T.C.
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M.Sc. THESIS

ESTIMATION of ENERGY CONSUMPTION DEMAND with ARTIFICIAL INTELLIGENCE METHODS

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FOREWORD

To Hasan Tiryaki (my advisor), for his academic counseling during my dissertation,

To B. Gültekin Çetiner, for voluntary counseling and guidance,

To Tarık Küçükdeniz due to his valuable advices,

To Erkan Güneş (TEDAS Engineer) who didn't leave me alone when we were visiting institutions for data collection challenge,

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To Murat Yiğit who is CEO of CK Bogaziçi, for his time and his goodwill, although we could not get the data we wanted,

I have a debt of gratitude.

And also,

To my precious family, who are always with me in most difficult times,

And to my dear friend(S) who has encouraged me to work always,

I owe you a **debt of gratitude** for all you have done for me.

December 2018 Ahmet Emre BALSEVER

ÖZET

YÜKSEK LİSANS TEZİ

ENERJİ TÜKETİM TALEBİNİN YAPAY ZEKA YÖNTEMLERİ ile TAHMİNİ

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Bu çalışma, günümüz hayat şartlarının vazgeçilmezi haline gelen elektrik enerjisinin, saatlik bazda tüketim talebinin tahmini üzerine yapıldı. Enerji Piyasaları İşletme A.Ş. şeffaflık platformu tarafından sağlanan Türkiye geneli net tüketim verileri kullanıldı. Oluşturulacak modelde kullanmak için Meteoroloji müdürlüğünden sıcaklık, yağış, bulutluluk, rüzgâr, basınç ve nispi nem değerleri alındı. Bu veriler yapay sinir ağı ve destek vektör makinesi ile kurulan modellerin eğitimi ve testi için kullanıldı. Yapılan çalışmalarda model oluşturma ve analiz için WEKA uygulaması kullanıldı. Analizlerin sonucunda yaklaşık %97 doğruluk oranı elde edildi. Neticede yapay sinir ağlarının tahminlerinin genel olarak daha doğru olduğu tespit edildi. Verilerin zamana bağlı değişiminden kaynaklı hatalardan kaçınmak için çapraz doğrulama metodu kullanıldı. Bununla beraber eksik veya yanlış veriyle karşılaştığında tahminde sapma oranının destek vektör makinesinde daha az olduğu gözlendi.

Aralık 2018, 56 sayfa.

Anahtar kelimeler: enerji talep tahmini, yapay sinir ağları, destek vektör makineleri, yapay zeka, veri analizi

ABSTRACT

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This study based on the estimation of the consumption demand on an hourly basis of electrical energy, which has become indispensable in today's living conditions. Net consumption data collected from the Energy Markets Management Inc. transparency platform. Temperature, precipitation, cloudiness, wind, pressure and relative humidity values were taken to decide a prediction model from the Turkish State Meteorological Service. These data were used for the training and testing of models established with artificial neural network and support vector machine. WEKA application used for modeling and analysis. About 97% accuracy obtained from the analyzes. As a result, the predictions of artificial neural networks were generally more accurate. Cross-validation method was used to avoid errors due to a time-dependent change of data. However, it observed that the deflection rate was less in the support vector machine when faced with missing or incorrect data.

December 2018, 56 pages.

Keywords: energy demand forecasting, artificial intelligence, artificial neural networks, data analysis, support vector machines.

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbol	**Explanation**
GWh	: Giga Watt Hour
MW	: Mega Watt
kWh	: Kilo Watt Hour

Abbreviation	**Explanation**
AI	: Artificial Intelligence
ANN	: Artificial Neural Network
API	: Application Programming Interface
SVM	: Support Vector Machine
MAE	: Mean Absolute Error
RMSE	: Root Mean Squared Error
CC	: Correlation Coefficient
MAPE	: Mean Absolute Percent Error
WEKA	: Waikato Environment for Knowledge Analysis
TC	: Transformer Center
GA	: Genetic Algorithm
ANFIS	: Adaptive-Network Based Fuzzy Inference Systems

1. INTRODUCTION

Nowadays we almost can say electricity is indispensable for our daily life. Every machine, light, car, computer, mobile phone need electricity to work. Factories, homes especially hospitals need it 24-hours. Still hard to store electricity so this translates into requirements to being uninterrupted, not only production quality but also associated production cost.

Electricity demand forecasting is a crucial task for the efficiently plan and operate power systems. The demand forecast is related to the estimation of hourly, daily, weekly and yearly values of system demand and intensive demand. These estimates sometimes categorized as short-term, medium-term and long-term forecasts depending on the time horizon.

The short-term demand forecast so far has attracted significant attention due to its importance in terms of electricity markets, unit commitment, economic shipment and power system control in the literature. However, despite its values for budget allocation and system planning, medium and long-term forecasts were not emphasized. [3]

During the manufacture of electricity, several contributions need to be taken into account to do it efficiently; between them, the most important one is an estimation of demand. One of important technical and economic tasks for energy providers and facilities is a short term energy consumption estimate. Short-term and operational estimates are required to regulate the power generation by power plants and to make the power resource efficient.

