automotive, economy and trade, for which legislation and infrastructure were put in place in the 1970s, it has succeeded in gaining the quality of a sector that can compete with international companies due to the intensive breakthroughs it has made since the early 1980s. The auto industry has become competitive with international companies especially in production since the early 1980s. The use of quality and qualified manpower in production in the sector made it a new production center and suitable for global markets. Today, it has become a sector that attracts the most foreign capital interest and investments are made in production and export [5].

In 1978-1982 making regulations aimed at reducing the foreign dependency in the Turkish automotive sector was brought to the fore. the scope of the seminar organized under the leadership of the National Productivity Center in 1980, emerging in Turkey and often and licensing of various countries "know-how" caught the large number of factories producing under patents were mentioned localization the requirements within a short time of production [26].

In 1985 due to the use of modern technology and capacity increases, Otosan started to produce Ford Taunus model and Oyak Renault started to produce Renault 9 Model as the second model. In the following years, the first diesel engine and the first local production started. In 1997 production of the first local production Honda Civic and Hyundai Accent started [5].

Due to the increasing local demand in 1996 and 1997, significant increases were observed in the automotive industry production However, since the last quarter of 1998, the Asian Crisis, which began in the Far Eastern countries in the middle of 1997 and expanded to Russia in 1998, has had a detrimental effect on the Turkish automobile industry. The impacts of this crisis on the automotive industry have been steadily fading since the middle of 1999.

The Customs Union Agreement came into force between 1996-2000 and marked the beginning of a new era. In this period, priority was given to the shares envisaged for the modernization investments of enterprises in the incentive certificates with financial support. In these years, investments in the production of new and up-to-date model vehicles have been encouraged. In this way, the automotive industry was included in the preferred sectors for incentives, technology importation and foreign capital partnerships were facilitated and supported. Also, during these years, modern production techniques were put into practice with intensive training programs and especially by establishing quality management systems, companies were certified in terms of quality competencies by international organizations [26].

In February 2001, due to the economic crisis that caused the unemployment of millions of workers, the closure of many companies, and the sudden rise in foreign exchange rates, the volume of production witnessed a drastic decline compared to the previous year. After the crisis, the sector began to recover and continued to increase its production of cars every year until 2008. The global economic crisis that erupted in 2008 hit the automotive industry in Turkey as well as in the world. Production volumes in 2009 were at their levels in 3 years. This sector, which increased its production of cars until 2012, stopped again in 2012 due to the crisis in the European Union countries, Turkey's largest trading partner. Due to the economic downturn in the European Union, the demand for cars decreased and the volume of production in our country decreased compared to the previous year. After 2012, car production increased rapidly. 61 in 2017, an all-time record was broken and more than 1 million vehicles were produced[6].

3.3. AUTOMOTIVE INDUSTRY MARKET

The added value provided by the automotive industry, its creation, employment and other sectors it interacts with have made it an important place in the national economy.

The global automotive industry is one of the key industries that supports both developed and emerging nations' steady economic growth, advances technological progress, and fosters the expansion of numerous other industries. The automotive industry is the fourth largest economy in the world, making up around 5% of the global economy and having a total market value of over $4 trillion. 80 million people worldwide are employed directly and indirectly by the automotive sector.

3.4. AUTOMOTIVE MARKET IN THE WORLD

The automotive industry is an important economic force and capital-intensive sector globally. The sector, which plays an important role in the development of countries, also supports the global economy. The automobile industry consumes the production of industries such as iron, petrochemicals, aluminum, steel, glass, carpets, textiles, plastics, and rubber. It is important to take advantage of the possibility that any problem in the sector to which this sector belongs can quickly spread to the other sector. China, the United States, Japan and India are emerging as major global auto markets.

3.4.1. Production Amount in The World

Automotive is one of the most important sectors in the global economy in terms of values such as size, interaction, volume and penetration. Catering to transportation needs, it has such a significant size that it will be the sixth largest economy in the world in terms of pendulum driving pleasure. Car production on a global scale returned to production of nearly 96 million vehicles in 2018, following the record of 97.4 million units reached in 2017 with 8 years of continuous growth.

The International Organization of Automobile Manufacturers (OICA) reported that worldwide auto output decreased 5.3% in 2019 to 91.8 million units following nine years of growth and a record 96.9 million units in 2018. Since 2010, Asia and Oceania have produced more than half of the world's automobiles, reaching 49.3 million units, with a 2% reduction due to decreasing production in China. The American region produced 16.7 million pieces, or 18% of the global output. 19.3% of the world's manufacturing, or 17.7 million pieces, were made in Europe.

Global production increased by 3 percent in 2021 compared to the previous year and amounted to 80 million 146 thousand units. More than half (58 percent) of the world's automobile production in 2021 was built in the Asia and Oceania region. Vehicle production in the region increased by 6 percent compared to 2020 and reached 46 million 734 thousand units. On a regional level, after Asia and Oceania, the largest producers are North America with 17 percent and the European Union (27) + UK regions with 17 percent. Compared to 2020, EU (27) + UK production decreased by 5 percent, while North American production remained at the same level.

Automobile production in the world increased by 2 percent in 2021 compared to the previous year and reached 57 million 54 thousand units. On a regional basis, the highest change in automobile production was in North America, which experienced a decrease of 21 percent, and South America, which experienced an increase of 11 percent.

Commercial vehicle production in the world decreased by 13 percent in 2021 compared to the previous year and amounted to 21 million 787 thousand units. The highest change in commercial vehicle production on a regional basis was in Africa with a decrease of 26 percent and in Europe with a decrease of 20 percent. While the Asia-Oceania region ranks first in the regional ranking of automotive production, the North America region ranks first in the commercial vehicle production order.

In the automotive production list for 2021, China ranks first with a production of 26 million 82 thousand units. Carrying out 33% of global production, China's automotive

production increased by 3 percent compared to the previous year. U.S. automotive production, which ranks second, compared to the previous year.

It increased by 4 percent to 9 million 167 thousand and its share in global production was 11 percent. Automotive production in Japan, which ranks third in global production, decreased by 3 percent compared to the previous year and amounted to 7 million 847 thousand units.

Table 3. 1. Change in the amount of vehicle Production in the world (OICA)

Region	**2020**	**2021**	**Rate of change**
Asia - Oceania	35.822.949	38.152.172	7 %
European Union (27)	12.045.399	11.289.861	-6%
North America	3.219.558	2.559.537	-21%
Other Europe	2.511.149	2.513.436	0 %
South America	1.747.457	1.932.721	11%
Africa	562.477	606.568	8 %
Total	55.908.989	57.054.295	2 %

3.4.2. World Automotive Sales

According to data provided by OICA approximately 91.3 million cars were sold globally in 2019. In China, which became the world's largest automobile market in 2018, sales decreased by 2% to 25.7 million vehicles in 2019. The Indian market on the other hand contracted by 13% in 2019 to 3.8 million units. Sales in the Americas fell 2% in 2019 to 25.3 million units. Sales in the European region recovered by 1% after a one-year decline to 20.8 million cars. In 2019, automobile sales in Spain decreased by 4% to 1.5 million units and sales of South and Central American countries decreased by 1% to 4.5 million units. Brazil, which has become the largest market in the region increased its automotive sales by 13% to 2.8 million units.

Due to the epidemic in the world in 2020, both vehicle production and sales were negatively affected. Japan's monthly auto sales fell to a nine-year low in April, falling

29% year-on-year to 270,000. In April, vehicle sales in the USA decreased by 46% year-on-year to 708 thousand units. According to the statistics of the European Automobile Industry Association (ACEA), new vehicle sales in the European Union, England and the European Free Trade Association (EFTA) countries decreased by 51.8% in March 2020 to 853 thousand units.

The global market increased by 5 percent in 2021 compared to the previous year and amounted to 82 million 685 thousand units. 52% of automotive sales in 2021 are located in the Asia Oceania-Middle East region. Sales in the region decreased by 6 percent compared to the previous year and were realized as 42 million 664 thousand units. While the North American market, which ranks 2nd in global automotive sales, increased by 4 percent, the EU(27)-EFTA-United Kingdom region, which ranked 3rd, was at the same level as last year.

Table 3. 2. Change in the amount of vehicle sales in the world (OICA)

Region	**2020**	**2021**	**Rate of change**
Asia - Oceania	40.322.544	42.663.736	6%
North America	17.445.480	18.160.120	4 %
EU (27) + EFTA + UK	14.079.756	14.133.619	0 %
South America	3.369.352	3.841.032	14%
Other Europe	2.633.142	2.741.274	4 %
Africa	924.046	1.145.007	24%
Total	78.774.320	82.684.788	5 %

3.5. TURKEY AUTOMOTIVE MARKET

Turkey is geographically closer to Europe and the structure of the export-oriented automotive industry contains many opportunities for automotive manufacturers. Turkey's automotive industry is not only one of the main driving forces in Turkey's economy, but also the beginning of an important export-oriented manufacturing sector in Turkey. It has an important role in the production of commercial and light commercial vehicles for national and international companies that feed both the strong local market, the European and Middle Eastern markets.

3.5.1. Turkey Automotive Production

The effect of the depreciation of TL in 2018 had a negative impact on the sector. The biggest impact on the Turkish automotive industry in 2018 was caused by fluctuations in exchange rates and inflation exceeding 20%. Total production in the automotive sector in Turkey was 1.55 million units, a decrease of 8.6% in 2018. In 2019 Turkey's total automotive production induced internal demand once again fell by 5.7% compared to the same period of the previous year declined to 1,461 thousand units. According to 12-month cumulative data, although automotive production contracted by 91% annually in April 2020, it contracted by 54% in May with normalization steps. According to the data of Automotive Industry Association, automobile production decreased by 24% and commercial vehicle production by 35.7% in the first four months of the year. Thus, in the first four months of 2020, production across the sector shrank by 28% to 352 thousand units.

