İSTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

ELECTRICITY CONSUMPTION FORECASTING WITH ARTIFICAL NEURAL NETWORK FOR FAST-MOVING CONSUMER GOODS SECTOR

M.Sc. THESIS

Gülfem YEŞİL

Department of Management Engineering

Management Engineering Programme

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Thesis Advisor: Assoc. Prof. Hür Bersam BOLAT

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

HIZLI TÜKETİM SEKTÖRÜ İÇİN YAPAY SİNİR AĞLARI İLE ELEKTRİK TÜKETİM TALEP TAHMİNİ

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Gülfem YEŞİL
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Gülfem YEŞİL, a M.Sc. student of İTU Graduate School of Science Engineering and Technology student ID 507161018, successfully defended the thesis entitled "ELECTRICITY CONSUMPTION FORECASTING WITH ARTIFICAL NEURAL NETWORK FOR FAST-MOVING CONSUMER GOODS SECTOR", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 3 May 2019
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To my family,

FOREWORD

I would like to thank my advisor Assoc. Prof. Hür Bersam BOLAT for giving me valuable advice and support always when needed. I would like to thank my dear professor Prof. Dr. Semra BİRGÜN for her labor on me. I would also like to thank Gökhan ALDEMİR for giving me valuable advice, support and motivation during my thesis study. Lastly I would like to thank to my mother Linda Belgin PAYASLI who make me come to these days and to my brother Ali Cem YEŞİL who support me always and to my friends especially Gökşen GÜLTEKİN and Tunahan GÖRMÜŞ who motivate me during this study.

I hope the thesis “ELECTRICITY CONSUMPTION FORECASTING WITH ARTIFICAL NEURAL NETWORK FOR FAST-MOVING CONSUMER GOODS SECTOR” which I wrote with high attention and effort will be beneficial for everyone who reads.

May 2019

Gülfem YEŞİL
(Management Engineer)

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ABBREVIATIONS

ANN	**:** Artificial Neural Network
D1	**:** Department 1
D2	**:** Department 2
D3	**:** Department 3
D4	**:** Department 4
D5	**:** Department 5
FMCG	**:** Fast-Moving Consumer Goods
LSTM	**:** Long Short Term Memory
RMSE	**:** Root Mean Squared Error
SCM	**:** Supply Chain Management
TZY	**:** Tedarik Zinciri Yönetimi
YSA	**:** Yapay Sinir Ağları
YTD	**:** Year to date

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ELECTRICITY CONSUMPTION FORECASTING WITH ARTIFICAL NEURAL NETWORK FOR FAST-MOVING CONSUMER GOODS SECTOR

SUMMARY

Under the ever-evolving technology and increasing competition conditions, companies should carry out their production and marketing activities effectively in order to maintain their assets. Companies should be able to distinguish their products or services from their competitors in a highly competitive environment. When the sectoral evaluated based fast moving consumer goods sector in Turkey it is one of the most intense competition in the sector so that firms in the start of the company's growth and profitability optimization are of great importance to the production stage.

Today, the most important requirements of developed and developing countries are energies. The level of development of countries is directly proportional to the energy they produce and consume. Although there are many different methods of energy production and consumption, all countries need cheap, abundant and clean energy sources. Increasing energy consumption under the condition of developing countries is an indicator of growth, so energy consumption is one of the most important indicators of economic development and social welfare. In Turkey, where the demand for electricity rises gradually as demand and supply come early bus bar is observed.

Production, production planning, demand planning is an operational level for supply chain management (SCM). One of the most important factors in production demand planning is energy estimation modeling. It is important to predict the total consumption of energy consumption and to make a production plan according to it and therefore to make all the functions in the supply chain cost and optimization plans. Fast-moving products include products that are regularly purchased or consumed quickly after being purchased. There is a continuous and rapid production in the fast-moving consumer goods sector. Planning of production according to demand and optimization studies are of great importance. In cold chain operations, there are points which are very important and critical to complete process, that means from production to the deliver

to customer. Temperature and air condition is the some of the most important conditions for cold chain.

In this thesis, energy consumption is estimated in production in the fast moving consumer goods sector. Artificial Neural Networks (ANN) method is used for estimation. Estimates are made for the following periods based on the last three years' electricity energy consumption and the other inputs from the compan

HIZLI TÜKETİM SEKTÖRÜ İÇİN YAPAY SİNİR AĞLARI İLE ELEKTRİK TÜKETİM TALEP TAHMİNİ

ÖZET

Tedarik Zinciri Yönetimi (TZY), özellikle hızlı tüketim malları sektörü olmak üzere tüm şirketler için en önemli unsurlardan biridir. Tedarik Zinciri Yönetimi, arz ve talebi yönetmeyi, hammadde ve parçaları tedarik etmeyi, üretim, depolama ve stok takibi, sipariş yönetimi, talep yönetimi, dağıtım ve teslimatı içeren birçok farklı aşamadan oluşmaktadır. Üretim TZY için operasyonel düzeyde bir faaliyettir.

Teknolojide artan süreklilik ve şirketler arasında giderek artan rekabet koşullarında şirketler varlığını devam ettirmek için üretim, satış ve pazarlama faaliyetlerini optimum şekilde yürütmelidirler. Bunun için yoğun rekabet ortamında ürün veya hizmetlerini rakiplerinden farklılaştırıp öne çıkabilmelidirler. Hızlı tüketim sektörü ise sektörel bazlı değerlendirildiğinde hızlı tüketim dünyada rekabetin en yoğun olduğu sektörlerden biridir dolayısıyla firmaların optimizasyona üretim aşamasından başlaması firmanın büyümesi ve karlılığında büyük bir önem taşımaktadır.

Günümüzde her aaşamada gelişme seviyesindeki ülkelerin en önemli gereksinimlerin başında enerji gelmektedir. Ülkelerin refah seviyeleri, üretilen ve tüketilen enerji miktarları ile doğru orantılıdır. Enerji üretimi ve tüketimi için birçok farklı seçenek bulunsa da, tüm ülkelerin uygun fiyatlı, yeteri miktarda ve temiz enerji kaynaklarına ihtiyaçları vardır. Her seviyedeki gelişmişlik düzeyinde önemli olduğu gibi özellikle gelişmekte olan ülkeler arasında enerji tüketiminin artması, gelişmenin göstergesidir, dolayısıyla enerji tüketimi, ekonomik büyüme ve sosyal refah açısından önemli göstergelerden biridir. Türkiye'de elektrik enerjisine olan talebin git gide yükseldiği ve taleple arzın başa baş geldiği gözlenmektedir.

Üretim, üretim planlama, talep planlama tedarik zinciri yönetimi için operasyonel seviyede bir aktivitedir. Üretim talep planlamada en önemli unsurlardan biri enerji tahmin modellemesinin yapılmasıdır. Enerji tüketimi tahmini toplam tüketimi ön görüp ona göre üretim planı yapılmasını ve dolayısıyla sonrasında tedarik zincirindeki tüm fonksiyonların maliyet ve optimisazyon planlarının yapılmasında önemi bir role

sahiptir. Hızlı tüketim ürünleri düzenli olarak satın alınan ya da alındıktan sonra tüketimi hızlı ürünleri içerir. Hızlı tüketim ürünleri sektöründe durmayan, sürekli ve hızlı bir üretim vardır. Üretimin talebe göre planlanması ve optimizasyon çalışmaları büyük önem taşır.

Bu çalışma dört ana bölümden oluşmaktadır. Bunlar giriş, literatür taraması, YSA modeli ve analizi, sonuçlar ve gelecek çalışmalar için öneriler kısımlarıdır. Çalışmanın giriş bölümünde enerji talep tahminlerinin günümüzde artan üretim ve tüketim hızları ile orantılı olarak her geçen gün daha önem kazandığı belirtilmiştir. Ayrıca, Soğuk Tedarik Zinciri ve Hızlı Tüketim Sektörü hakkında nicel bilgiler ile çalışmanın amacı ve kapsamı eklenmiştir. Çalışmanın ikinci bölümünde Yapay Sinir Ağları kısaca tanımlanmış, elemanları ve farklı model yapıları analiz edilmiştir. Ayrıca literatürde yer alan örnek çalışmalar özetlenmiştir.

Çalışmanın üçüncü bölümünde hızlı tüketim ve soğuk zincir sektöründe yer alan firmalarda gelecek enerji talebi tahmin etmede Yapay Sinir Ağları kullanarak iyi bir tahmin sonucuna ulaşılabilir mi sorusuna cevap aranmıştır. Elektrik enerji tüketiminin departmanlar bazında gelecek dönem tahmini yapılırken model çeşitli girdi kombinasyonlarıyla çalıştırılmıştır. Burada kullanılan girdilerin bazıları literatürde yer almakla birlikte bazıları ise sektörde çalışan uzman görüşleri alınarak modele eklenip çıkartılmıştır. Burada kullanılan girdiler sıcaklık, yoğuşma noktası, nem, rüzgar hızı, hacim ve çalışan sayısıdır. Ancak ilk olarak soğuk zincirde elektrik tüketimini etkileyen ilk dört girdi ile model kurulmuştur. Çünkü literatürde soğuk zincir sektöründe talep tahmini çalışmaları incelendiğinde bu dört girdi birçok çalışmada yer almaktadır. Daha sonra diğer iki girdinin (üretim hacmi ve çalışan sayısı) tüm kombinasyonları modele eklenip çıkarılarak sonuçlar kıyaslanmıştır. Bu sayede çalışmanın önemli bir katkısı olarak Yapısal Eşitlik Modeli'ndeki gibi analoji kurularak hangi girdi veya girdilerin elektrik enerjisi tüketimini etkilediği hangilerinin de önerildiği halde etkilemediği ortaya konmuştur. Kurulan modeller sektörde yer alan bir firmanın son üç yıllık verileri kullanılarak vaka analizi ile de örneklendirilmiştir.Burada girdilerin yüzde 70'ı öğrenme, yüzde 30'ı ise test etme verisi olarak kullanılmıştır. Çalışmanın ikinci katkısı olarak da uygulama kısmında bazı girdilerin eksik veya kayıp veri içermesi ile nasıl baş edildiği de gösterilerek Yapay Sinir Ağları uygulamalarında kayıp ve eksik veriler ile nasıl baş edildiği gösterilmiştir. Çalışmada karşılaşılan kayıp ve eksik verileri tamamlamada Lineer

Regresyon Yöntemi kullanılmıştır. Modellerin çalıştırılmasıyla ulaşılan ortalama kareli sapma değerleri oldukça düşük çıkmış ve modelin sektörde yer alan diğer firmalarda kullanılabileceğini göstermektedir.Ayrıca modeller ile gelecek dönem tahminleri yapılmıştır. Son olarak gelecek çalışmalar için tavsiyelerde bulunulmuştur.