Electricity market in Turkey (generation, transmission and distribution), until the early 2000s, has been used in state ownership and control. The change in market started in 2003 by transferring the state monopoly rights to private companies for production, transmission and distribution and by privatizing the energy assets. After the balance and reconciliation phase, which was initiated in 2006 and continued until the end of 2009, the participants realized tender and bilateral contracts. Within this year, day ahead planning was carried out. As a result of the development of the market, day ahead planning was transformed into the day ahead market in 2011. After successfully implementing the day ahead market, the system operator established the intraday market in 2014 under the control of the new market. Market Operator is EPIAS (Market Financial Settlement Center System). [18]

Artificial intelligence (AI) methods, including ANN and SVM, have been finding applications in data analysis engineering since the past decade. One application of AI is energy demand forecasting. The energy consumption demand forecasting mostly based on artificial neural networks. Energy usage generally expressed as a function of weather and time variables.

This paper presents a practical study of an hourly prediction, in which total use in Turkey for electrical energy has been estimated using WEKA. Additionally, an evaluation of the accuracy has also been made, in the prediction of ANN and SVM. Weka Knowledge Navigator is an easy-to-use graphical user interface that uses the power of weka software. Each great weka package represents attribute selection, clusterers, associations, classifiers, and filters. With a visualization tool that allows classifiers and clusters to visualize their estimates in two dimensions.

The research question of this paper is to analyze, how much the total demand of the Turkey energy use can be estimated using AI methods. An analysis is made using six different climate data and consumption data. Climate data are temperature, precipitation, pressure, relative humidity, wind, and cloudiness. The aim is to describe a model for processing these estimations and enable comparisons between different methods and machining processes.

The thesis is composed of six chapters. First one is the introduction and literature review, second includes the research design, used methods, the procedure for data collection, and data analysis procedure. The third chapter explains the result of the analyzes. The fourth one interprets the results, answers the research question, validate the approach, evaluate the research critically. Also, the fifth represents the contribution of the thesis to the knowledge, also include recommendations for further study. The last chapter includes the references and appendices.

1.1. LITERATURE REVIEW

The studies in the literature grouped under three main titles; they divided into a near term, medium term, and long term. We can see that the same techniques used for different processes. The first step in such study is to determine the problem that should be solved, and then the appropriate model should be found.

The demand forecast is the subject of the statistics field until the last ten years. The often used method consists of time series and long-term projections for the work done. As we approached our day, this situation has shifted short-term forecasting due to the changes in the energy sector. In other words, the pre-day and hourly estimates intensified. An element that supports this situation is the development of the science of data processing, the relationship between consumer demand, weather, social impact, economic level, such as the detection and analysis of data becomes possible.

After the acquisition of the needed data, the significant development has been the widespread use of techniques like as machine learning and artificial neural networks. In the last decade, when powerful processors also support data, a largeness of data or the complexity of the model has only increased the accuracy of the prediction.

Nonetheless, the subject is always uncertain when the subject is an estimation of the future, and it is still not easy to reach the necessary data. Based on some legal and commercial concerns, organizations refuse to share their data. Let's say have reached the data, also clearing and making it ready for processing is the hardest thing according to the researchers. We will examine some of these studies recently.

1.1.1. The Studies Performed in Turkey

One of the first studies in Turkey in 1995 about electricity load forecasting by Esiyok et al. In this study, daily energy consumption of 6 transformer centers (TC) in Istanbul recorded for 1993-1994 and daily data estimated by using ANN. The missing data found by interpolation analysis. The future values of the networks trained by extrapolation analysis will be determined, and the estimation realized. For five TC achieved 90% success and for one TC achieved 80% success.

In 1997, the consumption data of 1993 used in the research of Erkmen and Özdoğan. The Kohonen algorithm, a Genetic algorithm (GA) and ANN were applied separately and in a hybrid manner. The modified Kohonen algorithm classified the historical load data in the hybrid model. Then optimize the weights of the input values for the ANN using GA. Error rates in a prediction table containing 12 days of randomly selected weeks were determined as follows: Only for ANN 2.76%, 2.64% for GA and ANN hybrid, 1.89% for Kohonen and ANN hybrid, 0.96% for Kohonen, GA and ANN hybrid.

In 2002, Yalçınöz et al. conducted a monthly load estimation for the years of 2001-2004 in the Niğde region by using ANN and moving averages method. Monthly consumption between 1991-2001 taken as historical data. The real values of 2001 compared with the estimated values, and the results are in reasonable values in both models. For January, February, March, April, May, and December, ANN has less error rate.

By Topalli and Erkmen, the study conducted in 2003, short-term load forecasting depend on hybrid learning with a network application made for Turkey. In this model, data of 2000 applied to a randomly determined ANN, and a result was obtained, and new initial weight values obtained according to the errors in these results. This process has been repeated continuously until a predetermined value; thus offline learning has done. These initial weight values are used as initial weight values for the short-term load estimation for 2001. 2.31% error rate for the year 2000 and 2.45% error rate for the year 2001 has obtained.

With four different artificial intelligence methods in the study in 2003, Turkey's short-term load forecasting performed by Erkmen and Topalli. Firstly, historical data were classified, and ANN used. Secondly, data classified with Kohonen, and initial weight values were determined and used for ANN. Thirdly, a fuzzy network approach used. Finally, ANN based on learning used. The best method is the learning-based ANN system. 1.723% error rate for working days, 1.75% for Saturdays and 2.065% for Sundays.

In the study conducted by Ceylan and Demirören in 2006, the short-term hourly electric load forecasting for the Central Anatolia region was performed using a similar day approach and ANN. Load estimations made for some days of 2003 by using the electric load data and meteorological data of the years 2002 and 2003. The results also compared with the regression method. ANN results were found to be more successful.