In 2021, total production decreased by 2 percent and automobile production decreased by 8 percent compared to the previous year. total production was 1 million 276 thousand 140 units, while automobile production was at the level of 782 thousand 835 units.

3.5.2. Turkey Automotive Sales

Turkey car market, the general decline in consumer confidence due to rising interest rates and decreased by 23.3% on an annual basis in 2019. Between the years 2008-2016 Turkey car sales grew 93%, reaching 1,014 thousand units. In other words, Turkey automotive market grew almost twice in eight years. The total market in Turkey has exceeded the threshold of 1 million per year between 2015-2017. With the slowdown in automobile sales between 2016 and 2019, it fell to the lowest level of the last fifteen years with 492 thousand units in 2019. Turkey total vehicle market, January 2020 - April period was realized as 151 thousand units, showing an increase of 26% compared to the same period of the previous year.

Due to Weakness in the Turkish lira, Turkey continues to pose a risk for auto sales. Turkey's automotive sales in that a large share of imports and foreign currency input costs due to local production car about 70-80% of the Turkish lira weakening dollar and is a major cause of the rise in price against the euro. Automakers have had to reflect their prices on their selling prices to compensate for the increased costs on imported auto parts, which make up a significant portion of auto costs. Automobile prices rose by 12.2%, more than the average inflation of 11% in 2019. Turkey between April 2013- 2020 annual average car prices have increased by 16%. Total sales in 2021 increased by 63 percent compared to 2020 and amounted to 772 thousand 722 units.

PART 4

THEORETICAL BACKGROUND

This study's goal is to predict the demand for vehicles with c-segment automatic transmissions. Demand forecasting will be theoretically covered in this part, and the forecasting model will benefit from this knowledge.

4.1. DEMAND FORECASTING

Consumers' desire to purchase an item or service within a given price range is known as demand. Forecasting is the process of using known parameters to make predictions about the current condition of an unknown parameter. The technique of calculating customer demand for a commodity or service over the long term is known as demand forecasting. Different decision-making procedures may be presented to people, corporations, and organizations as they go about their everyday lives.

It is important to prepare the future in advance rather than leave it to chance in today's environment when uncertainties are at their peak. Future decisions are also influenced by the planning of these projects or plans to carry them out.

Demand forecasting is the process of gathering and evaluating past data to figure out and predict how much a company will sell in the future. Demand forecasts may be used to determine how much of these items will be sold, which products customers will demand, and when these demands will be satisfied.

4.2. FORECASTING METHODS:

Estimation methods are basically divided into two as qualitative and quantitative. Qualitative methods are referred to as subjective or judgmental methods. Quantitative

methods are based on mathematical techniques and popular with the use of computer programs in this field.

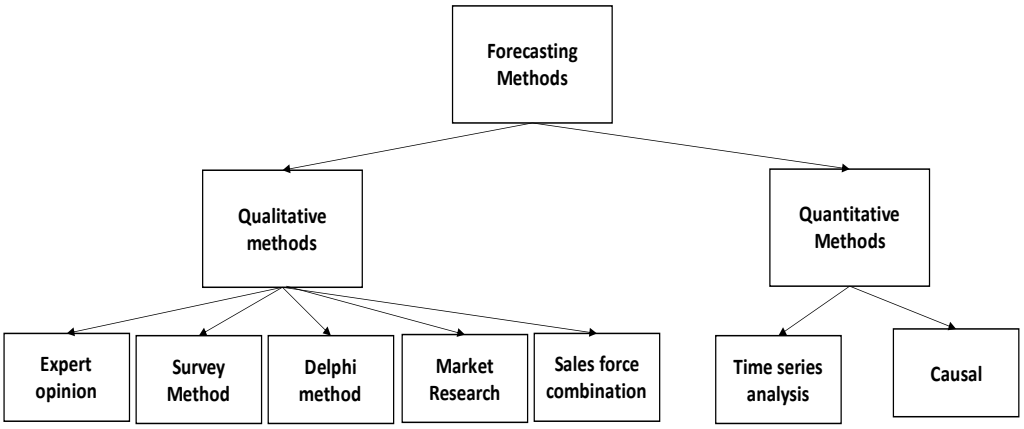

Figure 4. 1. Classification of forecasting method

4.2.1. Qualitative Methods

Research aimed at recognizing, understanding, and explaining the target audience. The purpose of these methods is to better understand the subject of research and to look at the events from the perspective of the target audience, rather than obtaining numerical results.

Qualitative methods are defined as research in which qualitative data collection methods such as observation, interview and document analysis are used and a qualitative process is followed for the purpose of revealing perceptions and events in a natural environment in a realistic and holistic way.

The most commonly used methods in practice are: expert opinion method, delphi method, survey method, market research method and sales force combination method.

4.2.1.1. Expert Opinion

It is an estimation produced by staff members who are knowledgeable about the issue based on their experience, knowledge, and intuition. This expert might come from the board of directors, finance, purchasing, sales, or production. This approach can be employed if quick choices are needed [27]. By doing so, data handling time can be reduced. This approach is better since it is less complicated, easier to use, and cheaper. However, it is more likely to result in incorrect results than other approaches since it is totally focused on human perceptions.

4.2.1.2. Survey Method

The researcher can easily reach large audiences in the researches carried out with the survey method. This method is frequently used to measure the reaction of the consumers to the relevant product before producing a new product, especially in the companies producing in the similar sector. However, since the source of the survey method, like the previous method is not based on scientific data but on personal knowledge and experience, there is a high probability of directing the researcher to erroneous results.

4.2.1.3. Delphi Method

The Delphi technique involves three basic sorts of participants: decision-makers, employees, and participants. The real forecasting is typically done by a team of 5 to 10 experts who make decisions. A number of surveys and survey findings are prepared, distributed, gathered, and summarized by the staff in order to help decision makers. Participants in surveys are frequently a collection of individuals from various locations whose choices are assessed. In order to make a prediction, this group offers suggestions to the decision-makers [28].

4.2.1.4. Market Research Method

This method relies on getting information from the customer or potential customers about the future purchase plan. This information is obtained through methods such as interviews, surveys, and telephone conversations. This method can be helpful not only when conducting forecasting research, but also in improving product design and planning for new products. However, results from this method may suffer from over-optimistic estimates from customer input.

4.2.1.5. Sales Force Combination

The seller predicts what the sales will be in their sales territory. They consider the previous sales trend when estimating. The estimates of each are then combined to obtain the total estimate. This method is similar to the method of obtaining the opinion of expert personnel. It should not be applied here if the sales personnel are new to the company and have little knowledge of the sector.

4.2.2. Quantitative Methods

This method is to find the demand quantities for future periods by using the demand values for the previous periods by statistical methods. This method is based on the assumption that the relationship between the factors affecting the incidence of demand and the number of demands will have the same trend for future times. Companies can use one or more of these methods depending on their operations.
Quantitative prediction methods are divided into two parts such as time series analysis and causal methods.

4.2.2.1. Time Series

Traditional econometric models' variables are driven by a theoretical basis. In other words, economic theory is used to explain how variables cause one another. In contrast to traditional models, the series that may be referred to as time series, however, can be

evaluated without the necessity for a theoretical basis. Time series are also referred to as models without theory as a result.

In other terms, time series is a collection of data that has been organized according to the time parameter. For the formation of the time series, it is sufficient that the periods occur at the same intervals. Due to this, time series features will also be present in daily stock returns, monthly inflation rates, and temperature readings that are monitored hourly. Due to the interdependence of the values in the data set, time series are predictable, meaning that future values may be predicted. Due to its significance in the financial sector, it has been employed with growing attention in the assessment of the future values of investment instruments.

Purpose of Time Series Analysis

Time series analysis enables the statistical analysis of the data observed in regular periods over time and the reliable prediction of the values that may be obtained in the future period. Studies are carried out in many different fields with time series. Although studies in the field of statistics and econometrics are intense the application area is quite wide.

The purpose of time series analysis is to replace the subjective and intuitive classical approaches with rationality during the decision-making process. Time series are analyzed for different purposes. These purposes can be listed as foresight, identification, explanation and control. The most important one among them is the analysis with the aim of predicting the future. While predicting the future with the time series, it is assumed that the past movements of the series will be in the same trend in the future. For prediction, it is necessary to observe the clear movements of the series. For this, in the first place, the properties of the series should be revealed, its components should be determined and the series should be free from the effects of these components [29].

Due to the uncertainties in the business and economic world, it is very important to make forecasting analyzes for the future with economic time series in terms of

planning and decision making. It provides the opportunity to determine the positive and negative developments of the series examined in the past, except for the future prediction to investigate the reasons and to prevent the wrong applications. After determining the operation of the event forming the time series, it is possible to see whether the system is progressing in the planned direction in the light of the past information and to ensure that the system is controlled.

Components of Time Series

A time series' data is influenced by a variety of factors. These components. Wave effects cause various variations in the observation values of the series, which grow and decrease with time due to a variety of social, economic, psychological, etc. [30].

The elements caused by these fluctuations are called time series components.
consists of four components. These

- Trend
- Seasonal components
- Cyclic fluctuations
- Irregular components

Trend

It is defined as a time series' long-term increase or decrease. In a time series, the trend component can have either a curved or linear shape. Depending on whether the increase or drop is continuous, the trend may alternatively be referred to as a stochastic trend or deterministic trend.