1. INTRODUCTION

Supply Chain Management is one of the most crucial thing for companies espacially for consumption sector. Supply Chain Management has a lot of different stages that includes managing demand forecasting, supply management for raw materials and parts , production process, warehousing and inventory and order management, claims management, delivery and distribution. Manufacturing is an operational level activity for SCM.(Koçtaş, 2006)

In today's increasingly competitive conditions, companies have to differentiate themselves from their competitors in order to maintain their competitive position and maintain their assets. In order to adapt to the conditions of competition, companies sometimes lose their productivity economically, which in turn removes companies from being sustainable (Yeşilyurt, 2016). In order for companies to continue their lives, they should not only resist competition, but they must also profit. Profit maximization starts with efficiency in production and the performance of firms in the fast moving consumption sector is directly dependent on their success in production performances (Grosskopf, Seldon, Tremblay, 2004).

Fast-moving consumer products are cheap products that are easily consumed or sold in a short period of time and whose usage is limited by day, month or year. The fast-moving consumer goods sector includes everything that is consumed quickly on the retailer shelves. Tiwari (2012) states that, while the main features of fast-moving consumer goods are low-priced and low loyalty, which are frequently purchased. In terms of firm, it has high sales volume, low profit margin, wide distribution network and fast stock turnover rate. In the sector, a complex supply chain is used which aims to ensure the availability of fast-moving consumer products every day. This chain requires close cooperation between retailers, manufacturers, suppliers, logistics service providers and businesses of various sizes. According to Dümrek (2018), fast consuming; the sum of activities related to the supply of the product or service directly to the absolute buyer.

For manufacturing companies facing ambigious, dynamic and competitive business environments, productivity is one of the most critical point. Productivity effect some features as sales growth and profitability improvement, which provide to a solid financial base for future growth of their business. (Lee, Kao, Yang, 2014)

If Turkey FMCG sector's data is analyzed, the largest share of the industry is food products with 75.5% in 2019. It is followed by personal care pruducts with 15,6 % and home cleaning products with 8,4 %. Fast moving products category shares for 2019 in Turkey are given as an example in the Figure 1 below.

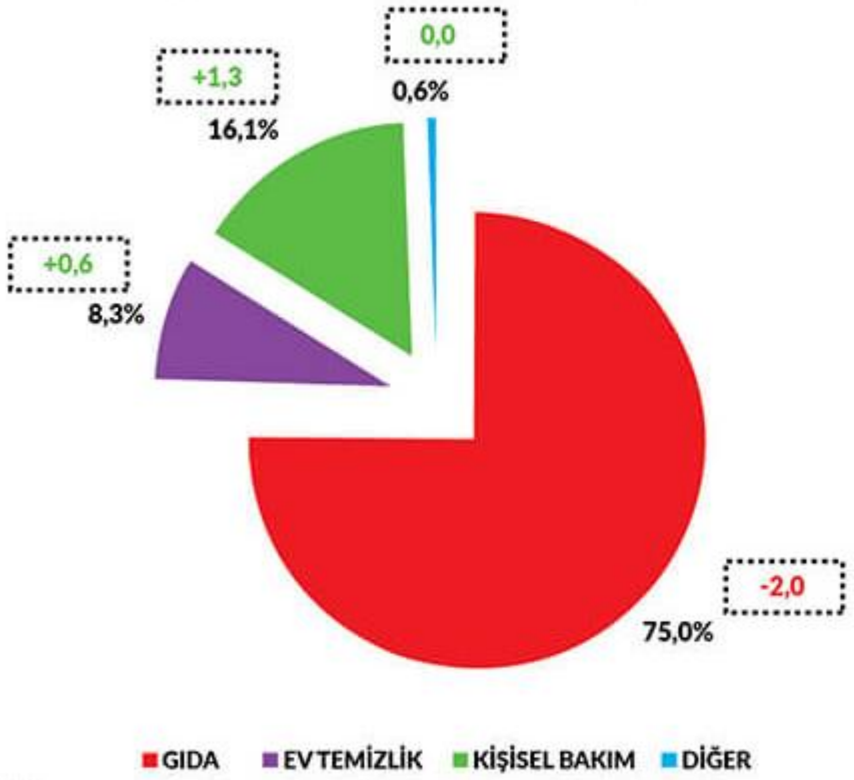

Figure 1.1: Fast moving products category shares for Feb'19 YTD in Turkey

Since the FMCG sector is a perpetual changing, dynamic and renovated sector, competition is in a high level. Due to intense competition conditions, companies should always be active and open to development. Moreover, since most of the fast-moving consumer products are basic needs, the sector is less affected by economic crises than other sectors. Nielsen, which compares overall market dynamics of the FMCG sector across Europe in 2017. According to the "Growth Reporter" reports of 2017 first quarter measured 21 among European countries (European countries are: Austria, Belgium , Czech Rep., Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, United Kingdom.), Turkey has the highest sales growth in nominal terms compared to the previous year by 11.6% has been the country of residence as shown in the Figure 2 (Growth Reporter, 2017).

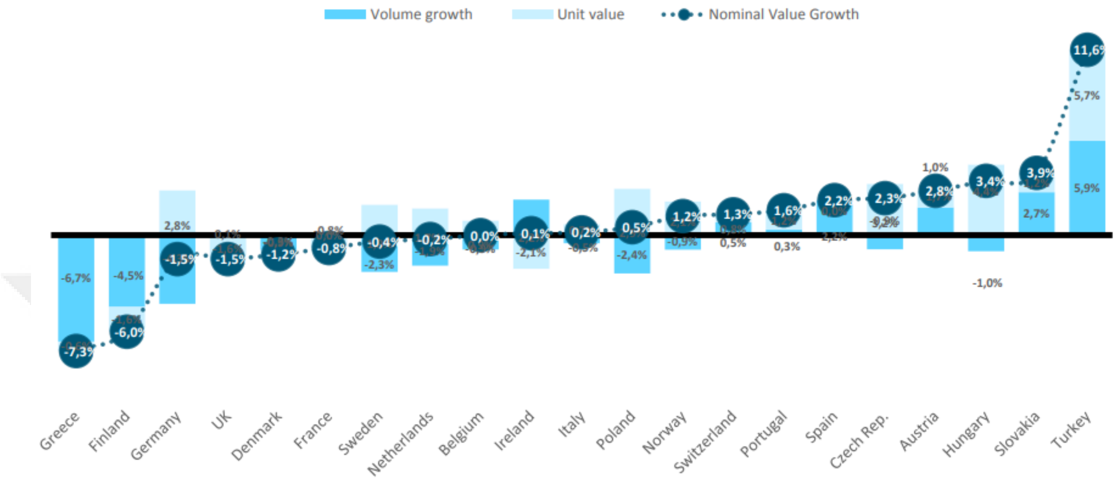

Figure 1.2: Q1 2017 Growth Rates Per Country Versus Q1 2016

Despite government support to transport fresh food in Turkey it is mostly experienced problems on the actual shipping and packaging without the necessary temperature controls. In this case the one hand, Turkey has been seen as negative cold air and cold supply chain logistics warehousing makes it one of the countries with the highest growth rates. (Utikad, 2019) According to Emanet (2018), cold chain according to engineering perspective is the need for monitoring of temperature, the placement and maintenance of equipment, the rapid transport of products, the electrical plug in refrigerated containers and cold storage keeping the doors closed.

There are different methods for energy production and consumption, that is the reason why all countries search and need to find low costly, ample and clean energy sources (Arı, 2007). In SCM, especially in production energy is one of the most important key of productivity. That is the reason why companies search the ways of optimisation of energy consumption (May, Barletta, Stahl, Taisch, 2015).

In this study, the estimation study based on artificial neural networks (ANN), which is one of the quantitative estimation methods, will be carried out. ANN is highly successful in estimating studies and can be used to model non-linear problems and prevent other estimation methods. For this reason, estimation studies are carried out and performed with ANN in the energy field.

With the development of technology, many techniques and methods, especially artificial intelligence, which is a method based on experimentation and calculation, have started to find many applications. In this study, artificial neural networks are used to define energy usage estimation. Thus, with the Artificial Neural Networks approach, it is aimed to define a function for the estimation of energy consumption in the production area of a company in the rapid consumption sector. In this study, considering the 2016-2018 periods, annual demand estimation is made by artificial neural network methods and electricity demand prediction studies are carried out for future years. Estimation of electrical energy consumption is of great importance for the company because it is one of the basic energy types used.

This study consists of four main parts. These are introduction, literature review, ANN model and its analysis, results and recommendations for future studies. In the introduction of the study, it is stated that energy demand forecasts are gaining importance with the increasing production and consumption rates. In addition, quantitative information about the Cold Supply Chain and the FMCG sector is added to the purpose and scope of the study. In the second part of the study, the Artificial Neural Networks are defined briefly, the elements and different model structures are analyzed. In addition, example studies in the literature are summarized.

In the third part of the study, the answer to the question whether a good estimation result can be reached by using Artificial Neural Networks in estimating the future energy demand in the firms which are in the fast consumption and cold chain sector. The model is run with various input combinations while the electrical energy consumption was estimated by departments. Some of the inputs used in the literature and some of them are added to the model by taking expert opinions in the sector. The inputs used here are temperature, wind speed , wet bulb, dew point, volume and number of employees. However, the model was first established with the first four inputs affecting the electricity consumption in the cold chain. Because, in the literature, these four inputs are included in many studies when the demand estimation studies in the cold chain sector are examined. Then all the other inputs (volume of production and number of employees) are added to the model and the results are compared. In this way, as an important contribution of the study, analogy, such as in the Structural

Equation Modelling, was established and it is demonstrated that which inputs affect the electrical energy consumption and which do not affect what is suggested. The models are analyzed by case analysis using the data of the last three years of a firm in the sector. 70 percent of the inputs are used as learning and 30 percent are used as test data. As the second contribution of the study, it has been shown how some items are dealt with missing data and how to deal with the missing data in Artificial Neural Networks applications. Linear Regression Method is used to complete the missing data. The average squared deviation’root values achieved by the operation of the models are quite low and show that the model can be used in the other companies in the sector. Finally, recommendations are made for future studies.

2. LITERATURE REVIEW

2.1 Artificial Neural Network

Artificial Intelligence Technology is developing more and more every day. Fuzzy propositions logic, Genetic algorithms Expert systems, Artificial neural networks, and Intelligent agents are most preferred systems among Artificial Intelligence Technologies. Artificial Neural Network works as biological neural networks (Aladag, Basaran, Eğrioglu, Yolcu, Uslu, 2009).