In a study conducted in 2011 by Toker and Korkmaz, Turkey's short-term hourly demand forecasts performed. Turkey's electricity consumption data of 2008-2009 and the Istanbul`s meteorological data used. Monthly seasonality in consumption data separated by spectrum analysis. Two different estimations made: day ahead hourly and one week before the hourly forecast. The MAPE value for the last five months of 2009 was 2, and the MAPE value for the week before was 4.

1.1.2. The Studies From Other Countries

In 2003, Papadakis et al., Using temperature and consumption data from Greece between 1986-1994, estimated the hourly electric load of the year 1995. Fuzzy mean and a system using the genetic algorithm have proposed. For each season, 28 fuzzy systems were produced separately for each day of the week. The MAPE value of the proposed system was 1.76, and it gave better results than artificial neural networks.

In 2006, Pandian et al. They estimated the hourly electric load for a region of India. For some selected days, the estimation was performed using fuzzy logic. Time and temperature have given as input to fuzzy logic and load selected as an output. The conventional method and fuzzy logic results compared, and fuzzy logic gave better results with 3% error rate.

Feng et al. In their study in 2006, they used to load and meteorological data from 1999-2001 to estimate the load for 2002. The proposed method is a fuzzy-based classification method that uses optimum rules with particle swarm optimization. The days grouped as weekdays, weekend, holidays and pre-holiday days. The proposed method was better than artificial neural networks and regression method. MAPE values found as follows; 1.73 on weekdays, 2.47 on the weekend, 3.46 on holidays and 2.39 on pre-holiday days.

In 2008, Soares et al. In a study conducted by the hourly electricity load forecast, it has made for a fraction of Brazil. It was estimated for the years 1999-2000 using the 1990-1998 hourly load data. The temperature data not used as load estimate input data, the load curves of the previous years have plotted for each hour.

In 2008, two different estimates made for Spain using time series in the study conducted by Cancelo et al. The first estimate is the daily load estimate from a few days in advance. In the first estimate, the daily estimate of 2006 made by using the data of 1993-2005, and MAPE error values for Sunday-Saturday were 1.35, 1.74, 1.53, 1.53, 1.72, 1.81, 2.01, respectively. In the second estimation, for the year 2006, the hourly load estimate was made one day before by using the data of 2001-2005. The MAPE value for all days is 1.66.

Dordonnat et al. In 2008, they used the methods of unrelated regression and Kalman filters to estimate the hourly load for France. The study was estimated from August 2003 to September 2004 using data from September 1995 to August 2003. The MAPE value of hourly electricity estimation found 1.39.

In 2010, Souzanchi et al. Estimated the daily load for the eastern part of Iran. The MAPE values of the estimate for 40 days using the ANFIS method were as follows: spring - working days were found to be 0.96, summer - working days were 0.85, fall - working days were 1.13, and winter - working days were 1.3.

In a study conducted by Fan and Hyndman in 2012, a half-hour electric load estimate was made for Australia. October 2008 and March 2009 estimated by using temperature and load values between 2004-2008. The generalized additive model was better than ANN and hybrid system. The MAPE value was 1.68 in the generalized additive model.

In 2013, Koo et al. analyzed an hourly electric load estimate for the last week of April 2008, using South Korea's 2007-2008 freight data. Data classified by K-Nearest Nighbor method estimated by using Sarıma and Holt-winters methods. The Holt-Winters method gave better results. The MAPE values were respectively 2.81 for weekdays, 1.73 for Monday, 6.98 for Saturday and 5.5 for the Sunday.

2. MATERIALS AND METHODS

The flow chart for the prediction run should first start with the determination of the data, then clean the data and prepare it for processing. When the data is ready, the appropriate model be searched for it and prediction is run with this model. Estimation errors should be analyzed, and if necessary, the data should be reviewed, or changes should be made to the model. This flow continues until the desired prediction results.

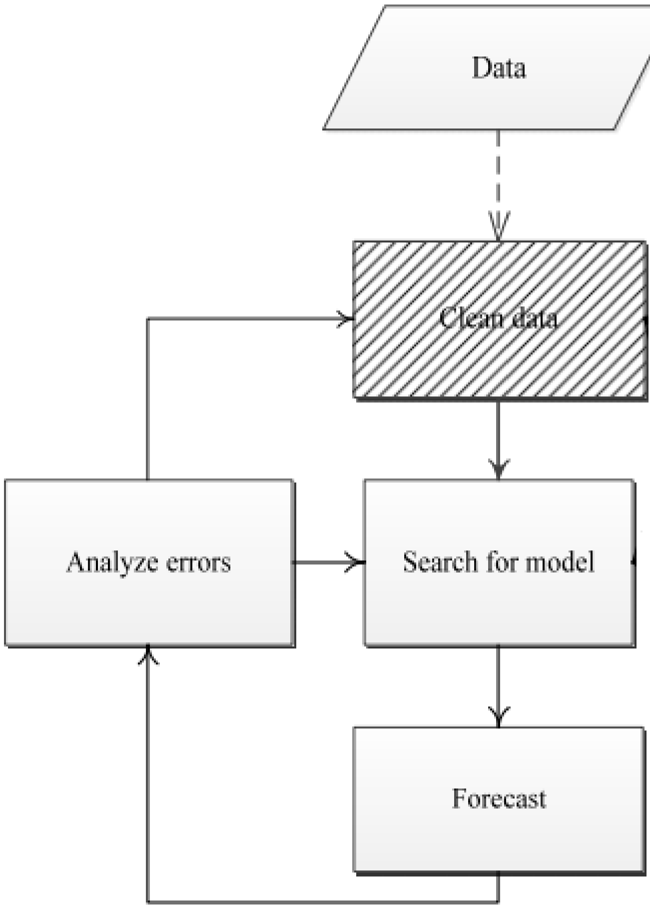


Figure 2.1: Model flow diagram.