The trend is observed in almost all time series. Trend is the change in the average of the variable studied over time, and accordingly, it emerges with downward or upward movements. The direction of the movement and the rate of change are mainly included in the analysis. Trend refers to the increases or decreases of the values in the series over the long term. In short, the trend is the long-term trend of the 11 series. An average of 15 to 18 months is needed for the trend to emerge.

Seasonal Ingredients

Repetitive movements in the time series, provided that the periods are not longer than one year, are called seasonal fluctuations. Increasing sales of scarves and caps in the winter months, and the increase in the amount of ice cream consumed in the summer months are examples of seasonal fluctuations.

Cyclical Fluctuations

For some reason, repetitive movements in the medium term in time series are called cyclical fluctuations. Usually, these fluctuations take two years or longer between them. An example of a cyclical movement in the economy is 5 declines from the welfare level, followed by a pause and a recovery phase. Cyclical movements and seasonal movements can be confused with each other because they are cyclical. If the changes in the time series do not have a certain period, this movement should be called cyclical movement.

4.2.2.2. Causal Methods

It is the examination of the causes that influence the level of demand and the modeling of the interaction structure between these causes and demand. Among the causal methods, the most frequently used methods are given below:

4.2.2.2.1. Regression Analysis

Regression analysis is a method used in the prediction model and examines the relationship between the dependent and independent variable, which indicates the desired result. There are different names according to the number of variables. If there is only one variable in the regression model, it is called Univariate Regression, and if there is more than one variable affecting the dependent variable in the model, it is called Multivariate Regression Model. Since the dependent variable is only a function of the independent variable in the linear regression model, there is a direct relationship between them.

$$Y = \alpha + \beta Xi + \varepsilon \quad \textbf{(4.1)}$$

It is a model that includes dependent and independent variables. Y estimation value Xi, which is one of the values in the example equation above, is called the independent variable, and the α values indicate the points that the equation intersects on the X axis. The ε value indicates the error values of the related equation.

4.2.2.2.2. Correlation Method

A method for testing a link between two components, or a component connection of two or more components, and determining the strength of this connection, if any, is correlation analysis. Knowing the direction in which the dependent component y will change when the independent component x changes is the goal of correlation analysis. The correlation analysis determines whether there is a linear link, and if so, the correlation coefficient determines how strong the connection is. The correlation coefficient, represented by the letter "R," ranges from -1 to 1.

$$\boldsymbol{R} = \frac{\sum_{i=1}^{n} y_i x_i - n\overline{yx}}{\sqrt{(\sum_{i=1}^{n} x_i^2 - n\,\overline{x^2})\,(\sum_{i=1}^{n} y_i^2 - n\,\overline{y^2})}} \quad \textbf{(4.2)}$$

$-1 \leq R \leq 1$ If $R = \pm 1$, there is a good linear relationship between x and y.
Usually, |R| The closer the value is to 1, the greater the linear connection. If R = 0, y and x can be independent. The values of the correlation coefficient are as follows:

0.90-1.00 : Very strong correlation
0.70-0.90: Strong correlation
0.40-0.70: Normal correlation
0.20-0.40: Weak correlation
0.00-0.20: Very weak correlation

4.2.2.2.3. Artificial Neural Networks

Ease of access to information sources and lower costs of research have made developments in science and technology more rapid and widespread in a shorter time. The developments that took place showed their effects on the economy and the financial sector in a short time. Artificial intelligence, which has been mentioned a lot in recent years, has begun testing in estimating the parameters used by decision makers in future planning. In the nineteenth century, research on the human brain lay based on the point where artificial intelligence technologies have reached today. These biological studies can be summarized in two items. The first is parallel action logic experienced in the billions of neurons in the human brain, and the second is adaptability and organizational success. These two fundamental logics played an important role in the simulation of an artificial neuron of a biological neuron and in the creation of artificial neural networks [31].

Structure of Artificial Neural Networks

Artificial neural networks consist of artificial nerve cells inspired by biological nerve cells. Extensions such as dendrites and axons provide information exchange in biological nerve cells, which are the basic elements of the human brain. Artificial nerve cells have similar properties and perform their functions in artificial neural networks.

Artificial Nerve Cell

Artificial nerve cells, which can be called imitation of nature examined under 5 headings. The inputs from the sections to be examined correspond to the transmitted information, the weights to the synapses, the coupling function to the dendrites, the activation function to the cell body, and the outputs to the axons [32].

1.Inputs

Information coming into the artificial neuron from outside or from any other artificial neuron in the neural network is called input. Although the information from the cells is called the input of the respective cell, it is the result of the previous elements.

2.Weights

The parameters that indicate the importance of the message reaching the cell and its effect on the cell. The weighting parameter does not provide information about the size or smallness of the effect. On the contrary, the size or smallness of the modulus gives information about the strength of the connection between the input and the cell. The weights that produce the optimal output are found by experiment during the training phase.

3.Summation Function

This function, which provides the calculation of the net input to the cell, is usually a weighted sum. Most of the time, the use of aggregation for the aggregation process has caused the aggregation function to be expressed as the "addition function". A simple sum function can be expressed as:

$$\boldsymbol{NET\ Input = \sum J = 1\ a_{ij}\ g_i} \qquad \textbf{(4.3)}$$

4. Activation Function

The activation function is the function that processes the net input to the cell and determines the output that the cell will produce in response to this input. It is also known as the function that limits the output of the artificial neuron. In some sources, the threshold value is also called the transfer or compression function. As in the addition function, different formulas are used in the activation function. The reason why linear functions are preferred is that the input and output are directly proportional

in linear functions. This is one of the main reasons why the first artificial neural network experiments failed.

As with the addition function, each process element can have the same addition function or different aggregation functions. This situation is completely dependent on the foresight of the designer and the results of his experiments. As a result, there is no formula that indicates the proper function.

Correct selection of the activation function is a factor that affects the performance of the network. If the selected activation function is not linear, the slope parameter needs to be determined. The slope parameter is an important factor that plays a role in reaching the appropriate result sufficiently.

Today, the sigmoid function is mostly used as an activation function. While the sigmoid function is preferred in ANNs used in solving nonlinear problems, it also provides an advantage for algorithms that need derivative information.

This function is a continuous and differentiable function. It is frequently used in ANN because it is not linear. This function generates a value between zero and one for each of the input values. The representation of the function is as in Equation **(4.4)** :

$$\boldsymbol{F(NET) = \frac{1}{1+e^{-NET}}} \qquad \textbf{(4.4)}$$

Here, NET represents the net input value to the process element. This value is determined using the addition function.

Table 4. 1. Activation functions

Function Type	Function
linear function	$F(NET) = NET$
Hyperbolic tangent function	$F(NET) = \frac{e^{NET} + e^{-NET}}{e^{NET} - e^{-NET}}$
Sigmoid function	$F(NET) = \frac{1}{1 + e^{-NET}}$
Threshold	$F(NET) = \begin{cases} 1, & NET > t \\ 0, & NET \leq t \end{cases}$

The general characteristics of the transfer functions in the table above are as follows:

1. The inputs in the linear activation function are the output of the cell as it is.

2. In the hyperbolic tangent activation function, the cell output is found by passing the incoming NET input value through the tangent function. It produces an output value in the [-1,1] range.

3. In the sigmoid activation function, it is the most used activation function in ANN. It is an ever-increasing function that provides a balance between linear and non-linear behavior. It is widely used in back propagation algorithm because it can be differentiated. The output value of the cell is in the range [0,1].

4. The threshold (step) activation function is mostly used in single-layer networks. The output value of the cell is in the range [0,1].

The data from the summation function is passed to the activation function to generate the output of the summation cell. A non-linear function is usually chosen as the activation function. The "non-linearity" characteristic of artificial neural networks comes from the nonlinearity of the activation functions. When choosing the activation

function, care should be taken to choose a function whose derivative can be easily calculated.

5. Outputs

It is the output value determined by the activation function. This value is either sent as an input to another artificial neuron or sent to the external environment. An ANN cell has multiple inputs but only one output.

Artificial Neural Networks

Biological neural networks can create a lot of connections thanks to their three-dimensional structure. On the contrary, in artificial neural networks, which imitate nature, layers are used to create connections. They usually consist of three parts: the input layer, the Intermediate layer, and the output layer. Intermediate layer can be more than one [33].A multi-layer neural network is shown in (Figure 4.2).