Biological Neural network structure of the information between the recipient and response nerves between the forward and feedback as a result of the evaluation and the formation of reactions, ANN is similar to the logic of study (Tosun, 2007). The terminology of the neural system elements in the Artificial Neural Network model is like; neuron-processing element, dentrit-collection function, cell body-activation function, axon-output. A biological neural network structure is shown below Figure 2.1.

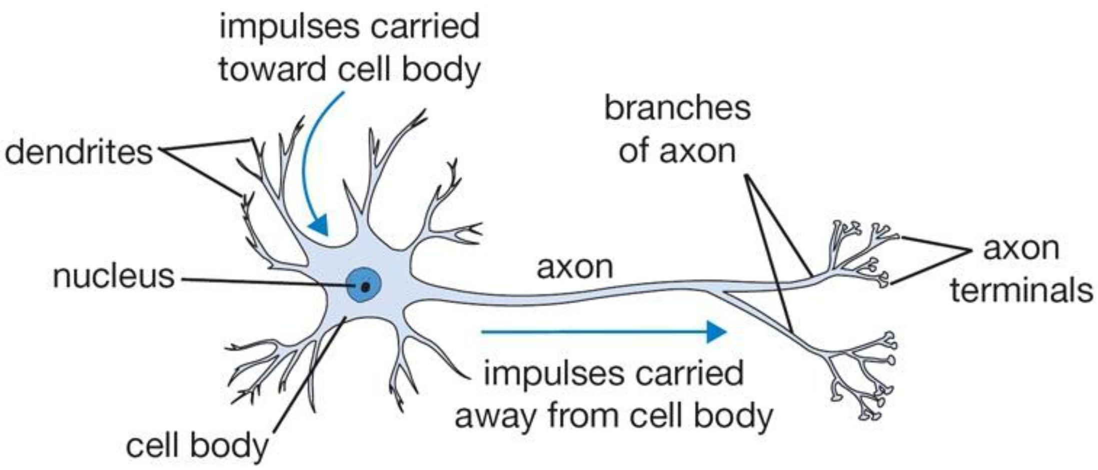

Figure 2.1 : Biological Representation of a Nerve Cell.

ANN working process in computer systems is like the human brain. The learning process is occured with the examples. These networks consist of interconnected process elements (artificial nerve cells). Each connection has a weight value. The knowledge of the network is hidden in the network. Artificial neural networks offer a different calculation method than the known calculation methods. It is possible to see successful applications in almost all areas of life by adapting to the environment, adaptive, incomplete information, making decisions under uncertainties and tolerating errors (Johnson, Blumstein, Fowler, Haselton, 2013). Despite, in the determination of the structure of the network to be formed, the lack of a specific standard in the selection of network parameters, the ability to show the problems with only numerical information, how to finish the training, and the network's behavior cannot be explained, the interest in these networks is increasing day by day. Artificial neural networks are the most powerful techniques especially in classification, pattern recognition, signal filtering, data compression and optimization studies. It is possible to see successful examples in our daily lives in many areas such as data mining, optical character transport, optimum route determination, fingerprint recognition, material analysis, work scheduling and quality control, medical analysis (Waibel, Hanazawa, Hinton, 1995).

Artificial neural networks have been developed by the biological nervous system. Synapses are important for biological nerve cells to communicate with each other through them. Axons send information of a nerve cell to other cells. Similarly, artificial nerve cells collect the information coming from outside by an addition function and pass it through the activation function to produce the output and send it to the other cells (process elements) over the connections of the network. There are different collection and activation functions. The values of the connections of the artificial neural networks are called the weight values. The process elements come together in parallel to each other in 3 layers to form a network. These are;

• Input layer
• Intermediate layers
• Output layer
(Öztemel, 2003).

The information is transmitted from the input layer to the network and processed in intermediate layer or layers and sent to the output layer. Information processing means that information coming to the network is converted to output using the weight values of the network. In order to produce the correct outputs for the inputs, the weights must have the correct values. The process of finding the true weights is called the training of the network. These values are initially assigned randomly. Then, weights are changed according to the learning rule of the network when each sample is shown to the network during training. Then another sample is presented to the network and weights are changed again. These operations are repeated until all the samples in the network training set produce true outputs. Once it is achieved, the samples in the test set are displayed on the network. If the network provides correct answers to the samples in the test set, the network is considered to be trained (Jain, Mao, Mohiuddin, 1996).

It is not known what each weight means after the weights of the network have been determined. Therefore, artificial neural networks are likened to “black box”. Although it is not known what the weights mean individually, it can be said that the network gives its decision on the inputs by using these weights and the intelligence of the network is stored in these weights (Jaeger, 2002).

Multilayer perceptron neural networks have been developed to solve the problem of learning non-linear relationships. Multi-layer perceptron networks are the most widely used model of ANN. (Güler, Übeyli, Güler, 2005). These networks, in particular, are capable of providing solutions to 95% of engineering problems. Multilayer perceptron networks emerged as a result of efforts to solve the XOR problem.

The training of the multilayer perceptron network is based on the generalized delta rule. The logic of the learning rule used is that minimization of the difference between the outputs produced by the network and the expected outputs. During the learning, the inputs are first presented to the network and the output from these inputs is generated. This process is called forward calculation. Then the output produced is compared with the expected output and the error is distributed backwards and the weights are changed. This is called backward calculation. Factors affecting the learning of multilayer networks are as follows;

- Selecting samples
- Presenting of inputs and outputs to the network
- Digital display of inputs and outputs
- Assigning initial values of weights
- Determination of learning and momentum coefficients

• Weighing times of weights
• Scaling of inputs and outputs
• Determination of stop criterion
• Enlarging and pruning networks
(Öztemel, 2003).

In order to measure the training performance of the multilayer networks, after the end of the training, the examples that the network did not see during the training are shown to the network and the decision of the network is examined. If the results produce the right answers to the examples, then performance is good and the event is learned.

In recurrent networks, the outputs of the process elements are sent not only forward, but also backward (Hecht-Nielsen, 1992). In general, it is possible to talk about fully recurrent and partially recurrent networks. Figure 3 shows a recurrent neural network with two inputs, one output and two hidden layers as an example.

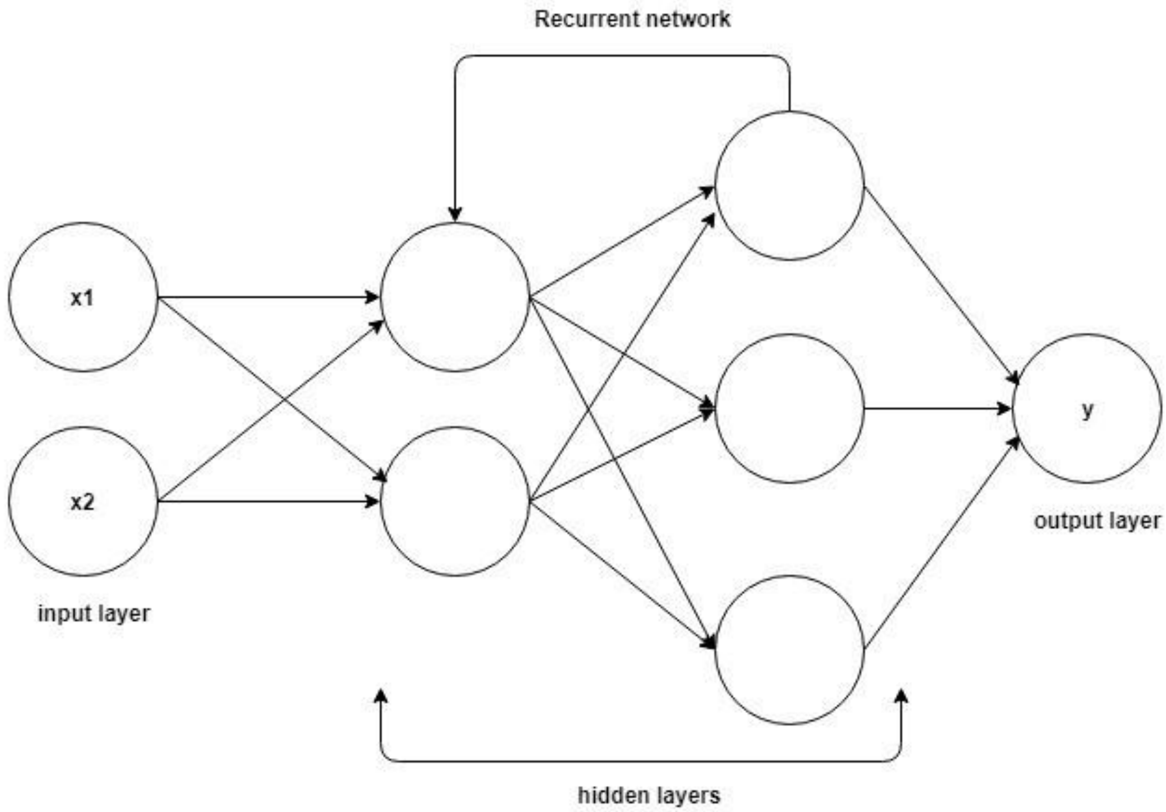

Figure 2.2 : Recurrent Neural Network (URL 4).

Examples of other networks that are widely used nowadays are:

• Hopfield network
• Conterpropogation network

• Cognition and Neocognition

• SOM network

(Öztemel, 2003).

2.2 Example Studies For Artificial Neural Network

In this paper, an early stopped training approach (STA) is introduced to train multi-layer feed-forward neural networks (FNN) for real-time reservoir inflow forecasting. The methodology is assessed using multivariate hydrological time series from Chute-du Diable hydrosystem in northern Quebec (Canada). The performance of the model is compared to benchmarks from a statistical model and an operational conceptual model. Since the ultimate goal concerns the real-time forecast accuracy, overall the results show that the proposed method is effective for improving prediction accuracy. Moreover it offers an alternative when dynamic adaptive forecasting is desired (Coulibaly, Anctilb, Bobéec, 2000).

In this paper, 18-month forecasts were made to measure the decreasing trend of groundwater level in ANNs. Seven different types of network architecture and training algorithms were investigated and compared in terms of model predictive efficiency and accuracy. Different experimental results show that accurate predictions can be made with a standard forward neural network trained with the Levenberg-Marquardt algorithm, which provides the best results for predictions up to 18 months (Daliakopoulosa, CoulibalyaIoannis, Tsanisb, 2005).