2.1. DATA

The first task for estimation is to select the data to be estimated. Then the estimates can be successful if the independent variables that affect the dependent variable are selected correctly.

2.1.1. Consumption Data

First of all, it has to be the knowledge of the data to predict, because if the data history is unknown, then data cannot predict.

In this study, we use data provided by the Energy Markets Management Inc. (EPIAS) platform, which is between Jan-2016 – December-2017, hourly consumption data of Turkey.

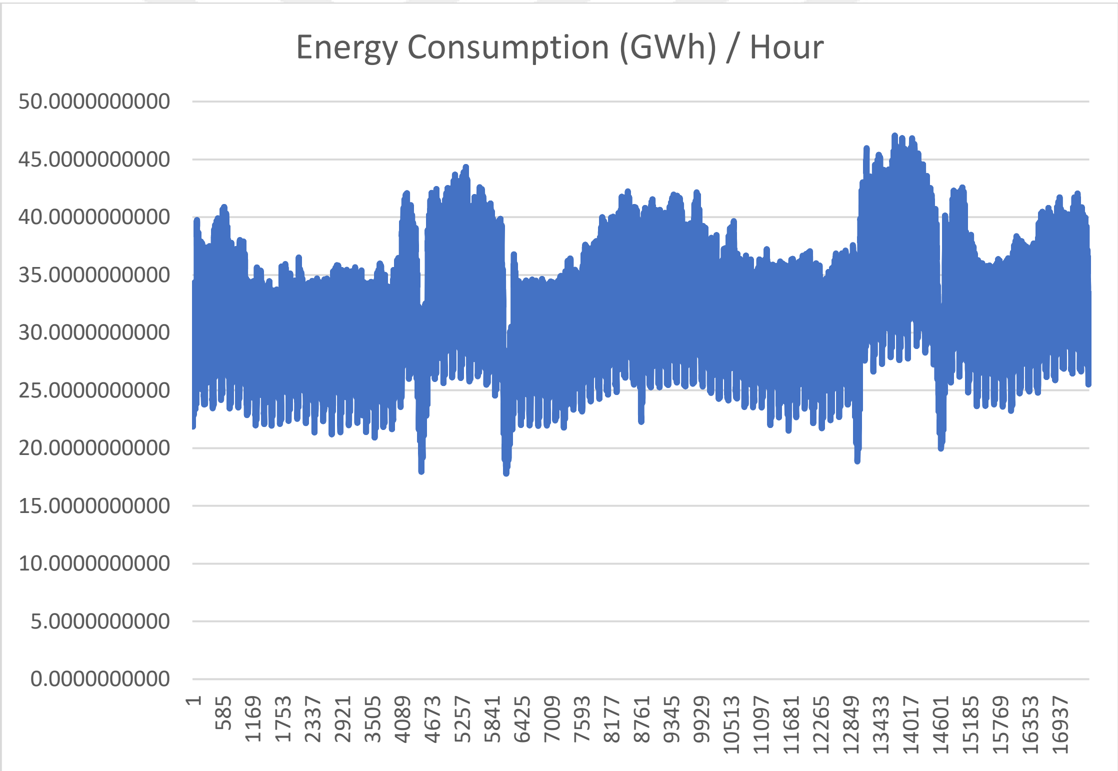


Figure 2.2: Consumption data graph.

2.1.2. Meteorological Data

```
Istasyon_No|Istasyon_Adi|YIL|AY|GUN|SAAT|SICAKLIK_°C
17020|BARTIN|2016|1|1|0|-4.8
17020|BARTIN|2016|1|1|1|-3.7
17020|BARTIN|2016|1|1|2|-4.8
17020|BARTIN|2016|1|1|3|-5.6
17020|BARTIN|2016|1|1|4|-7.4
17020|BARTIN|2016|1|1|5|-7.0
17020|BARTIN|2016|1|1|6|-6.0
17020|BARTIN|2016|1|1|7|-5.8
17020|BARTIN|2016|1|1|8|-5.5
17020|BARTIN|2016|1|1|9|-4.4
17020|BARTIN|2016|1|1|10|-3.0
17020|BARTIN|2016|1|1|11|-1.2
17020|BARTIN|2016|1|1|12|-1.3
17020|BARTIN|2016|1|1|13|-0.4
17020|BARTIN|2016|1|1|14|-0.2
17020|BARTIN|2016|1|1|15|-1.1
17020|BARTIN|2016|1|1|16|-1.5
17020|BARTIN|2016|1|1|17|-1.8
17020|BARTIN|2016|1|1|18|-1.6
17020|BARTIN|2016|1|1|19|-1.5
17020|BARTIN|2016|1|1|20|-1.9
17020|BARTIN|2016|1|1|21|-2.3
17020|BARTIN|2016|1|1|22|-2.8
17020|BARTIN|2016|1|1|23|-3.4
```

Figure 2.3: Meteorological data.