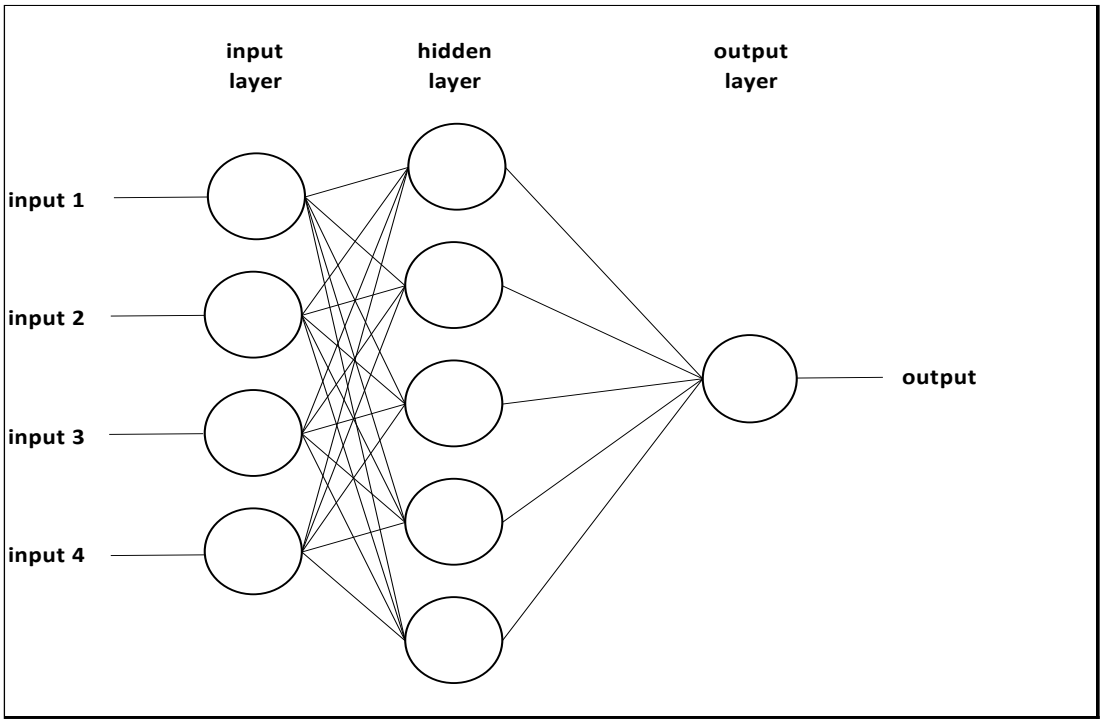

Figure 4. 2. Multi-layer neural network

1. **Input Layer**

Artificial nerve cells in the input layer transmit the data they receive from the outside to the Intermediate layer without any processing. The number of cells in the layer is equal to the input variables and each cell transfers the data it receives to all cells in the next layer.

2. **Intermediate Layer**

It is the layer where the data transferred from the input layer is processed and transmitted to the output layer. In an artificial neural network, there can be more than one, and each intermediate layer can have more than one artificial neuron. This layer is also called the "hidden layer" since there is no information about the weights and bonds of the artificial nerve cells in the intermediate layer. Input and target data given to the network are matched and recorded in this layer. This method is called intuitive estimation that is intelligence.

Depending on the data sets to be analyzed, it is stated that the ideal number of intermediate layers and the number of cells in the intermediate layer are found by experiment. Having fewer neurons than required in the middle layer reduces the sensitivity of the output, and too many causes memorization problems [34].

3.Output Layer

It is the layer where the output obtained from the information transmitted by the middleware is exported. The number of cells in the layer is as much as the dependent variable that needs to be obtained.

Artificial Neural Network Models

Artificial neural networks are divided into two as feed-forward and feedback networks.

1. Feed Forward Networks

The feedforward architecture was developed in the 1970s. Several researchers independently contributed to the development of this architecture. The main contribution was made by Rumelhart, Hinton and Williams (1986). After its emergence, it gained great popularity due to its effectiveness and very usefulness and is still known as the most widely used type of mesh. It is used in many different application areas and its biggest feature is that it can be effective in problems with nonlinear structures.

In feedforward neural networks, signals only go in one direction, from the input layer to the output layer. The outputs of the cells arranged in layers are given as inputs to the following layer by their weights. The input layer, on the other hand, directs the information given to it from the outside to the cells in the hidden layer without making any changes. The information set in question is transmitted to the output of the network after being processed in the middle layer and the output layer. Due to these structures, it can be said that feedforward networks have a nonlinear stationary structure [35].

2. Feedback Networks

A feedback process exists in feedback networks. The signal in these networks travels from the input layer to the output layer. However, neurons in a layer can receive signals from themselves and other neurons in the layer, or neurons in other layers at the same time [31].

The most widely used artificial neural network type in time series is the three-layer feed-forward model. For univariate time series, the inputs of the network are the past or lagged variables, and the output is the predictive values.

General Features of Artificial Neural Networks

Common features of artificial neural networks are as follows:

1. Learning: ANNs can learn using data, thanks to training or initial experience. it can provide solutions to very complex problems that cannot be solved by traditional methods.

2. Nonlinear structure: One of the most important features of artificial neural networks is that they give better results in nonlinear structures that exist in real life. Even if all the parameters on which the events depend are known, the relationships among the parameters may not be linear. It is difficult to work with traditional linear methods when faced with nonlinear structures. Therefore, ANN is one of the most important methods used in solving complex nonlinear problems.

3. Distributed Memory: In artificial neural networks, the information is spread over the network and the values of the connections of the cells with each other show the information of the network. Artificial neural networks can store information in distributed memory.

4. Real-time processing: Since artificial neural networks can operate in parallel, they can work in real-time. Thanks to its distributed parallel structures, it has the ability to process much more data per unit time.

5. Creating its own relationship: Artificial neural networks create their own relationships according to the data and do not contain equations.

6. Generalization: Artificial neural networks can generalize about unseen situations by learning on known examples because of their learning capabilities. Most traditional methods cannot work with incomplete and noisy information. However, ANN can perform much better in such cases.

7. Parallelism: Since parallel processors are used in neural networks, the effect of a slow unit does not slow down the entire system. This leads to the conclusion that artificial neural networks are faster and more reliable. Traditional methods

usually consist of serial operations. In these methods, while a serial operation is taking place, the slowness of any unit slows down the entire system.

8. Unlimited number of variables and parameters: Artificial neural networks can work with an unlimited number of variables and parameters. With ANN, an infinite number of variables can be trained so that each of them can use only when needed.

9. Information storage: In artificial neural networks, the values of the network connections are measured and these values are stored in the connections.

10. Adaptation: ANN definition or parameters can be trained repeatedly to provide suitable solutions to the changing problem or system. This feature has made ANN widely used in areas such as target recognition, adaptive pattern recognition, classification, signal processing, automatic control and system identification and modelling.

Prediction Accuracy

The ability of the model to produce outcomes that are similar to those shown in the historical data is known as predictive accuracy. There are many ways to evaluate a prediction model's performance, including:

• Errors occurring in the mean absolute percent error are displayed as a percentage. In this way, the error criteria can be compared. It is indicated by the expression MAPE (Mean Absolute Percentage Error). It is formulated as follows;

$$\boldsymbol{MAPE} = \frac{(\mathbf{100}) \sum_{i}^{n}=\mathbf{1} |\boldsymbol{PE_i}|}{\boldsymbol{n}} \quad \textbf{(4.5)}$$

Mean Squared Error (MSE) The mean square error is a measure that identifies without being informed whether the magnitude of the error is positive or negative [36]. It is indicated by the expression MSE (Mean Square Error) defined in Equation 4.6 as;

$$\boldsymbol{MSE = \frac{SSE}{n} = \frac{\sum_{i=1}^{n} e_i^2}{n}}$$

PART 5

SALES FORECAST WITH ARTIFICIAL NEURAL NETWORKS

In this section, the statistical values of the data are interpreted. In the previous section, the demand forecasting methods that mentioned theoretically will be examined on the causal demand forecast, which is suitable for our data. Artificial neural networks and regression models were used.

5.1. DATA DESCRIPTION

In this research, sales forecast is made for the c segment vehicles in Turkey. independent variables benefited from Turkish Statistical Institute and investing resources. c segment sales amount which is the dependent variable benefited from odd reports. Statistical values of the data are given in the table below.

Table 5. 1. Statistical value of 120-month data between 2012-2021

Statistical value of the data (2012-2021)								
	C segment	**Consumer price index**	**Producer price index**	**Dollar rate**	**Interest rate**	**Consumer confidence index**	**GDP (million)**	**monthly sales rate**
Minimum	3969	201.98	201.20	1.75	4.85	68.5	275.5	0.0249
Maximum	36096	686.95	1022.25	13.47	25.50	97.4	562.3	0.1851
Mean	14767.90	333.73	350.00	4.22	12.48	87.506	406.7	0.0830
Std. Deviation	6895.784	113.35	162.53	2.46	5.14	6.1820	64.9	0.0314

Sales of all c segment vehicles in the country for 120 months (2012-2021) are obtained. The table below shows the monthly sales amounts.

Table 5. 2. Monthly sales of c segment vehicles (2012-2021)

Month/year	C segment	Month/year	C segment
2012/1	4.280	2017/1	8.809
2012/2	5.360	2017/2	10.248
2012/3	8.347	2017/3	17.408
2012/4	8.062	2017/4	17.515
2012/5	8.260	2017/5	19.871
2012/6	8.560	2017/6	20.326
2012/7	7.510	2017/7	18.206
2012/8	6.855	2017/8	15.591
2012/9	9.309	2017/9	17.601
2012/10	12.608	2017/10	22.633
2012/11	3.969	2017/11	26.177
2012/12	14.478	2017/12	34.154
2013/1	4.836	2018/1	11.031
2013/2	7.574	2018/2	13.600
2013/3	9.243	2018/3	20.499
2013/4	10.929	2018/4	19.037
2013/5	11.718	2018/5	20.848
2013/6	10.601	2018/6	14.260
2013/7	10.584	2018/7	14.612
2013/8	9.765	2018/8	10.783
2013/9	11.261	2018/9	7.336
2013/10	10.095	2018/10	7.079
2013/11	13.097	2018/11	16.900
2013/12	19.898	2018/12	20.748
2014/1	5.020	2019/1	3.977

Month/year	C segment	Month/year	C segment
2014/2	5.637	2019/2	7.240
2014/3	9.321	2019/3	15.198
2014/4	10.577	2019/4	10.384
2014/5	10.607	2019/5	12.424
2014/6	11.113	2019/6	16.452
2014/7	11.198	2019/7	6.920
2014/8	8.255	2019/8	8.734
2014/9	11.757	2019/9	14.569
2014/10	11.821	2019/10	17.010
2014/11	13.416	2019/11	19.886
2014/12	24.692	2019/12	26.734
2015/1	5.944	2020/1	9.828
2015/2	9.052	2020/2	16.715
2015/3	15.529	2020/3	15.882
2015/4	17.229	2020/4	8.524
2015/5	15.453	2020/5	8.885
2015/6	17.176	2020/6	24.174
2015/7	16.987	2020/7	28.788
2015/8	11.321	2020/8	20.341
2015/9	13.861	2020/9	30.762
2015/10	12.381	2020/10	30.579
2015/11	15.157	2020/11	25.716
2015/12	29.132	2020/12	36.096
2016/1	5.725	2021/1	16.382
2016/2	11.404	2021/2	15.936
2016/3	17.157	2021/3	28.915
2016/4	17.860	2021/4	15.928
2016/5	20.609	2021/5	15.334

Month/year	C segment	Month/year	C segment
2016/6	20.954	2021/6	22.059
2016/7	11.754	2021/7	11.628
2016/8	14.145	2021/8	15.246
2016/9	12.903	2021/9	15.817
2016/10	17.081	2021/10	13.218
2016/11	28.977	2021/11	14.657
2016/12	31.428	2021/12	16.106

Vehicle sales have increased over the past five years, as indicated in the graph. Sales fall off in 2021 as a result of the pandemic's worldwide effects on the economy in 2019–2020.