In this thesis, a review of ANN species is presented. In a new methodology for grouping binary and binary (fuzzy) problem sets, the Self-Organizing Map (SOM) and Competitive Neural Network (CNN) application were performed simultaneously. An input measure based on the arithmetic mean of five different performance measurements well-known in the literature has been proposed and used for the evaluation and comparison of cell solutions. In addition, the performance criteria in articles from problem sets are used once again to evaluate and compare cell solutions. The results of SOM and CNN were compared with the results in the literature and it was suggested that Matlab 7.5 could be used to encode neural networks and to find the best groups. (Özkan, 2010).

In this paper, the application and comparison of different artificial neural networks in the prediction of 1 hour forward wind speed was investigated. The performance of the model was evaluated according to three measures as mean absolute error, root mean square error and mean absolute percentage error. The results show that no single neural network model performs better than the others in terms of all evaluation criteria, even for the same wind data set. In addition, the choice of type of neural networks for best performance also depends on the data sources (Li , Shi, 2010).

Energy demand forecast based on artificial neural networks (ANN) in this thesis was carried out with the cause-and-effect relationships. By doing research on ANN which are widely used in the field of energy, prediction models were investigated. ANN model has been established with GDP, population, import, export, building surface area and the number of vehicles for Turkey net energy demand forecast between 1970-2010 years. Regression and time series models were developed in order to evaluate success and predict performance of ANN model and comparisons are made. As a result of the analyzes and comparisons, ANN performs seen more successful predictions and Turkey net energy demand forecast between 2011-2025 years were estimated (Es, 2013).

In this paper, estimation results of gas demand using artificial neural networks are presented. The design and training of the MLP (multi-layer sensor model) was carried out using data describing the actual consumption of natural gas in Szczecin (Poland). The model takes into account the calendar (month, month, day of the week, hour) and weather (temperature) factors, which have a significant impact on gas consumption by individual consumers and small industries. It has been found that the model with artificial neural networks can be used successfully to estimate gas consumption at any time of the day and at any time of the year (Szoplik, 2015).

In this paper, a methodology based on artificial neural networks (ANNs) is presented to estimate electricity prices. Since the performance of an ANN estimation model depends on appropriate input parameter sets, the focus is on the selection and preparation of basic data, which have a significant impact on electricity prices. The results show that the overall methodology leads to favorable electricity price estimates, while the estimation errors are low or even lower than other estimation models for electricity prices known from the literatüre (Keles, Scelle, Paraschiv, Fichtner, 2016).

In this paper, a data-driven forecasting model for the electricity usage of buildings throughout the day is applied. Using variable significance analysis, the key variables were: day type indicator, time of day, HVAC set temperature program, outdoor dry temperature bulb and outdoor humidity. The results show that the proposed model with adaptive training methods can estimate electricity consumption and the highest electricity usage of daily buildings over a period of 15 minutes, in a test case of a commercial building complex (Chae, Horesh, Hwang, Lee, 2016).

The aim of this study is to examine artificial neural network (ANN) based models for daily price estimation. Training data are clustered in homogeneous groups and a specific estimator is used for each cluster. The models were tested on a dataset of atypical price models and many outliers. This approach makes the price forecasting problem a more challenging task, providing evidence that the proposed models can be considered as useful and robust forecasting tools to the actual needs of market participants, including the traditional generation companies and self-producers, but also the retailers/suppliers and aggregators (Panapakidis, Dagoumas, 2016).

In this study Artifical Neural Network is a key method to address the issue of nonlinearity of building energy data and the robust calculation of large and dynamic data. They demonstrate TxAIRE Research houses in terms of development and validtion. They used solar radiation, outdoor temperature and number of days as inputs and house and heat pump energy usage amount as outputs. The models based on Levenberg-Marquardt and OWO-Newton algorithms promise results of coefficients of determination within 0.87–0.91, which is comparable to prior literatüre (Biswas, Robinson, Fumo, 2016).

Sales forecasting of a company in retail sector has been made by using statistical demand forecasting methods of Artificial Neural Network and Exponential Smoothing. Statistical error measures are applied to the solution and they show proposed solution that our model is consistent and acceptable. Different from the studies in literature, to forecast sales demand, models designed by taking consideration of internal dynamics which could affect demand. In the study, it has been possible to compare with actual sales of products and forecasts obtained by established models (Polat, 2016).

In this study Grey forecasting models is crucial to forecast energy demand, particularly the GM(1,1) model, because they are able to construct a forecasting model using a limited samples without statistical assumptions. To improve prediction accuracy of a GM(1,1) model, its predicted values are often adjusted by establishing a residual GM(1,1) model, which together form a grey residual modification model. However, since both models are usually established in the traditional manner, they focus on the latter issue, incorporating the neural-network-based GM(1,1) model into a residual modification model to resolve the drawback. They have very good prediction accuracies of the proposed neural-network-based model using real power and energy demand cases. Experimental results verify that the proposed prediction models perform well in comparison with original ones (Hu, Jiang, 2017)

In the study, two different routes of approximately 20 kilometers to the province of Istanbul were analyzed by artificial neural networks. The speed data on these routes are collected by GPS for 5 months and minutes. The results of the test showed that the estimates were more successful when performed on a shorter distance route. It has also been discovered that depending on the characteristics of the path analyzed, it is possible to use similar inputs of information. (Çakmak, 2017).

It ıs usen in that paper machine learning techniques powerful evolutionary optimization algorithm, covariance matrix, adaptation evolutionary strategy, as a means of training neural networks to predict short term power demand, wind power generation and carbon dioxide intensity levels in Ireland over a two month period. The covariance matrix adaptation evolutionary strategy trained network also gives accurate predictions when predicting multiple time steps into the future (Mason, Duggan, Howley, 2018).

Electric energy is an energy source that can be transported by transmission and distribution networks, but cannot be stored in the region where electricity is produced. The estimates made by the electricity distribution companies show the 10 year forecast of the country. Accuracy rates of the estimations will make the planning and investment studies based on these estimates healthier. In this study, the electricity consumption forecasts of an electricity distribution company operating in Konya in the next 10 years were obtained by different methods and the method that should be used by the company for the next forecasting processes was determined (Yapıcı, 2018).

It is analyzed performances of several machine learning methodologies such as random forest, support vector machines and gradient boosting method in short term load forecasting. Performances of these methods are compared with performances of three naive methods, several time series methods and linear regression. All methods are tested on a dataset which includes hourly electricity load information of a region of a country and hourly temperature values of cities in that region. For machine learning methods and linear regression, a feature set is constructed based on calendar, temperature and past load information. Minimum absolute percentage error (MAPE) is used as performance metric to compare methodologies. According to results of experiments, machine learning methods showed better performance than conventional methods in short term load forecasting (Kuru, 2018).

This paper proposes a method for estimating energy consumption in public buildings and thus achieves energy savings without affecting comfort and goodness to improve energy efficiency. The prediction of energy consumption is inevitable for intelligent system operations and planning. To estimate this consumption, an Elman neural network was proposed and a genetic algorithm was used to optimize the weight of the models. This paper concludes that the proposed method optimizes the estimation of energy consumption and improves the results obtained in previous studies (Ruiz, Rueda, Cuéllar, Pegalajar, 2018).

In this article, artificial neural network (ANN) is used in order to successfully estimate natural gas consumption during hot mix asphalt production process. Data for the production of hot mix asphalt for 2014 for testing purposes. As independent variables in modeling; moisture content, hourly capacity, type of asphalt mixture produced and temperature of produced asphalt. According to the obtained modeling results, it is concluded that ANN can be used successfully in predicting natural gas consumption in the production of hot mix asphalt (Androjića, Dolaček-Aldukc, 2018).

In this study, short term load estimation for Faisalabad Electricity Supply Company was realized by using artificial neural network method. Among the many features derived only from the historical electrical charge and air temperature data, the features which are more effective than the others for load estimation were determined by these methods and the effects of different feature selection methods on the performance of artificial neural networks were examined. As a result, it was found that the performance of neural networks using the variables selected by correlation analysis had higher predictive success (Khan, 2019).

The parameters measured in meteorology are influenced by various factors such as terrain shapes, current latitude and altitude, making it difficult to predict. Estimation with statistical models provides both cost and time benefits. In this study, regression model and artificial neural network model and maximum and minimum temperature estimation were made by using meteorological data measured in Karaman, where agricultural production is intensive, and their consistency was compared (Kav, 2019).

2.3 Studies About FMCG And Cold Chain Sectors

The study pharmaceutical companies in Turkey, hospitals, drug stores and pharmacies across was made to bring the heavily incomplete applications and solutions for the problems during the making of logistics processes determining the current situation in Turkey of made cold chain subject of drugs logistics activities . In this research, it is aimed to determine the processes performed or incomplete in this process. Survey method was used as the research method. A survey of pharmaceutical companies operating in Turkey created for the purpose of research firms 78 is incorporated, and the obtained data was analyzed with SPSS findings are set forth (Emanet, 2018).

In the other study, temperature data logger design with USB interface was performed to document unwanted temperature and humidity in cold chain logistics. The most efficient use of the microcontroller has been selected. The interface is designed to introduce the desired conditions to the device. Thanks to this interface, it is provided to operate the data in real time by entering the data receiving frequency, upper-lower limit values, time and date (Güzel, 2018).

The effects of outsourcing in cold chain logistics management on business performance a case study on food supply chain. The aim of this study is to investigate the impact of outsourcing on the performance of the food supply chain in cold chain logistics with a special position in supply chain management and a more complex structure (Alanur, 2014).

In this study it is focud on the improvement of the supply chain structure of a fast-moving consumption company in the Fortune 500 list. The main aim of the study is to determine the place where the company has more than one supplier and production facilities located in different parts of the world. to improve the structure of the supply chain. This alternative is based on the strategy of positioning distribution centers among the production facilities and suppliers in the supply chain structure. There are two main objectives in terms of supply chain improvement. These objectives are reducing the total supply chain cost and increasing the customer satisfaction rate (Aksu, 2014).

Supply chain management have more than one factor whish are important for operation. One of them is distribution management for which the most important model is vehicle routing problem. In this thesis, a vehicle routing application has been made in the fast moving consumer goods sector. The Territory Planner was used to optimize distribution routes (Koçtaş, 2006).

The logistics system of a fast consumer goods manufacturer remodeling. In this thesis, the company's cold chain distribution from the order process to the placement of the product on the chain store shel the performance, cost and quality of the process, work flow plan and system modeling intended to improve. Within the scope of the thesis, the actual targeted distribution network system approach and industrial engineering tools. Since the main performance indicators are determined as the distribution time and cost, the non-storing status and the fresh product rate in the shelf, the aim of this study was to increase the satisfaction of the target retailer and the customer. After identifying the existing problems and making recommendations to improve the existing system operations, the two main problems have been identified as the storage system design and vehicle routing problem. The results dedicated storage policy turn and full turnover policy approaches have been considered in relation to the storage system design (Oluk, 2006).