Weather conditions have always been an essential factor in the load estimation. While meteorological elements such as humidity, wind, rain, cloud cover, and storm can be taken into account, the temperature is the most effective and popular, and it is easier to measure. It is possible for temperature variables to explain more than 70% of load variance, according to the GEF2012Com data set. [21]

The meteorological data for example temperature, wind speed, cloudiness, relative humidity, and precipitation are considered reliable and predictive sources. Therefore, it is necessary to formulate forecasting and prediction models with meteorological data. [18]

Meteorological data used in the study obtained from the Turkish State Meteorological Service. It is the only legal organization which provides all meteorological information in Turkey. The data arrived on an hourly basis for 81 cities in .txt format, and it was separated with a sign "|" as shown above. Each line has the average data of an hour. In other words, for each of the 81 provinces of Turkey, data of 17521 lines will be processed in each data type.

Climate data generated by collecting the values from the locations placed different parts of the country. There were gaps in the data sets from time to time, depending on the conditions of the area where the stations located and the conditions of the faults. We have created an interface in Visual Studio to determine these and bring the data to the format that can be processed in calendar format day by day.

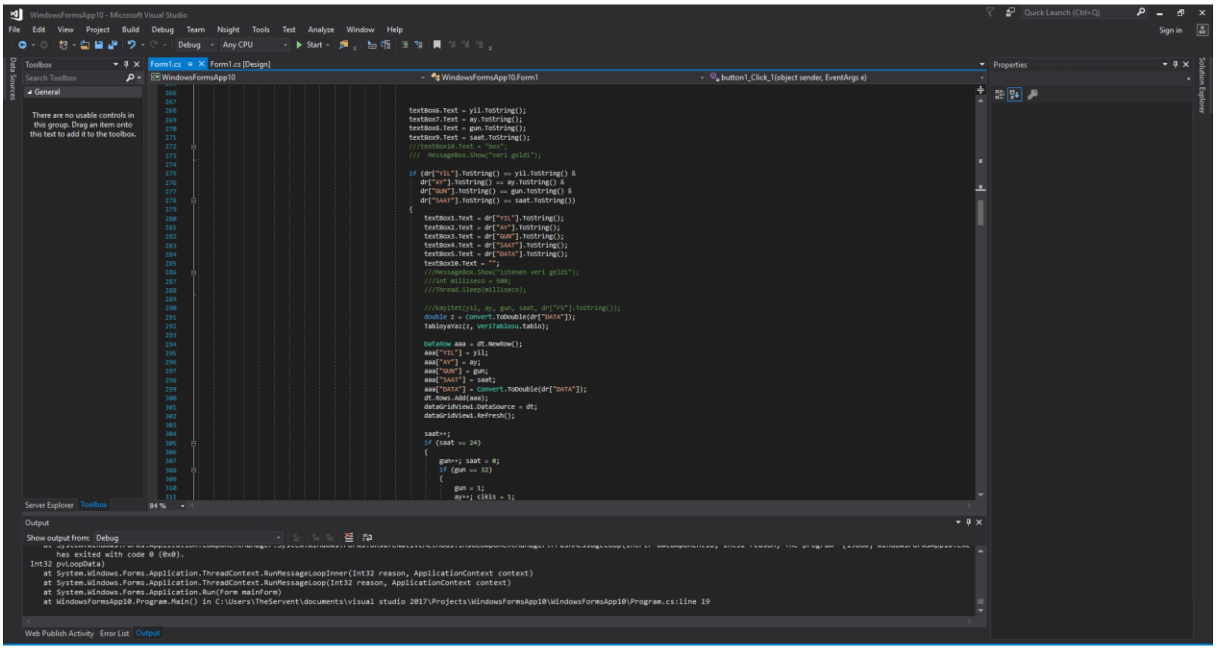


Figure 2.4: Code section of program.

This program is going to step by step according to the calendar flow, and if the data for that day exist, the program saves it in a place, but it does not exist then the program assigns the constant number in that place (constant number to detect later to make the necessary correction).

6 type of the data for 81 provinces, 17521 lines, using this program it took about three days to bring the format that we wanted to use.

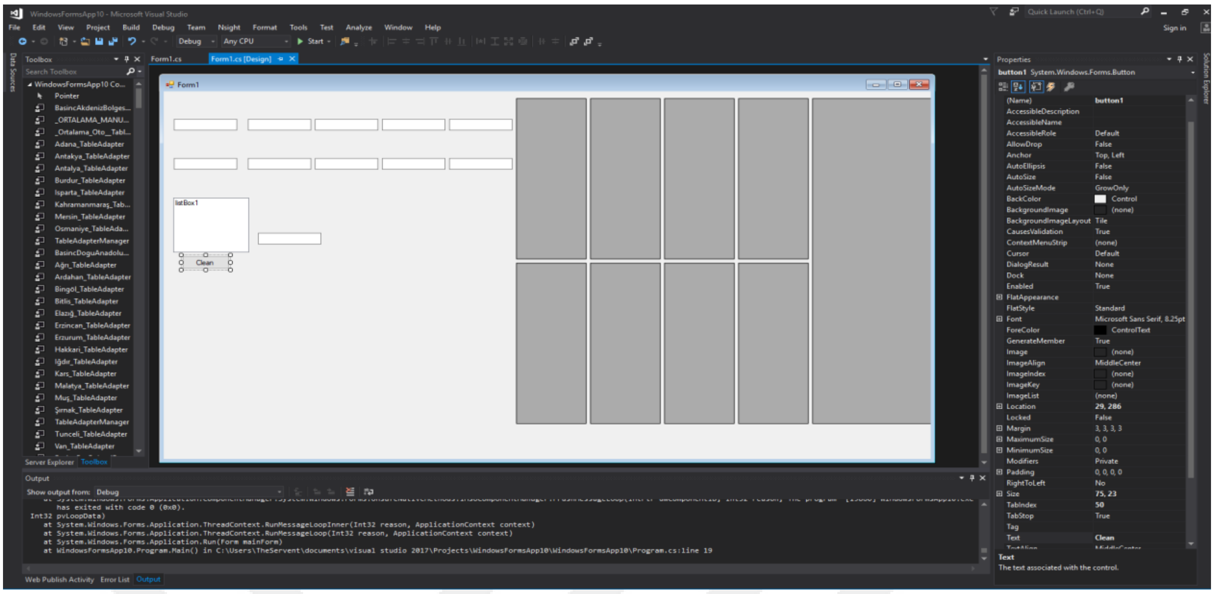


Figure 2.5: Winform design.