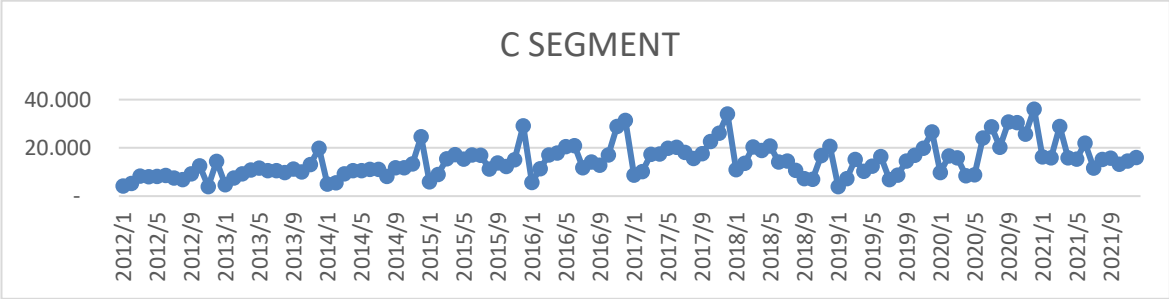

Figure 5. 1. Monthly sales of c segment vehicles in Turkey (2012-2021)

When the average of the 10-year sales amount is taken, it is seen that the data are divided into three groups. 4% to 6% of sales are in January and February, and they are the months with the lowest sales. November and December are the months with the highest sales, with 10%-12%. the average sales rate of the other months is between 7% and 9%.

Table 5. 3. Average sales of a 10 years c segment vehicle

Month	**2012-2021 average sales (thousand)**	**Percentage**
JAN	7.58	4%
FEB	10.28	6%
MAR	15.75	9%
APR	13.60	8%
MAY	14.40	8%
JUN	16.57	9%
JUL	13.82	8%
AUG	12.10	7%
SEP	14.52	8%
OCT	15.45	9%
NOV	17.80	10%
DEC	25.35	14%

In the study, it is aimed to predict the sales of the C segment and to determine the factors affecting it. The factors affecting domestic sales demand are as follows:

1. **Consumer Price Index**: It is the index that measures the changes in the prices of goods and services purchased by the consumer. The change in the prices of goods and services on certain days of each month of the year is measured by these weights to reach the consumer inflation figure for that month. The figure below shows the change in CPI between 2012-2021.

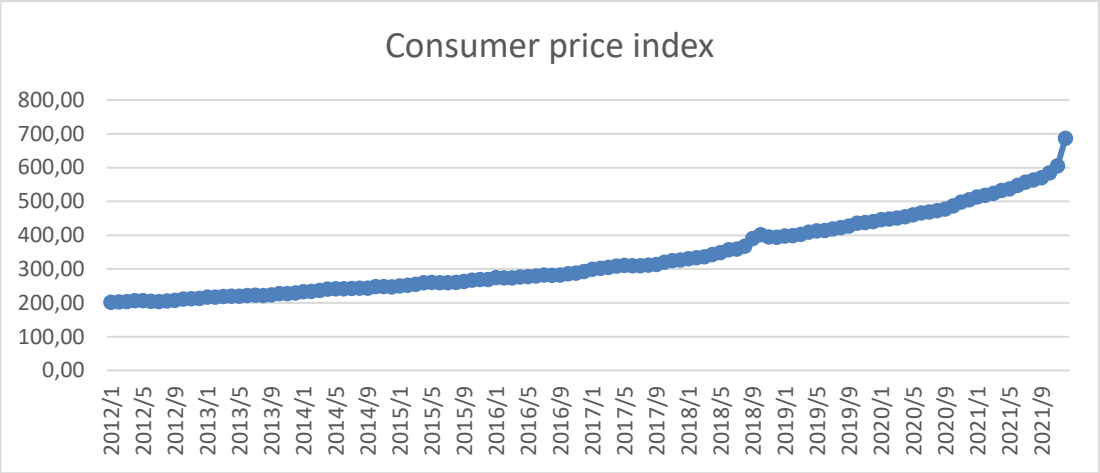

Figure 5. 2. Change of Consumer Price Index (2012- 2021)

2. **Consumer Confidence Index:** It is an indicator that aims to measure consumers' personal financial situation and current situation evaluations regarding the general economy, their expectations for the future, and their spending and saving trends in the near future. The figure below shows the change in consumer confidence index between 2012-2021.

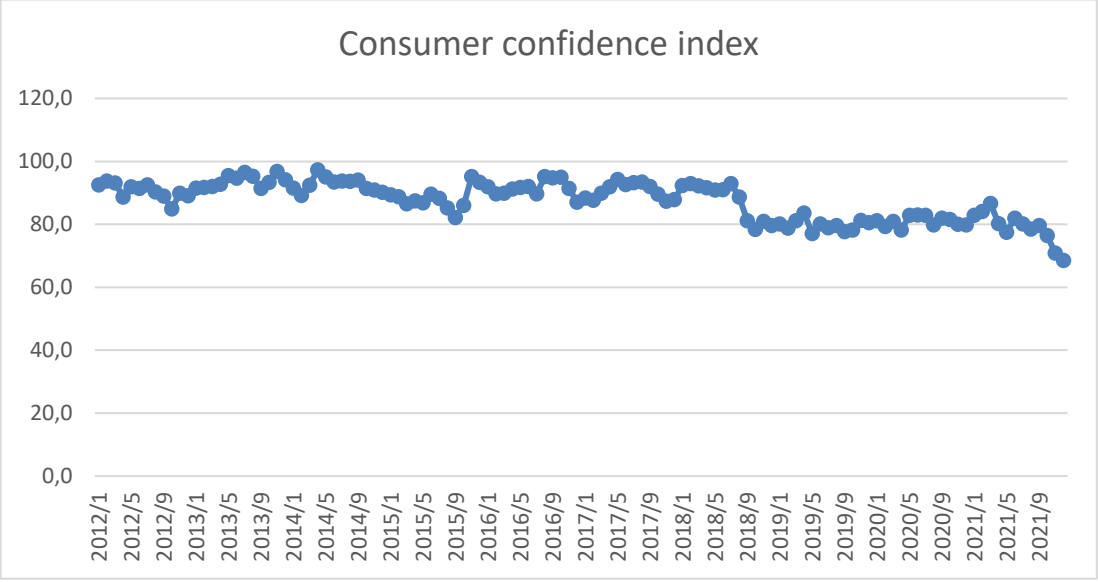

Figure 5. 3. Consumer Confidence Index Change (2012- 2021)

3. **Producer Price Index:** It is the price index that measures the price changes of the products produced in the national economy in a certain reference period and that are subject to sales to the country, by comparing the producer prices over time. It is used to determine the monthly and annual inflation figures. The following (Figure 5.4) shows the change in the producer price index between 2012-2021.

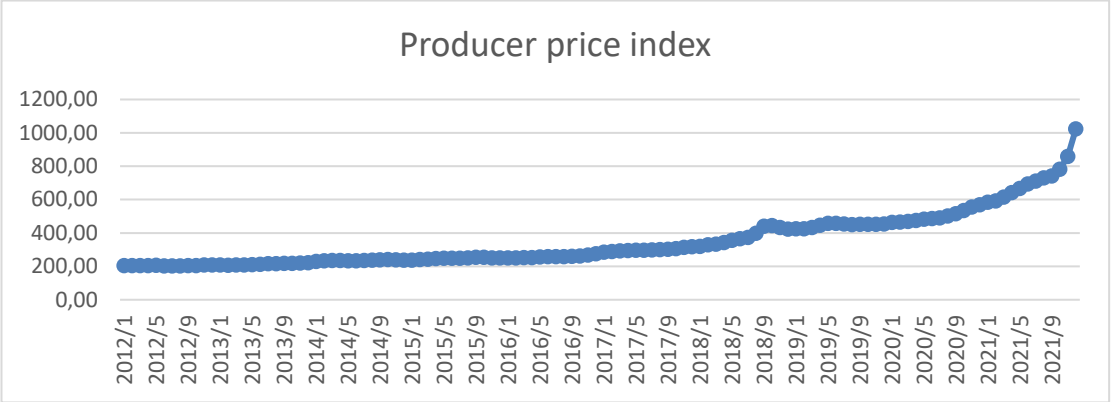

Figure 5. 4. Change of producer price index (2012- 2021)

4. **Dollar Rate:** Indicates the value of one American dollar in Turkish lira. Since many vehicles are bought from abroad in dollars. The figure below shows the monthly change in the dollar rate between 2012 and 2021.