3. ANN MODEL AND ITS ANALYSIS

In this model, it is aimed to estimate energy consumption in production in the fast moving consumer goods sector. Artificial Neural Networks (ANN) method is used for estimation. Estimates are made for the following periods based on the last three years' electricity energy consumption and the other inputs from the company. The model is analysed for 5 different departments of company with 6 different inputs set to see the inputs that effect output for each department.

In literature researchs, demand forecasting methods based on cause and effect relations by using ANN methods can utilize different inputs. Temperature, dew point, wet bulb and wind speed are most common used inputs to build the ANN model for electricity demand forecasting in FMCG sector for cold chain. But also experts recommend to use number of workers and volume of production as the other inputs. The inputs for ANN model can be seen at Table 3.1 below. The data set consist of 1096 daily data, in below it is shared for 31 days. All of the rest data can not be shared due to confidentiality of the company.

Table 3.1 : Data set.

Day	*D1*	*D2*	*D3*	*D4*	*D5*	*Temperature °C (°C)*	*Dew Point °C (°C)*	*Wet Bulb °C (°C)*	*Wind Speed - km/h (kmh)*	*Volume (Liton)*	*Workers*
1	60,852	103,89	19,103	93,04	611,487	4,04	0,46	2,63	16	76197	239
2	8615	21131	27400	27622	189802	6,21	2,96	4,76	15	598102	239
3	9286	18333	7742	8259	105455	8,29	6	6,98	14	97959	239
4	704,5	2099,5	1354	3358	17019,5	9,17	6,79	7,81	17	86973	239
5	8997,5	17389	7401,5	6856	85762	8,29	5,75	6,86	23	16748	239
6	8871,5	17021	6812	5392	73325,5	5,33	0,92	3,69	30	21199	239
7	824	2141,5	3025	4296	19526	3,96	-1,54	2,08	14	110069	239
8	792,5	2148	3175,5	2800	18733,5	5,13	-0,71	2,67	9	129236	239
9	648,5	1988	1519	2588	14785,5	7,75	4,29	5,68	7	132911	239
10	645	2110	2439	3283	18782	8,38	5,5	6,82	15	146168	239
11	799,35	2158,7	1395,9	2425	16281,4	6,79	2,67	4,84	14	110825	239
12	47,749	123,33	22,261	89,78	11717,4	5,04	0,46	3,36	15	116090	239
13	797	2153,5	2655	2629	20381	5,58	-0,21	3,25	12	142635	239
14	4727,1	11818	7575,4	12937	96726,6	6,79	3,54	5,05	10	192957	239

Table 3.1 (Continued) : Data Set.

15	685,5	2022	2278,5	2580	18378	10,21	7,83	8,42	12	153027	239
16	653	2038	2338	2954	19970	11,5	8,29	9,39	12	132319	239
17	714	2158	2383,5	2951	19972	10,83	8,71	9,49	12	157367	239
18	897,96	2272,9	3128,2	3224	22024,3	8,92	6,54	7,68	34	156237	239
19	804	2320,5	1994,5	2744	20446,5	2,63	1,08	2,17	23	124544	239
20	883,61	2274	3360,1	2797	24331,3	1,71	0,46	1,22	14	139334	239
21	816,64	2213,9	3303,8	2420	22693,4	2,75	1,54	2,32	8	153358	239
22	620,68	1835,9	1022,4	1233	14216,4	6,08	5,13	5,46	10	138270	239
23	1037	2670	3677	3804	28053	8,71	6,29	7,39	12	145666	239
24	1254,5	2931	3121,5	3842	27866	9,88	7,29	8,09	17	122002	239
25	492,5	903	2189	2273	11883	5,58	1,25	3,98	18	123384	239
26	949,5	2172,5	2892,5	3225	21969,5	3,25	-3,08	1,2	14	130922	239
27	951	2355	2312	2364	20507,5	3,33	-2	1,58	9	96605	239
28	763	1638	603	1403	11111	4,67	-1,08	2,66	6	123142	239
29	571,5	1103,5	229,5	234,5	6798	5,13	2,67	4,04	11	52823	239
30	219,5	697,5	80,5	274,5	4946	5,5	2,17	4,11	8	94542	239
31	186,5	617,5	49,5	272,5	4494,5	5,67	2,08	4,19	11	90354	239

70% of inputs are used for learning algorithm, 30% of them are used for testing. For these percentages, literature researchs are taken into consideration and by using trial and error approaches (Zhang et al., 1998). The model consist of six inputs and one output for the forecasting for electiricity consumption. There are 4 different models for each department so there are 20 modeles to be analysed. Temparature, wet bulb, wind speed, dew point are the constant inputs accordingly experts ant litterature. Number of worker and volume of production are added as two other inputs to analyse if they are effect output or not. For first model inputs are temparature, wet bulb, wind speed, dew point. For second model inputs are temparature, wet bulb, wind speed, dew point and number of worker. For third model inputs are temparature, wet bulb, wind speed, dew point and volume of production. For fourth model inputs are temparature, wet bulb, wind speed, dew point, number of worker and volume of production.

Figure 3.1 shows the conceptual ANN model with inputs, outputs and hidden layers in backpropagation form. Output is the electricity consumption value for each five departments. Therefore below model is applied for each Department separately.

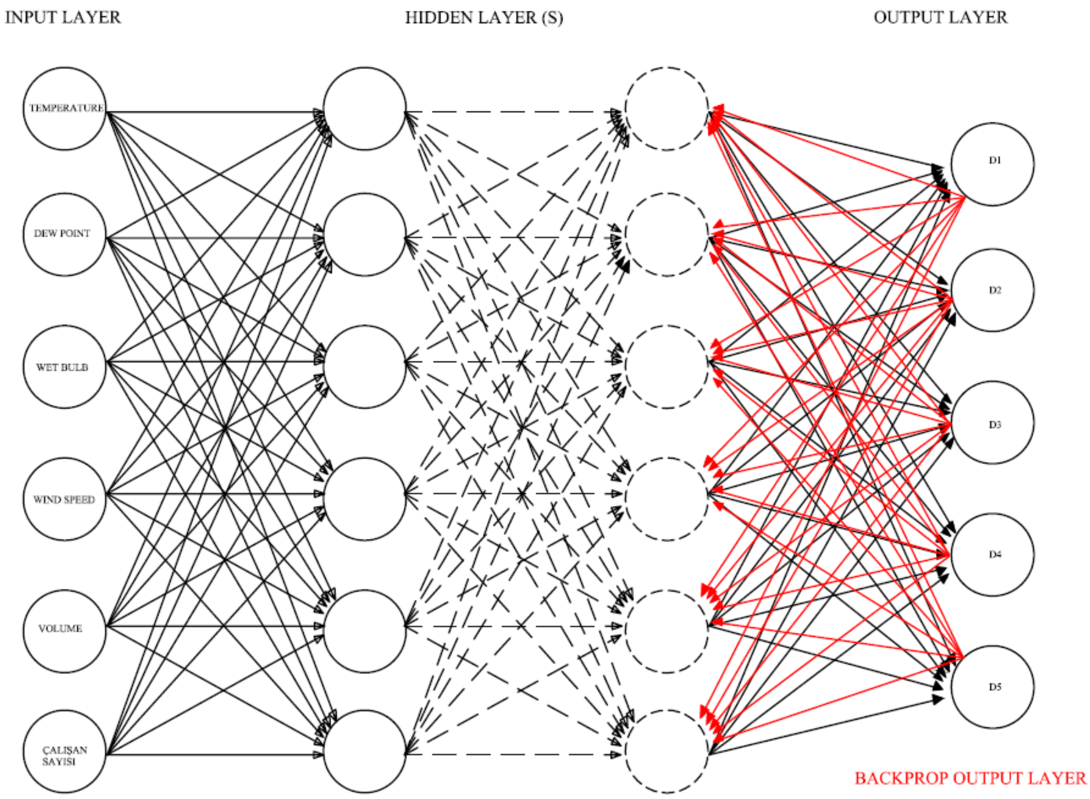

Figure 3.1 : ANN Model in backpropagation form.

On the data set there were missing values with %33 of data for volume of production. For handle this challenge, it is tried two different methods for missing value imputation; which are using mean and linear regression. Linear regression method is preferred because of the low percentage of missing value and because of the all the rest data set inputs and outputs are complete. In addition, Root Mean Square Error (RMSE) values are lower than the other imputation method. In figure 3.2 it is shown the volume of production with the imputation of linear regression.

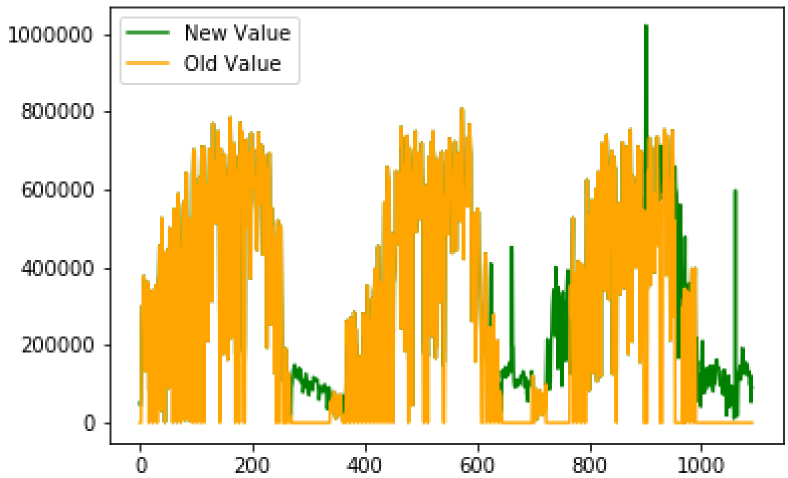

Figure 3.2 : Volume Prediction

To train and test data and run the model, Python programming language is used thanks to its dynamism, flexibity and free. The Python codes of model can be seen at Appendix A.

The electiricity values in data set were drawn between zero and one for easier processing. The formula to fit values between zero and one can be shown in the equation 3.1 below.