The data were sorted by seven geographic regions during the data editing, to calculate the hourly average of each region. The hourly averages in the model used as independent variables.

The program was run separately for each data type. On the screen, each column gives the data of a region. In the large column, missing data can be followed. Small cells show the current year, month, day, time and data information.

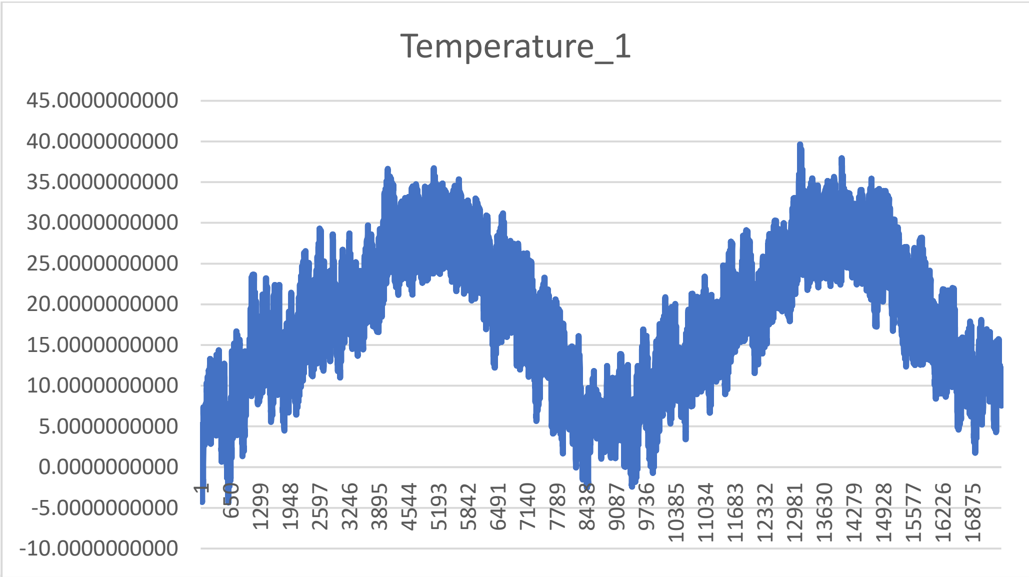


Figure 2.6: Temperature data graph.

Chart of the Mediterranean region of Turkey shows the average hourly temperature data in 2 years. Temperature is considered to be an essential variable in electricity consumption as it directly affects cooling and heating systems; also, the operating temperature for all electrical devices is an important criterion. The effect of the air temperature on the performance of the running appliances and the electricity consumption should be taken into account. In our study, we used hourly temperature changes as independent variables.

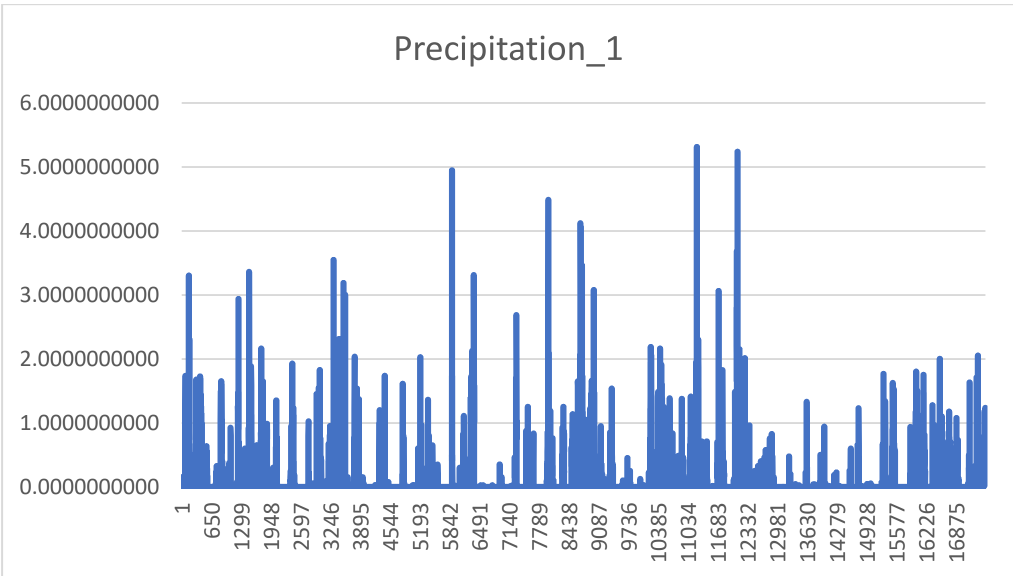


Figure 2.7: Precipitation data graph.

In this graph, the average amount of rainfall in the Mediterranean region observed. The unit quantity calculated in Kg / m ^ 2. It does not have a periodic distribution, such as heat. It affects the electricity consumption as a result of some effect of rain. For this reason, we used this data in our study.