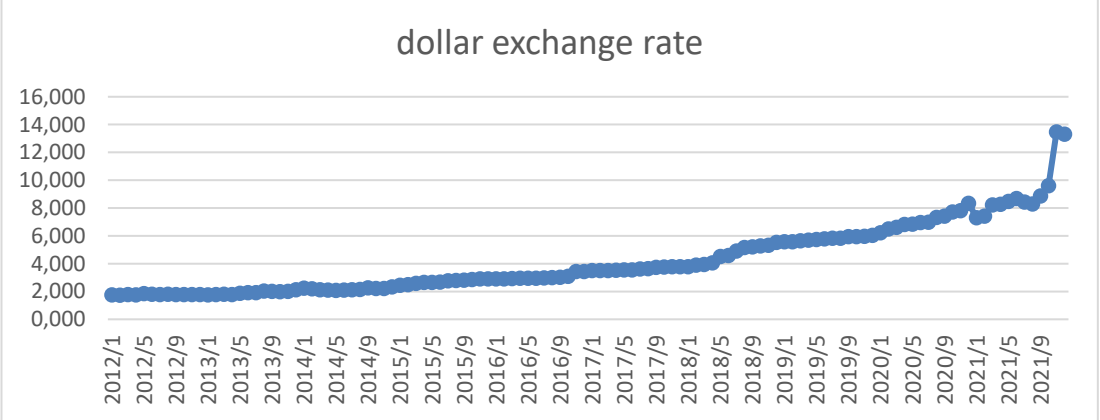

Figure 5. 5. Dollar exchange rate (2012- 2021)

5. **Interest Rate:** It is the percentage of earnings obtained from the assets loaned to individuals by banks and similar places.

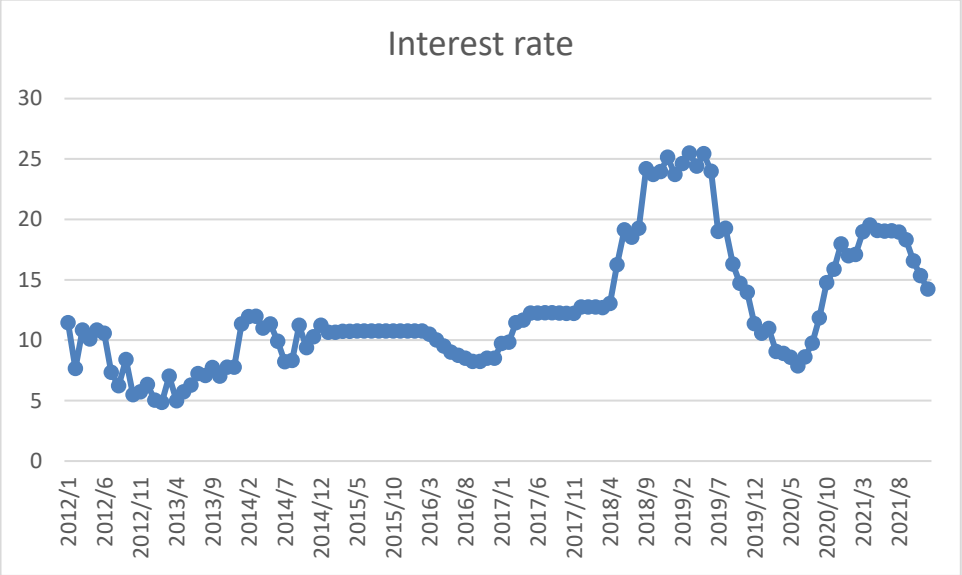

Figure 5. 6.Interest rate change (2012- 2021)

6. **GDP**: It expresses the monetary value of all final goods and services produced within the borders of a country in a certain time.

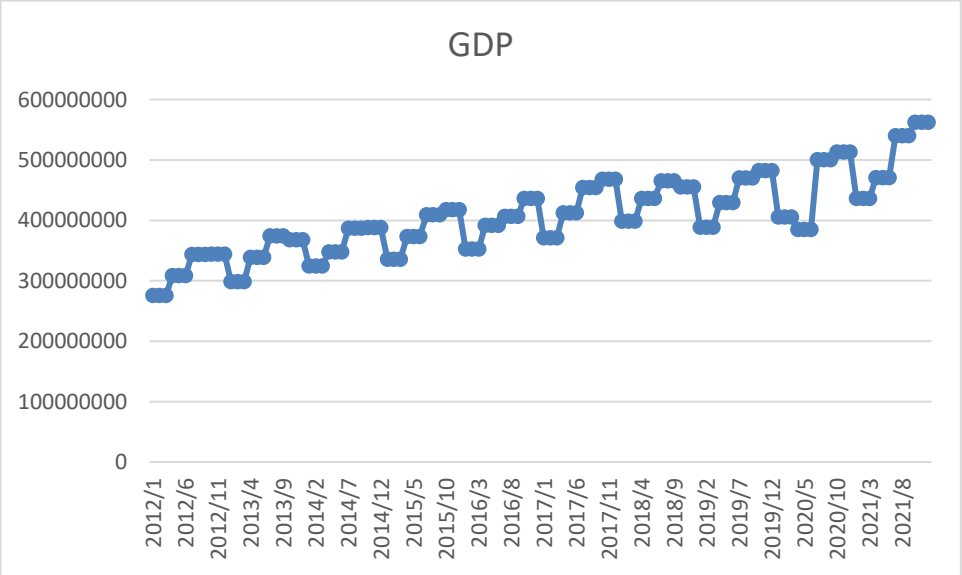

Figure 5. 7. GDP rate change (2012- 2021)

7. **Monthly Sales Rate**: monthly sales rate from total annual sales.

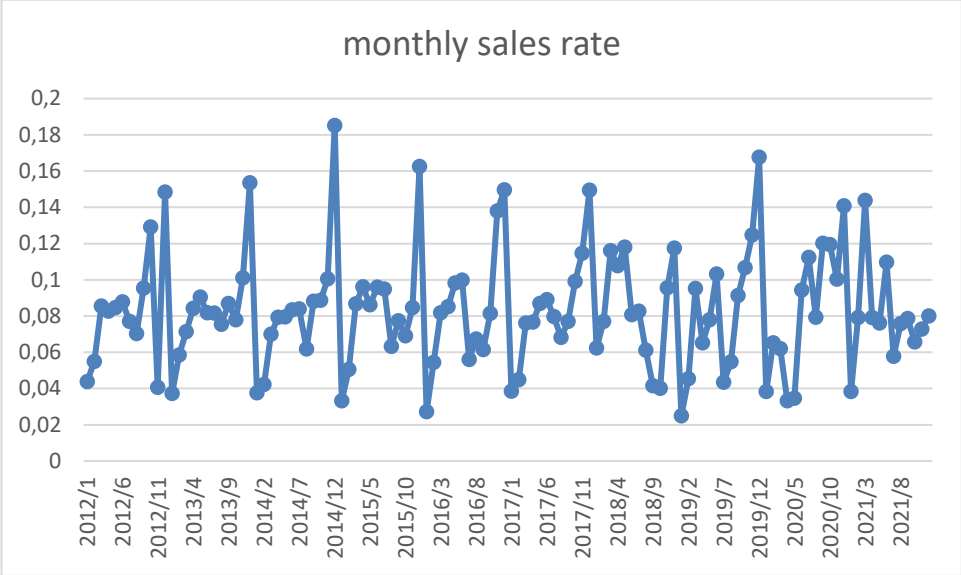

Figure 5. 8.monthly sales rate change (2012- 2021)

The network structure of the model is as follows: Consumer price index, producer price index, interest rate, consumer confidence index, GDP, monthly sales rate and dollar rate as input variable. the sales amount of the c segment as output. The following (Figure 5. 9) shows the network structure.