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{3.1}$$

z_i : New value of *i*'th onservation

x_i : Value of *i*'th onservation

min (x) : Minimum value of data set

max (x) : Maximum value of data set

The performence of ANN model associate with Root Mean Square Error (RMSE). Min RMSE means better performence of training stage of ANN model. Residuals are difference between forecated and actual data in a regression or ANN model; RMSE shows spread of residuals. RMSE is the standard deviation of the residuals (prediction errors). Root mean square error is usually used not only in forecasting and regression analysis, also in climatology to verify results. The formula to calculate RMSE can be shown in the equation 3.2 below.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(P_i - O_i\right)^2}{n}} \tag{3.2}$$

P_i : Predicted value of the *i*'th observation

O_i : Observed value of the *i*'th observation

n: Data size

For Department 1 (D1), all inputs effect the amount of electricity consumption. For D1 figure 3.3 shows min RMSE value for training and testing data. Activation function of hidden layer and output layer are chosen 'Relu' and 'Selu' because of they flexibility and effectivity for the our data set. Value of y can be [0,+∞) so for the data set as usen in this thesis Relu can learn and give better result. Selu is usen for negatif values of y. As in the data set there are no negatif value for all departments "Relu" is used as activation function. There is 1 hidden layers and the learning rate is 0,01. When the model is run for 100 epochs with batch size 10, the results with min RMSE are shown in the figure below.

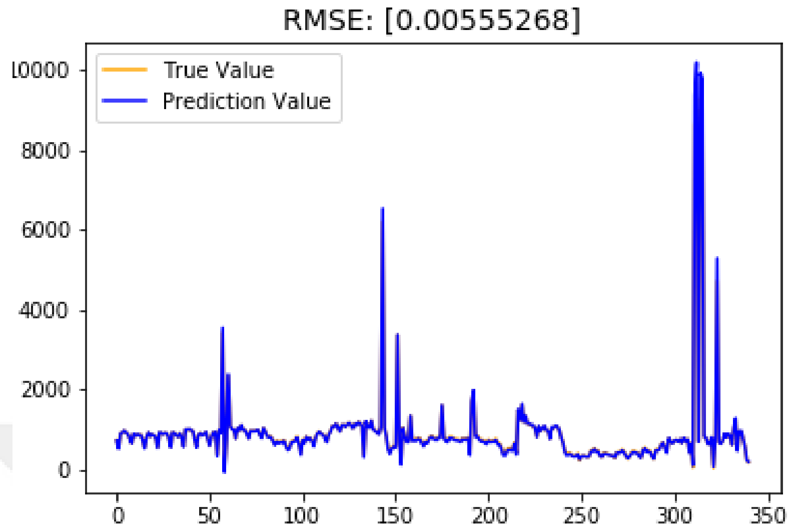

Figure 3.3 : RMSE value for testing data for D1

For Department 2 (D2), temparature, wet bulb, wind speed, dew point and number of worker effect the amount of electricity consumption as input. Volume of production does not effect output value. Moreover, figure 3.4 shows min RMSE value for training and testing data for department 2. Activation function of hidden layer and activation function of output layer are chosen ‘Relu’. There are 4 hidden layers and the learning rate is 0,01. When the model is run for 100 epochs with batch size 10, the results with min RMSE are shown in the figure below.

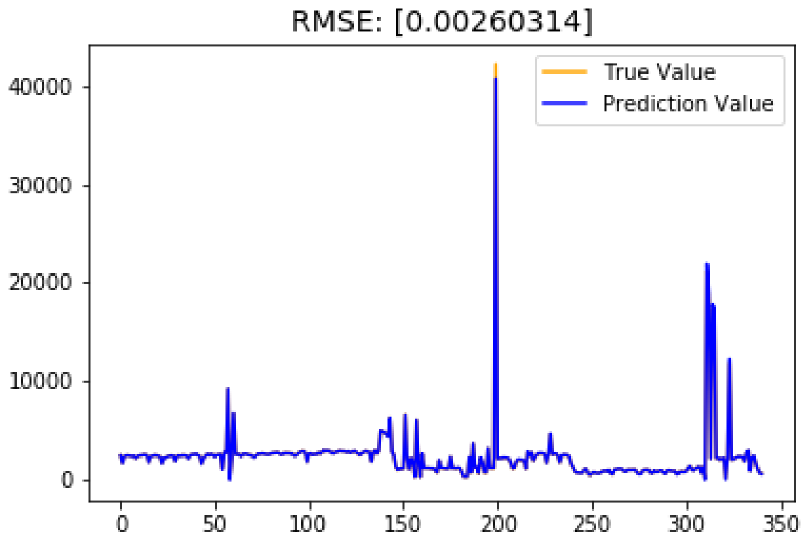

Figure 3.4 : RMSE value for testing data for D2

For Department 3 (D3), temparature, wet bulb, wind speed, dew point and number of worker effect the amount of electricity consumption as input. Volume of production does not effect output value. Moreover, figure 3.5 shows min RMSE value for training and testing data for department 3. Activation function of hidden layer and activation function of output layer are chosen ‘Relu’. There is one hidden layer and the learning rate is 0,01. When the model is run for 100 epochs with batch size 10, the results with min RMSE are shown in the figure below.

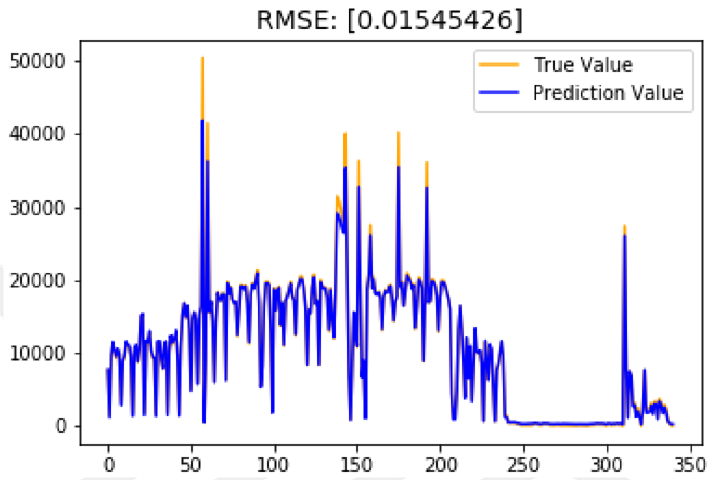

Figure 3.5 : RMSE value for testing data for D3

For Department 4 (D4), all inputs effect the amount of electricity consumption. For D4 figure 3.6 shows min RMSE value for training and testing data. Activation function of hidden layer and activation function of output layer are chosen ‘Relu’. There is one hidden layers and the learning rate is 0,01. When the model is run for 100 epochs with batch size 10, the results with min RMSE are shown in the figure below.

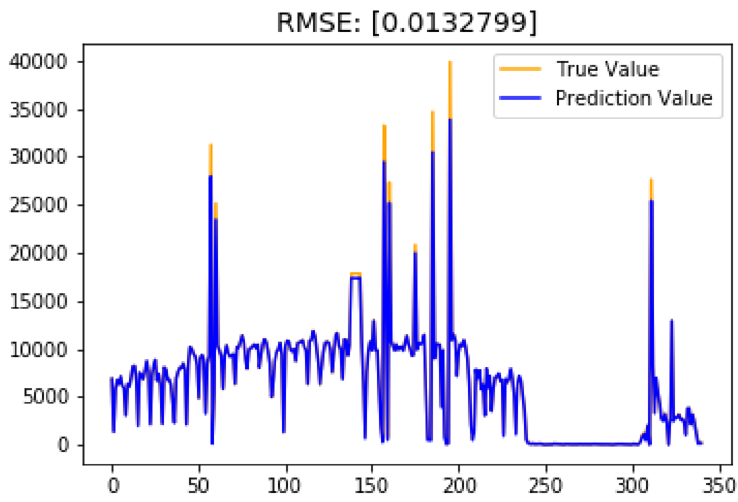

Figure 3.6 : RMSE value for testing data for D4

For Department 5 (D5), temparature, wet bulb, wind speed, dew point and number of worker effect the amount of electricity consumption as input. Volume of production does not effect output value. Moreover, figure 3.7 shows min RMSE value for training and testing data for department 5. Activation function of hidden layer and activation function of output layer are chosen ‘Relu’. There are 2 hidden layers and the learning rate is 0,01. When the model is run for 100 epochs with batch size 10, the results with min RMSE are shown in the figure below.

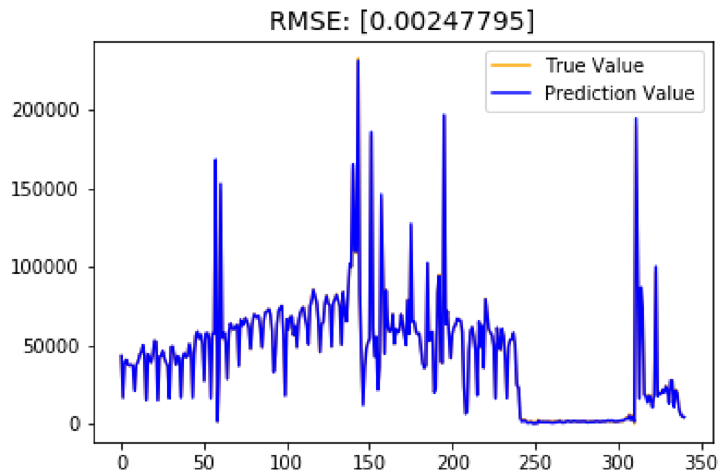

Figure 3.7: RMSE value for testing data for D5

Belong the results as shown in figures the inputs, temparature, wind speed, dew point, wet bulb and number of workers effect as input each Departments. Volume of production effect only two Departments as input. RMSE values are between 0,0025-0,0155, which means models fit with electricity consumption forecasting.

After training data set, the values are turn back real values to predict future electricity consumption volume. The fourmula usen is as below equation 3.3.

$$z_i = (x_i * (yRef(max) - yRef(min))) - yRef(min) \qquad (3.3)$$

z_i : New value of i’th observation

x_i : Value of i’th onservation

yRef(max) : Maximum value of i’th observation in test data set for test

yRef(min) : Minimum value of i’th observation in test data set for test

For future prediction long short term memory (LSTM) is used because its flexibility and performance for multiple inputs. In below table 3.2, it can be shown some data set prediction for 31 days. Due to company confidentiality rules it can be shared only 31days.

Table 3.2 : Future forecast by ANN.