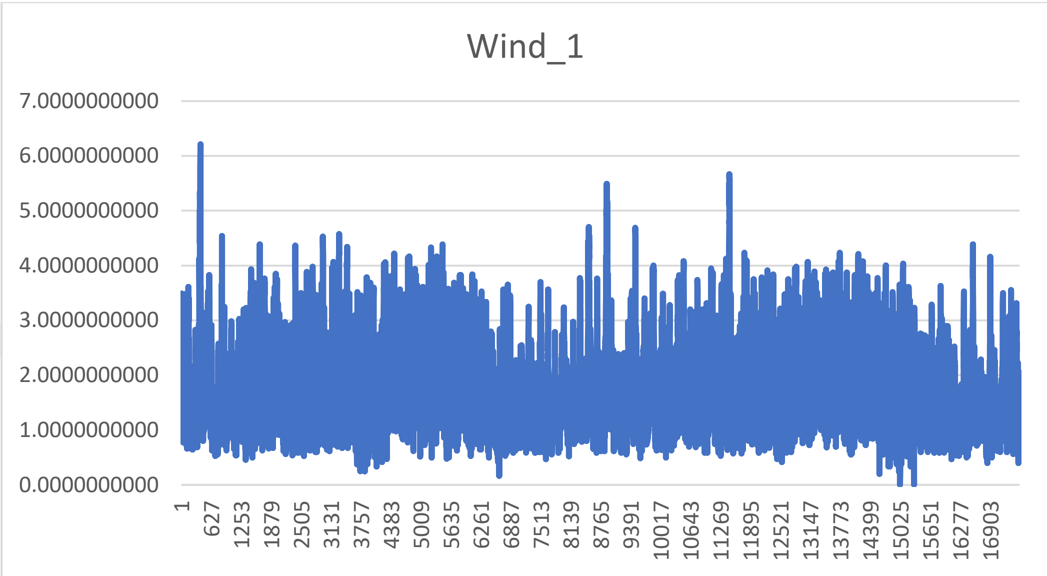


Figure 2.8: Wind speed data graph.

The wind speed in the graph is the average data for the Mediterranean region. It is calculated in m / s, the average of the region is below 4 m / s. It is included in the model assuming an effect on energy consumption.

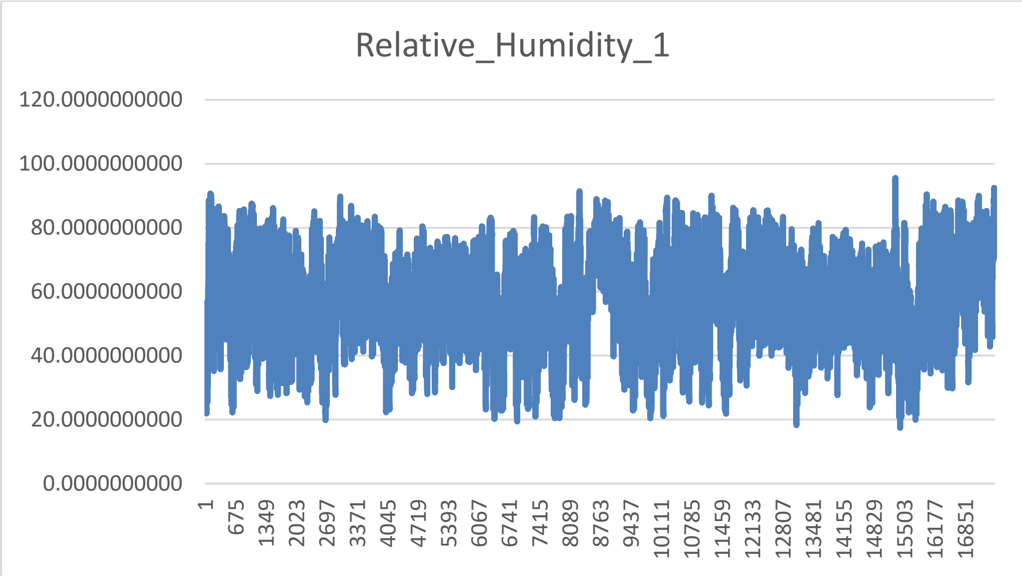


Figure 2.9: Relative humidity data graph.

The mean relative humidity in the Mediterranean region ranged from 40 to 80 percent. Since the humidity affects the operation of the air conditioning systems. Humidity is included in the model, assuming it will have an impact.