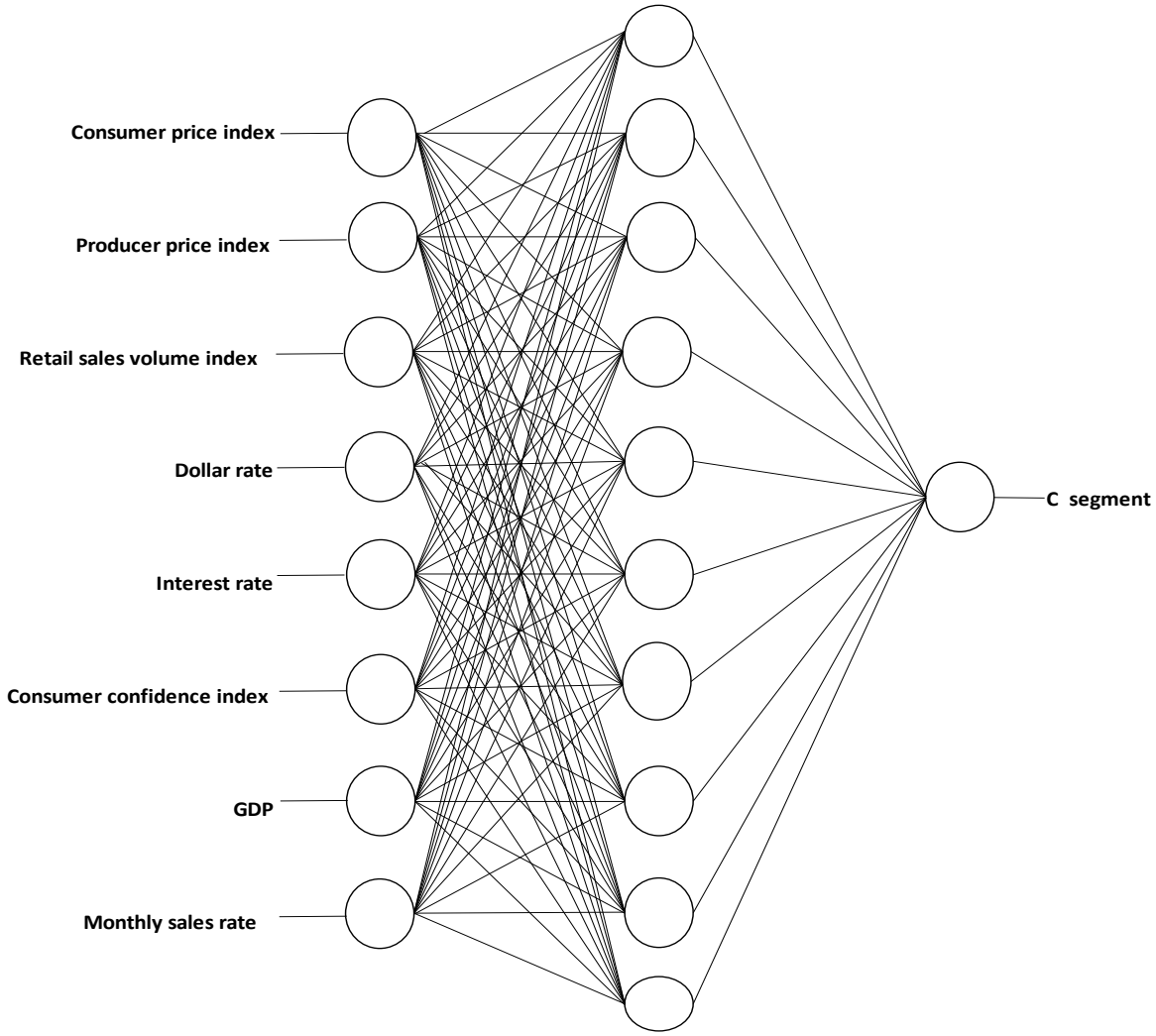

Figure 5. 10. Network structure of the model

5.2. FORECAST MODELS

Prediction models and their performance are constructed in this part, regression and artificial neural networks are discussed. The purpose of this research is to estimate the demand for the c segment in Turkey. Data from c-segment vehicle sales from 2012 to 2021 were utilized in the modeling for this purpose.

The 120 data points are split between the first 108 and the last 12 months in accordance with the estimating methodology created. The initial dataset 108 month is utilized for model construction in all of the approaches examined. The remaining 12 months of data are used to test the model.

5.2.1. Regression Model

Using Minitab, a multiple regression model was created for sales data. The line was fitted to the first 108 data points, and the remaining 12 data points were utilized to determine this model's MAPE.

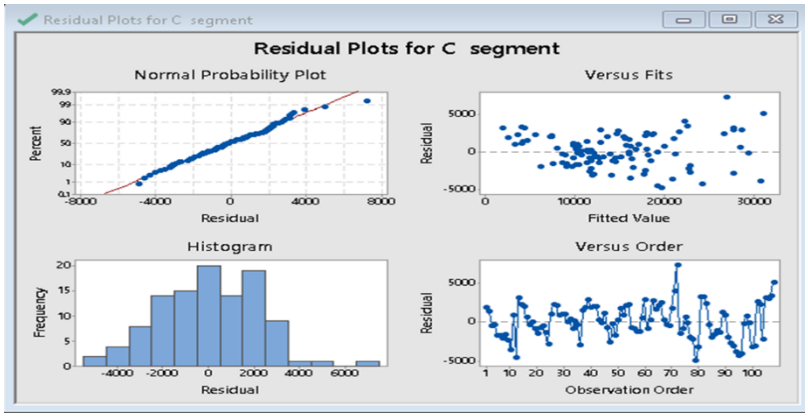

Figure 5. 11. Multiple Regression Model Residual plot

The residual vs. fit-value plots, the residual histogram, and the normal probability plot for the multiple regression model are all displayed in (Figure 5.10). The following predictions from the regression model for the previous 12 months are displayed in conjunction with the actual data and this model's estimated MAPE in (Table 5.4).

Table 5. 4. Multiple regression model forecasts and MAPE

Real	Forecast
16382	4970
15936	9235
28915	22504
15928	10819
15334	5605
22059	9025
11628	2162
15246	4995
15817	1014
13218	8581
14657	20176
16106	8059
MAPE:0.544517	

5.2.2. Artificial Neural Network Model

MATLAB R2016b (64 bit) package program was used for ANN design c segment vehicle. Before the data was solved with the MATLAB program, all data were normalized in Microsoft Excel and arranged to be between [0.1 - 0.9]. While normalizing, the following formula was applied for each data below.

$$X'' = \frac{X - X_{m/n}}{X_{max} - X_{min}} \quad \textbf{(5.1)}$$

X'': Normalization Value

X: Actual Value in Relevant Column and Row

$X_{m/n}$: Smallest Value Found in Related Column

X_{max}: Largest Value Found in Related Column

After the data has been normalized, it is attempted to be estimated using the nntool application in the MATLAB program. The parameters that comprise the ANN architecture are established. The number of cells in the input layer has been set to seven. In order to generate a c segment vehicle sales estimate, the number of cells in the output layer is set to 1. The number of hidden layers has not been extensively discussed in the literature; most researchers utilized only one hidden layer[25], although it was agreed that using more than one for difficult issues would be beneficial. As a result, it was determined that one hidden layer would appropriate.

The tangential hyperbolic Logsig (Sigmoid) in the hidden layer and the linear activation functions in the output layer do not change. The Learngdm algorithm was chosen as the learning algorithm because of its speed and popularity. The system changes the learning and momentum coefficients, as well as the starting values of the interconnection weights, using the learning algorithm. In the output layer, the linear transfer function is utilized. The constructed network is seen in (Figure 5.11).

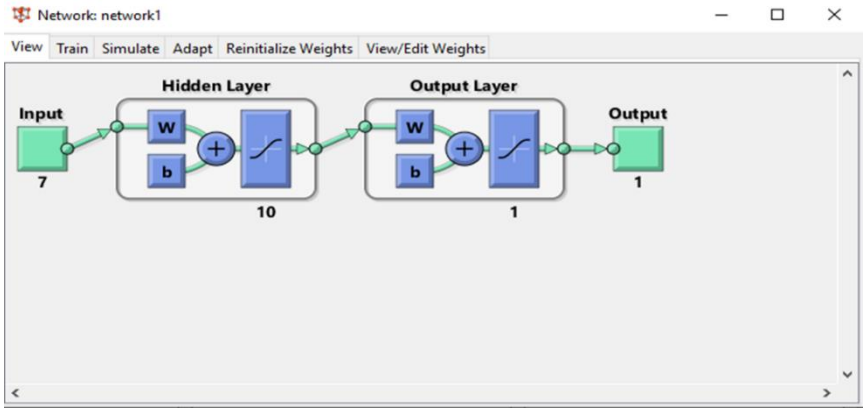

Figure 5. 12. Neural network illustration

The MAPE and Correlation coefficient (R) values of the models developed in the application are shown in the table below (Table 5.5). Aside from these model trials, numerous different models have been tested. For testing, models with the highest Correlation coefficient (R) value and the lowest MAPE value are evaluated.

Table 5. 5. MAPE and regression values of the models

Network Type: Feed Forward Backprop **Training Function: Trainingdx** **Learning Function: Learngdm** **Activation Function: Logsig (Sigmoid)** **Number of Hidden Layers: 1**		
Number of neurons	**R**	**MAPE test**
10	**0,95446**	**0.101267205**
15	0,89957	0,250636336
20	0,90321	0,235662236
25	0,94383	0,122055463

A neural network model is developed, and the success of training, validation, and testing is measured. Correlation coefficient (R) values quantify the relationship between outcomes and goals. R value 1 indicates a strong relationship, whereas R value 0 indicates a random relationship. The data set's general correlation coefficient was obtained to be 0.95446. The values between outputs and targets are quite near to one, as seen in (Figure 5.12).

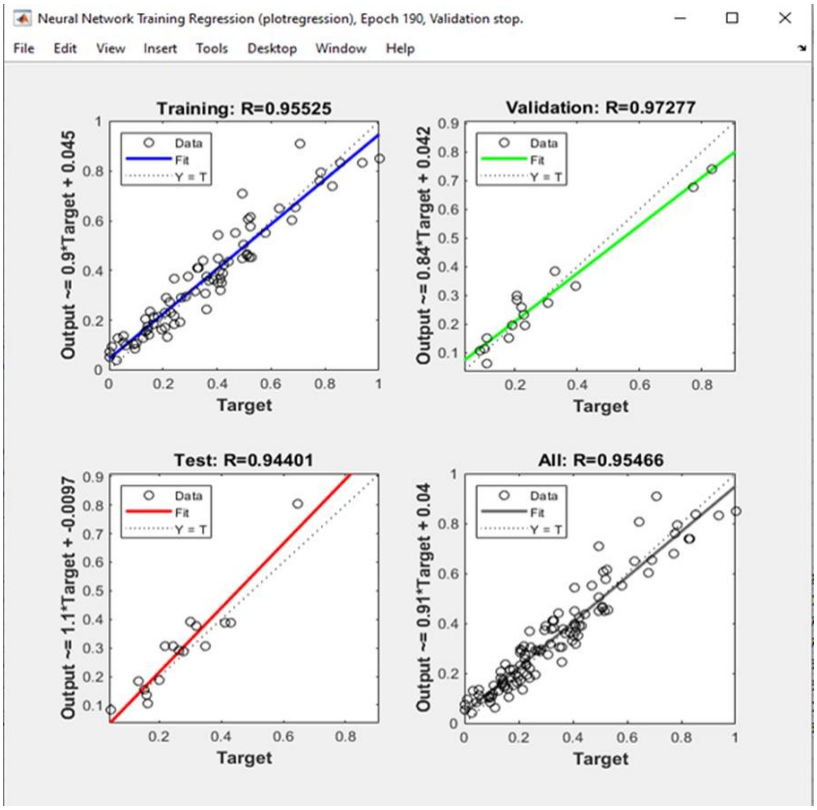

Figure 5. 13. Regression plots

The performance of the Neural net fitting is measured by MSE (Mean Square Error). MSE refers to the mean square difference between outputs and targets. The MSE values and performance graph at each step of the model created in (figure 5.13) are given.