Day	*D1*	*D2*	*D3*	*D4*	*D5*
1	66,11	141,35	23,67	69,97	446,22
2	8729,89	22159,53	24124,74	25980,95	119206,2
3	10729,47	19243,79	6367,5	7800,25	97014,3
4	668,48	1981,71	917,64	2908,02	14655,93
5	9117,48	18235,34	6516,64	7979,28	61506,56
6	9136,39	12387,19	9927,35	4593,43	84112,77
7	728,1	1719,72	2334,56	2268,7	12320,16
8	517,9	1363,5	3086,63	2705,1	15366,18
9	704,49	2704,86	1882,13	1946,26	10789,3
10	653,6	2212,7	2147,41	3087,51	11796,15
11	923,6	2265,96	1148,05	2290,41	14978,25
12	45,31	116,41	15,09	77,76	10090,19
13	807,63	2258,31	2337,59	3059,73	14616,79
14	4868,27	8601,11	11039,87	11021,86	110956,47
15	605,72	1623,76	1758,45	1362,49	11595,82
16	426,74	1293,67	2272,57	2853,91	16380,42
17	775,64	2936,16	2953,3	2218,87	14574
18	909,94	2383,54	2754,2	3032,92	13832,5
19	928,98	2435,85	1640,4	2591,11	18810,04
20	838,43	2146,43	2277,21	2422,34	20952,36
21	827,54	2321,64	2908,82	2816,41	16275,21
22	639,22	1336,15	1490,02	1050,75	16307,86
23	916,31	2144,13	2837,75	2008,61	17700,37
24	819,82	1860,53	3034,14	3711,96	22857,12
25	535,02	1228,61	2712,3	1709,37	8671,28
26	962,16	2278,24	2546,7	3032,95	13798,08
27	1098,83	2472,07	1901,53	2232,22	18866,15
28	723,99	1546,1	408,67	1214,74	9567,97
29	579,12	1157,21	202,06	272,92	4875,37
30	238,45	949,01	99,74	206,43	3609,2
31	164,79	495,88	38,2	143,91	2835,86

Table 3.3 : Results and analysis of departments

Department	Operation	Inputs	Analysis	Suggestions for Improvement
D1	Departments of stockage, waste administrative and quality departements	Temparature, wet bulb, wind speed, dew point, number of worker effect and volume of production	The consumption of electiricty by workers can be analysed and the root cause can be found. Accordingly the root cause the company should take precautions needed and do changes. The company should search the ways to reduce electricity consumption during the production.	1.The reason causing excessive consumption should be identified and corrected. 2.Better and less energy consuming lamps should be preferred. 3.The consumption on waste department should be analysed and energies can be reused by a recyling system.
D2	Production of goods	Temparature, wet bulb, wind speed, dew point and number of worker effect	The consumption of electiricty by workers can be analysed and the root cause can be found. Accordingly the root cause the company should take precautions needed and do changes.	1.Baseload times should be analysed and consumptions during these times can be increased. 2.For baseload anlysis otomation systems can be used. The reason causing excessive consumption should be identified and corrected. 3.Better and less energy consuming lamps should be preferred.
D3	Production of ancillary goods	Temparature, wet bulb, wind speed, dew point and number of worker effect	The consumption of electiricty by workers can be analysed and the root cause can be found. Accordingly the root cause the company should take precautions needed and do changes.	1.Baseload times should be analysed and consumptions during these times can be increased. 2.For baseload anlysis otomation systems can be used. The reason causing excessive consumption should be identified and corrected. 3.Better and less energy consuming lamps should be preferred.
D4	Production of final goods	Temparature, wet bulb, wind speed, dew point, number of worker effect and volume of production	The consumption of electiricty by workers can be analysed and the root cause can be found. Accordingly the root cause the company should take precautions needed and do changes. The company should search the ways to reduce electricity consumption during the production.	1.Baseload times should be analysed and consumptions during these times can be increased. 2.For baseload anlysis otomation systems can be used. The reason causing excessive consumption should be identified and corrected. 3.Better and less energy consuming lamps should be preferred. 4.Energy consumption between lines can be reduced by automation systems.
D5	Department where there are systems which serve energy use for other departments	Temparature, wet bulb, wind speed, dew point and number of worker effect	The consumption of electiricty by workers can be analysed and the root cause can be found. Accordingly the root cause the company should take precautions needed and do changes.	1.Since energy is a constantly rotating thing, a system of recycling and reuse of waste energy should be established. 2.For baseload anlysis otomation systems can be used. The reason causing excessive consumption should be identified and corrected. 3.Better and less energy consuming lamps should be preferred. 4.Pipes and fittings should be examined for reducing losses from transferring energy from one place to another.

4. CONCLUSION AND RECOMMENDATION

Energy is the most important requirements of all over the world. The amount of energy is directly proportional to the level of deveploment of a country. All countries need cheap, abundant and clean energy sources. In Turkey, where the demand for electricity rises gradually as demand and supply come early bus bar is observed. FMCG sector is growing year by year in Turkey. There is a continuous and rapid production in FMCG. Therefore accurate forecasting of electricy consumption is too crucial for all sectors especially FMCG and cold chain sectors.

The purpose of the study is to put forward an artificial neural networks model to estimate electricy consumption for FMCG sector. Therefore, with the ANN approach, it is aimed to define a function for the estimation of energy consumption in the production area of a company in the rapid consumption sector. The model is supported by a real data set considering the 2016-2018 periods, annual demand estimation is made by artificial neural network methods and electricity demand prediction studies are carried out for future years. Estimation of electrical energy consumption is of great importance for the company because it is one of the basic energy types used. The main contribution of the study is the input selection procedure for the model, that is the new input is added to model if there is an improvement on RMSE, and vice versa. Production volume is only chosen as input for two departments. For other tree departments it does not improved the RMSE value. The number of workers is an important input for all departments. The other contribution of the study is integrating neural network with missing value and used methods to avoid it.

For the future study, the model should be tested as new case studies with data of the other companies in the same sector. Moreover, the model can be integrated with the other sectors'electricity consumption forecasting whether the model is fit the other sectors or not. The most important further study is comparing the result in the input selection stage with the Structural Equational Modelling's results. Also, the other recommended inputs can be added to check the accord to the model. Therefore, researchers should find other new and real indicators to define real inputs which gives the less RMSE especially for sustainable supply chain management. The last but not least, researchers can use the other missing values imputation methods.