As seen in the (figure 5.13), the lowest error rate for the validity set of the network was reached in the 183rd iteration and the training was terminated. Although the graph shows the change cycle of the training set and test set error rates, the training stop is made by considering the values of the validity set.

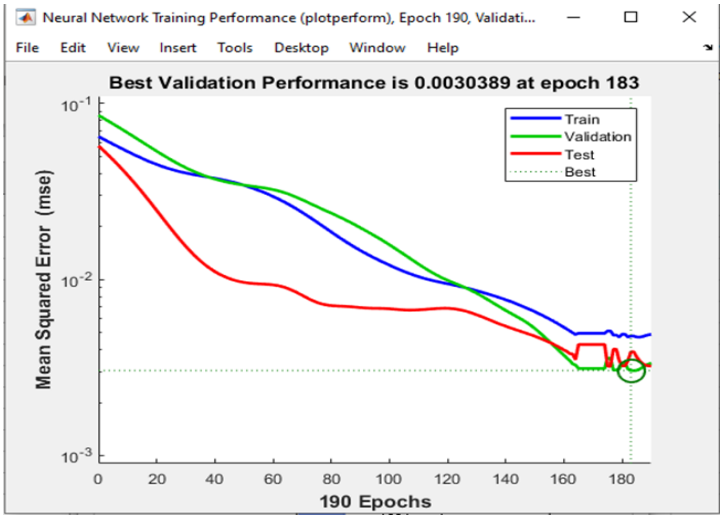

Figure 5. 14. Validation performance

Testing the results

After training the model, it is desired that the prediction results will be produced by selecting the 12-month input data created for the test. After coming to the "Simulate" tab on the training screen and selecting the data we have reserved for the test instead of "Inputs" this time, the name of the test results that are desired to be displayed as test output on the "Workspace" screen should be changed from the Output section. After clicking "Simulate Network", results will be shown for the test data.

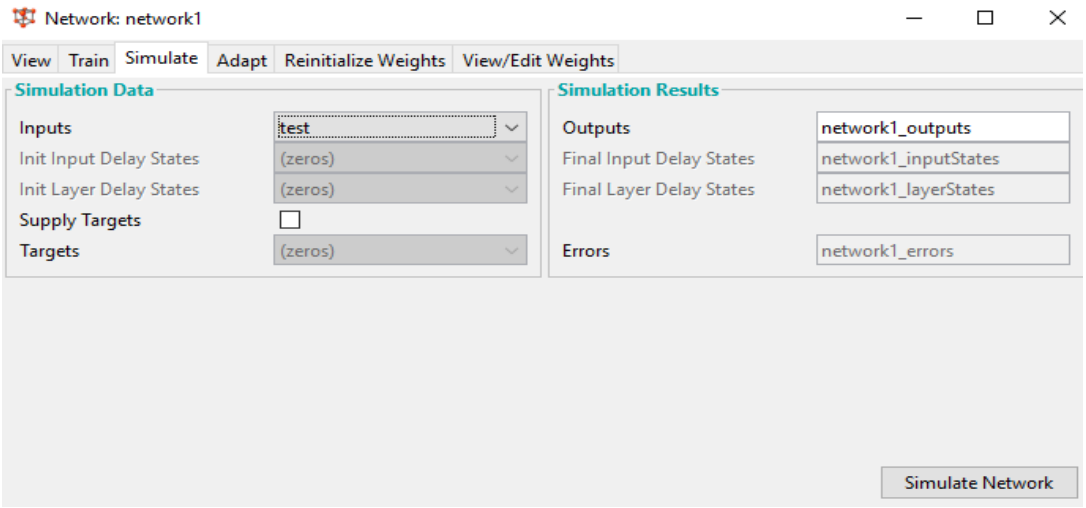

Figure 5. 15. Forecast values for 12-month test data with ANN

After estimating the normalized values for the 12-month data of 2021, the values are converted to actual forecast values and compared with the actual value is given in the table below.

Table 5. 6. ANN model Forecasts and MAPE

Real	Forecast
16382	13034
15936	17623
28915	29068
15928	18528
15334	16898
22059	25788
11628	10776
15246	13839
15817	16345
13218	14370
14657	16695
16106	15459
MAPE: 0.101267205	

PART 6

CONCLUSION

In this part, the findings from the suggested models are compared using the performance measure MAPE. Simple linear and neural network models were looked at in this study.

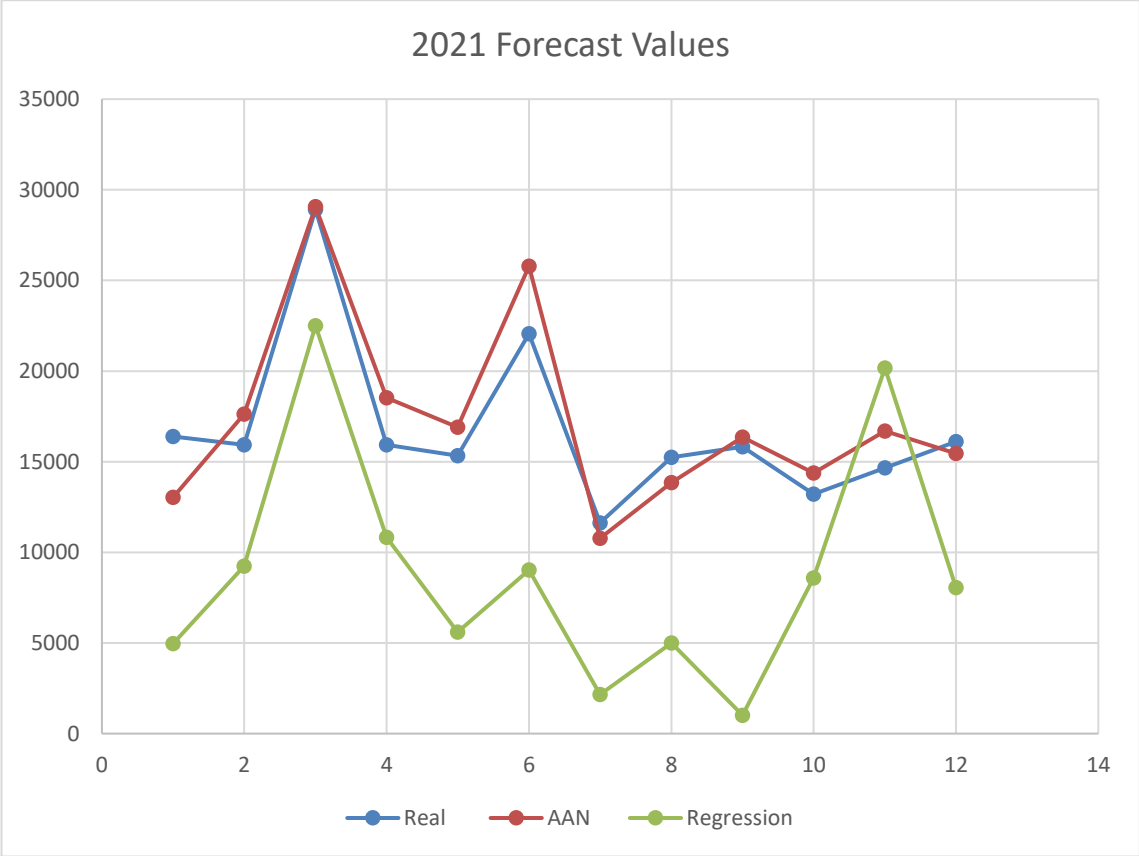

Figure 6. 1. Comparison between actual and predicted values

(Table 6.1) shows the MAPEs associated with the models and ranks them by MAPE value.

Table 6. 1. Comparison of Forecast and MAPE values

Month/year	Real	AAN	Regression
01/2021	16382	13034	4970
02/2021	15936	17623	9235
03/2021	28915	29068	22504
04/2021	15928	18528	10819
05/2021	15334	16898	5605
06/2021	22059	25788	9025
07/2021	11628	10776	2162
08/2021	15246	13839	4995
09/2021	15817	16345	1014
10/2021	13218	14370	8581
11/2021	14657	16695	20176
12/2021	16106	15459	8059
MAPE		0.101267205	0.544517
R		0.95466	0.8824

ANN provided the lowest MAPE value among the examined models. In addition, a forward-looking estimation will be made of the method with the lowest MAPE value, and its outputs will be taken to achieve the purpose of the research.

This study can be used as a helpful resource for automotive sector managers in their future decision making and planning studies. The parameters used in the study have a high accuracy rate. By using these parameters in future research, sales forecasts can be made in different areas of the automotive sector. Alternatively, researchers can estimate automobile sales using different numbers and types of variables.

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RESUME

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