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APPENDICES

APPENDIX A: Codes of the model in Phython.

```
import numpy as np
from numpy import array
import matplotlib.pyplot as plt
import pandas as pd
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras import optimizers
from keras import initializers
from sklearn.preprocessing import RobustScaler
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import MinMaxScaler
from sklearn.utils import shuffle
from keras.layers import LSTM
from pandas import DataFrame
from statsmodels.tsa.arima_model import ARIMA

def split_sequence(sequence, n_steps_in, n_steps_out):
	X, y = list(), list()
	for i in range(len(sequence)):
		# find the end of this pattern
		end_ix = i + n_steps_in
		out_end_ix = end_ix + n_steps_out
		# check if we are beyond the sequence
		if out_end_ix > len(sequence):
			break
		# gather input and output parts of the pattern
		seq_x, seq_y = sequence[i:end_ix], 
sequence[end_ix:out_end_ix]
		X.append(seq_x)
		y.append(seq_y)
	return array(X), array(y)


linreg = LinearRegression()

full_data = pd.read_csv('data.csv').iloc[:,1:13]
data_With_Null = pd.read_csv('data.csv').iloc[:,1:13]
data_Witouth_Null = 
data_With_Null[data_With_Null['Volume'] != 0]
```

```
train_data_x = data_Witouth_Null.iloc[:,:10].values
train_data_y =
data_Witouth_Null.iloc[:,10].values.astype(float)

linreg.fit(train_data_x,train_data_y)

test_data =
data_With_Null.iloc[:,:10].values.astype(float)
volume_predicted =
pd.DataFrame(linreg.predict(test_data))

for count in range(0,len(data_With_Null)):
     if(data_With_Null['Volume'][count] == 0):
          data_With_Null['Volume'][count] =
volume_predicted[0][count]

     if(data_With_Null['Volume'][count] < 0):
          data_With_Null['Volume'][count] = (-1) *
(data_With_Null['Volume'][count])

plt.plot(data_With_Null['Volume'], color="green",
label='New Value')
plt.plot(full_data['Volume'], color="orange", label='Old
Value')
plt.title('Volume Prediction')
plt.legend()
plt.savefig('VolumePrediction.png')
global_data_set = data_With_Null

del count, train_data_x, full_data, train_data_y,
data_Witouth_Null, data_With_Null, test_data,
volume_predicted


for count in range(4,5):

     dataset =
pd.DataFrame(data=global_data_set.iloc[0:,0:])
     ## Tum dataseti 0 - 1 arasina kucultuyorum
     dataset_min = np.amin(dataset)
     dataset_max = np.amax(dataset)

     dataset_min = dataset_min.values.reshape(1,12)
     dataset_max = dataset_max.values.reshape(1,12)

     for e in range(0,len(dataset)):
        for f in range (0,12):
             dataset.iloc[e,f] = (dataset.iloc[e,f]-
dataset_min[0,f])/(dataset_max[0,f]-dataset_min[0,f])

     column_name = dataset.columns[count]
```

```
     data_only_department = dataset[[column_name]]
     data_with_air = dataset[[column_name, 'Temperature',
'Dew Point', 'Wet Bulb', 'Wind Speed']]
     data_with_volume = dataset[[column_name,
'Temperature', 'Dew Point', 'Wet Bulb', 'Wind Speed',
'Volume']]
     data_with_workers = dataset[[column_name,
'Temperature', 'Dew Point', 'Wet Bulb', 'Wind Speed',
'Calisan Sayisi']]
     data_with_everything = dataset[[column_name,
'Temperature', 'Dew Point', 'Wet Bulb', 'Wind Speed',
'Volume', 'Calisan Sayisi']]

     x_train_air = np.float64(data_with_air[:750])
     x_test_air = np.float64(data_with_air[750:])
     y_train_air = np.float64(data_only_department[:750])
     y_test_air = np.float64(data_only_department[750:])

     x_train_volume = np.float64(data_with_volume[:750])
     x_test_volume = np.float64(data_with_volume[750:])
     y_train_volume =
np.float64(data_only_department[:750])
     y_test_volume =
np.float64(data_only_department[750:])

     x_train_workers =
np.float64(data_with_workers[:750])
     x_test_workers = np.float64(data_with_workers[750:])
     y_train_workers =
np.float64(data_only_department[:750])
     y_test_workers =
np.float64(data_only_department[750:])

     x_train_everything =
np.float64(data_with_everything[:750])
     x_test_everything =
np.float64(data_with_everything[750:])
     y_train_everything =
np.float64(data_only_department[:750])
     y_test_everything =
np.float64(data_only_department[750:])


     first_layer = 1
     max_node = 1
     rmse = 10
     name_of_model = "a"
     for ee in range(0,4):
        #Air
        if(ee == 0):
            max_node = 5
```

```
            for gg in range(1,max_node):
                  regressor = Sequential()
                regressor.add(Dense(gg,
kernel_initializer =
initializers.RandomNormal(stddev=0.001) , activation =
'selu' , input_dim = 5))
                regressor.add(Dense(1 ,
kernel_initializer =
initializers.RandomNormal(stddev=0.001) , activation =
'relu'))
                sgd = optimizers.SGD(lr=0.01, decay=1e-6,
momentum=0.9, nesterov=True)
                regressor.compile(optimizer = sgd , loss
= 'mean_squared_error' )

                counter = 1
                for ppp in range (100):

regressor.fit(x=x_train_air,y=y_train_air,batch_size=10)

plt.plot(regressor.predict(x_train_air),color="blue")
                    plt.plot(y_train_air,color="orange")
                    plt.show()
                    print(counter , 'Air', gg , 'node')
                    counter = counter+1

                y_pred = regressor.predict(x_test_air)

                mse = 0
                totalerror = 0
                for mmm in range (len(y_test_air)):
                    totalerror = totalerror +
((y_test_air[mmm]-y_pred[mmm])**2)
                mse=totalerror/len(y_test_air)
                rmse_tmp = mse **(1/2)
                if (rmse_tmp<rmse):
                    rmse = rmse_tmp
                    first_layer = gg
                    name_of_model="Air"
        #Volume
        if(ee == 1):
            max_node=6
            for ii in range(1,max_node):
                regressor = Sequential()
                regressor.add(Dense(ii,
kernel_initializer =
initializers.RandomNormal(stddev=0.001) , activation =
'selu' , input_dim = 6))
                regressor.add(Dense(1 ,
kernel_initializer =
```

```
initializers.RandomNormal(stddev=0.001) , activation =
'relu'))
                sgd = optimizers.SGD(lr=0.01, decay=1e-6,
momentum=0.9, nesterov=True)
                regressor.compile(optimizer = sgd , loss
= 'mean_squared_error' )

                counter = 1
                for pppp in range (100):

regressor.fit(x=x_train_volume,y=y_train_volume,batch_siz
e=10)

plt.plot(regressor.predict(x_train_volume),color="blue")

plt.plot(y_train_volume,color="orange")
                    plt.show()
                    print(counter , 'Volume', ii ,
'node')
                    counter = counter+1

                y_pred = regressor.predict(x_test_volume)

                mse = 0
                totalerror = 0
                for mmmm in range (len(y_test_volume)):
                    totalerror = totalerror +
((y_test_volume[mmmm]-y_pred[mmmm])**2)
                mse=totalerror/len(y_test_volume)
                rmse_tmp = mse **(1/2)
                if (rmse_tmp<rmse):
                    rmse = rmse_tmp
                    first_layer = ii
                    name_of_model="Volume"
        if(ee == 2):
        #Workers
            max_node=6
            for ll in range (1,max_node):
                regressor = Sequential()
                regressor.add(Dense(ll,
kernel_initializer =
initializers.RandomNormal(stddev=0.001) , activation =
'selu' , input_dim = 6))
                regressor.add(Dense(1 ,
kernel_initializer =
initializers.RandomNormal(stddev=0.001) , activation =
'relu'))
                sgd = optimizers.SGD(lr=0.01, decay=1e-6,
momentum=0.9, nesterov=True)
                regressor.compile(optimizer = sgd , loss
= 'mean_squared_error' )
```

```
                counter = 1
                for ppppp in range (100):

regressor.fit(x=x_train_workers,y=y_train_workers,batch_s
ize=10)

plt.plot(regressor.predict(x_train_workers),color="blue")

plt.plot(y_train_workers,color="orange")
                    plt.show()
                    print(counter , 'Workers' , ll ,
'node')
                    counter = counter+1

                y_pred =
regressor.predict(x_test_workers)

                mse = 0
                totalerror = 0
                for mmmmm in range (len(y_test_workers)):
                    totalerror = totalerror +
((y_test_workers[mmmmm]-y_pred[mmmmm])**2)
                mse=totalerror/len(y_test_workers)
                rmse_tmp = mse **(1/2)
                if (rmse_tmp<rmse):
                    rmse = rmse_tmp
                    first_layer = ll
                    name_of_model="Workers"
        if(ee == 3):
        #Everything
            max_node=7
            for rr in range (1,max_node):
                regressor = Sequential()
                regressor.add(Dense(rr,
kernel_initializer =
initializers.RandomNormal(stddev=0.001) , activation =
'selu' , input_dim = 7))
                regressor.add(Dense(1 ,
kernel_initializer =
initializers.RandomNormal(stddev=0.001) , activation =
'relu'))
                sgd = optimizers.SGD(lr=0.01, decay=1e-6,
momentum=0.9, nesterov=True)
                regressor.compile(optimizer = sgd , loss
= 'mean_squared_error' )

                counter = 1
                for pppppp in range (100):

regressor.fit(x=x_train_everything,y=y_train_everything,b
atch_size=10)
```

```
plt.plot(regressor.predict(x_train_everything),color="blu
e")

plt.plot(y_train_everything,color="orange")
                    plt.show()
                    print(counter , 'Everything', rr ,
'node')
                    counter = counter+1

                y_pred =
regressor.predict(x_test_everything)

                mse = 0
                totalerror = 0
                for mmmmmm in range
(len(y_test_everything)):
                    totalerror = totalerror +
((y_test_everything[mmmmmm]-y_pred[mmmmmm])**2)
                mse=totalerror/len(y_test_everything)
                rmse_tmp = mse **(1/2)
                if (rmse_tmp<rmse):
                    rmse = rmse_tmp
                    first_layer = rr
                    name_of_model="Everything"

     print('name: ' , name_of_model)
     print('layer: ' , first_layer)

     input_number = 0
     if(name_of_model == 'Air'):
        input_number = 5
        x_train_use = x_train_air
        y_train_use = y_train_air
        x_test_use = x_test_air
        y_test_use = y_test_air
     if(name_of_model == 'Volume'):
        input_number = 6
        x_train_use = x_train_volume
        y_train_use = y_train_volume
        x_test_use = x_test_volume
        y_test_use = y_test_volume
     if(name_of_model == 'Workers'):
        input_number = 6
        x_train_use = x_train_workers
        y_train_use = y_train_workers
        x_test_use = x_test_workers
        y_test_use = y_test_workers
     if(name_of_model == 'Everything'):
        input_number = 7
        x_train_use = x_train_everything
        y_train_use = y_train_everything
```

```
        x_test_use = x_test_everything
        y_test_use = y_test_everything

     y_test_min_use = dataset_min[0,count]
     y_test_max_use = dataset_max[0,count]
     regressor = Sequential()
     regressor.add(Dense(first_layer,  kernel_initializer
= 'uniform' , activation = 'selu' , input_dim =
input_number))
     regressor.add(Dense(1 ,  kernel_initializer =
'uniform' , activation = 'selu'))

     sgd = optimizers.SGD(lr=0.01, decay=1e-6,
momentum=0.9, nesterov=True)
     regressor.compile(optimizer = sgd , loss =
'mean_squared_error' )

     counter = 1
     for p in range (len(x_test_use)):

regressor.fit(x=x_train_use,y=y_train_use,batch_size=5)

plt.plot(regressor.predict(x_train_use),color="blue")
        plt.plot(y_train_use,color="orange")
        plt.show()
        print(counter)
        counter = counter+1

     y_pred = regressor.predict(x_test_use)

     predictiondeneme = regressor.predict(start=0,
end=10)
     mse = 0
     totalerror = 0
     rmse = 0
     for m in range (len(x_test_use)):
        totalerror = totalerror + ((y_test_use[m]-
y_pred[m])**2)
        mse=totalerror/len(x_test_use)
        rmse = mse **(1/2)

     print(rmse)

     for k in range(0,len(y_test_use)):
        y_test_use[k] = (y_test_use[k]*(y_test_max_use-
y_test_min_use))+y_test_min_use

     for l in range(0,len(y_pred)):
        y_pred[l] = (y_pred[l]*(y_test_max_use-
y_test_min_use))+y_test_min_use
```

```
    plt.plot(y_test_use, color="orange", label='True
Value')
    plt.plot(y_pred,color= "blue", label='Prediction
Value')
    plt.legend()
    error = str(rmse)
    plt.title('RMSE: ' + error, fontsize=14)

    filename = str(count)
    plt.savefig(filename + name_of_model + 'PLOT.png')
```

APPENDIX B: Codes of the future prediction model in Phython.

```
   dataset_prediction = 
pd.DataFrame(data=global_data_set.iloc[0:,0:])
     data_only_department = 
dataset_prediction[[column_name]]
     data_with_workers = dataset_prediction[[column_name,
'Temperature', 'Dew Point', 'Wet Bulb', 'Wind Speed',
'Calisan Sayisi']]
     dataset_prediction = data_with_workers
     raw_seq = np.float64(data_with_workers.iloc[0:,
:].values)

     scaler = MinMaxScaler(feature_range=(0, 1))
     raw_seq = scaler.fit_transform(raw_seq)
     n_steps_in, n_steps_out = 90, 1

     X, y = split_sequence(raw_seq, n_steps_in,
n_steps_out)

      n_features = 6
     X = X.reshape((X.shape[0], X.shape[1], n_features))
     y = y.reshape((y.shape[0], n_features))
     y = y[:, 0]
     model = Sequential()
     model.add(LSTM(10, activation='tanh',
return_sequences=True, input_shape=(n_steps_in,
n_features)))
     model.add(LSTM(10, activation='tanh'))
     model.add(Dense(n_steps_out))
     model.compile(optimizer='adam', loss='mse')
     model.fit(X, y, epochs=100, verbose=0, batch_size =
20)

     pred_list = []
     x_input = 
np.float64(dataset_prediction.iloc[0:n_steps_in,:].values
)
     scaler = MinMaxScaler(feature_range=(0, 1))
     x_input = scaler.fit_transform(x_input)
     for predictCount in range(0,365):
          x_input = x_input.reshape((1, n_steps_in,
n_features))
          predictedValue = model.predict(x_input,
verbose=0)
          pred_list.append(float(predictedValue))
          x_input = np.delete(x_input, 0)
          x_input = np.append(x_input, predictedValue)
```

```
     pred_list = np.array(pred_list)
     pred_list =  pred_list.reshape(-1, 1)
     scalerY = MinMaxScaler(feature_range=(0, 1))

     data_only_department =
scalerY.fit_transform(data_only_department)
     pred_list = scalerY.inverse_transform(pred_list)
     data_only_department =
scalerY.inverse_transform(data_only_department)

     pred_list_positive = [abs(k) for k in pred_list]

     plt.plot(pred_list_positive, color="orange",
label='Future Value')
     plt.plot(data_only_department[666:,:], color="red",
label='Real Value')
     plt.legend()
     plt.show()
```

CURRICULUM VITAE

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