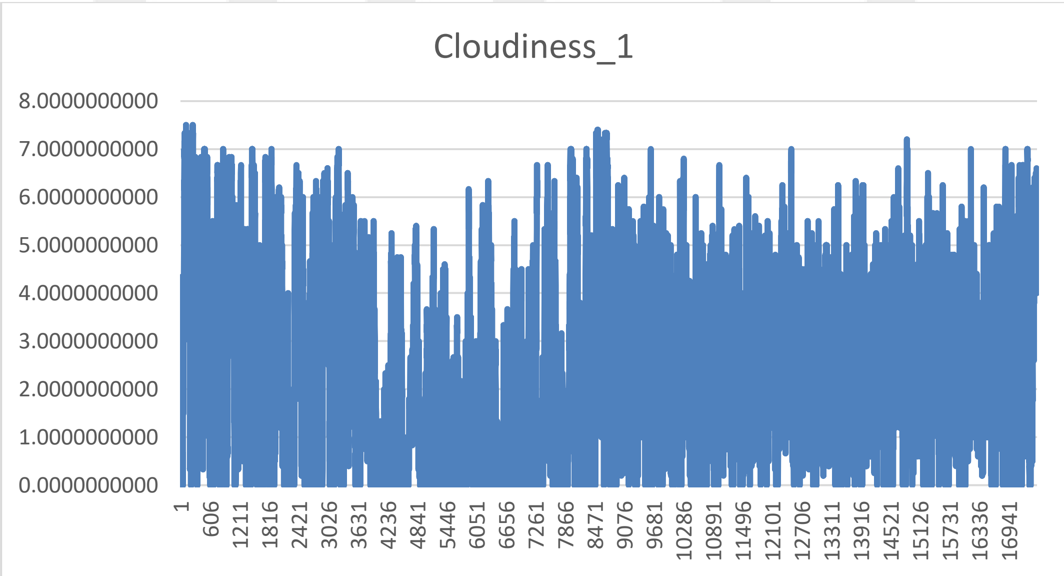


Figure 2.10: Cloudiness data graph.

The graph above shows the cloudiness of the Mediterranean region. The values calculated by taking the regional average. Since cloudiness affects lighting systems and warming due to sunlight, it is also included in the model assuming it affects energy consumption.

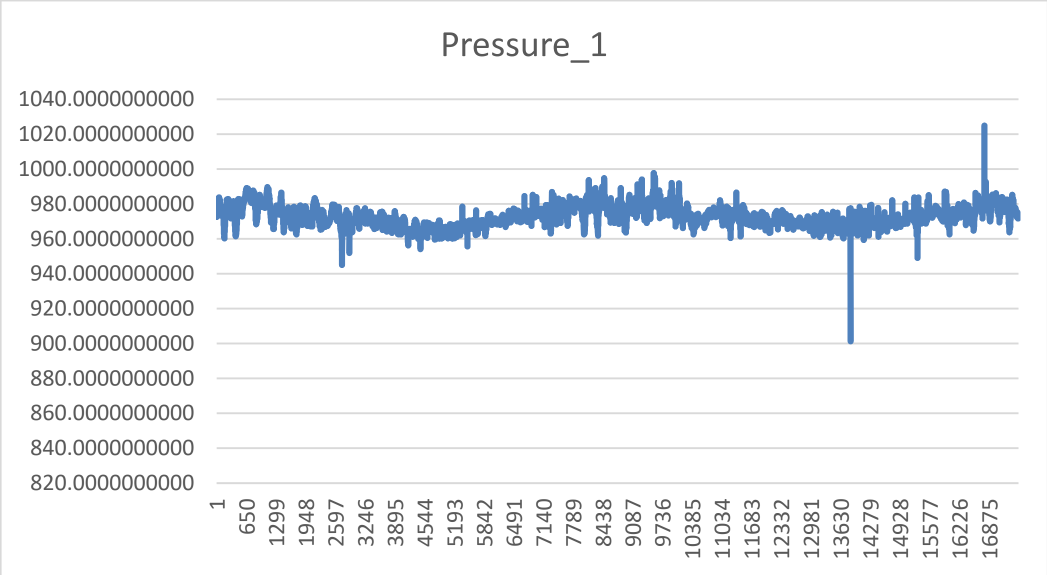


Figure 2.11: Pressure data graph.

Atmospheric pressure or barometric pressure; values were in hectopascal (hPa). Although there is no study about pressure effect in consumption demand in the literature, the pressure data was also used with the thought that it would increase the accuracy of the model since it was directly related to other climate data.

2.1.3 Normalization of Data

We also normalized the data to be between 0 – 1 using an easy formula which is defined below.

"E" used as a variable in the calculations below. The other variables in the dataset normalized in the same way.

For the variable E in the ith row, normalized value is e_i, calculated as:

$$\text{Normalized } (e_i) = \frac{e_i - E_{min}}{E\max - E_{min}} \tag{2.1}$$

Variable:

E_{max} = the maximum value of E

E_{min} = the minimum value of E

2.2. ARTIFICAL INTELLIGENCE

Artificial Intelligence looks at what people do better and study to do it with the computer better than human. The primary purpose of artificial intelligence is to improve computer behavior and thus can be called intelligent. The theories and ideas expressed by Greek philosophers and scientists constitute the origins of AI.

AI is a research area where intelligent thinking viewed as a form of computation that can be formulated and ultimately mechanized. However, To achieve this should be addressed two critical issues. The first issue is knowledge manipulation, and the second is knowledge representation. Mechanized intelligence lies the intersection of these two issues.

AI combines pure logic with precision and processing power to reduce the error of operation while solving problems. Many jobs in industries taking over by robot expert systems already. These jobs dangerous for human or exceed human abilities. It can be emphasized that AI has many potential applications. For autonomous control and target identification, the army goes into the entertainment industry for robotic pets and computer games.

It is possible to learn about AI with an open-source framework, in practice, AI is hard. “The software is free, and we can rent the hardware for pennies an hour in the public cloud, but AI is data science, and that has two matter – one is the data, and the other is the science.” All AI works through learning by example to find patterns in sets of data. [41]

Actually, AI concerned with a broad field of science, not only computer science but also, philosophy, linguistics, psychology, and other areas. AI is interested in working with a computer to do work that requires human intelligence. There are many perspectives on AI, and many definitions can be found. Below listed some of those bright definitions for fundamental characteristics.

Some general definitions:

- “Artificial intelligence is usually a computer-operated system that exhibits behavior based on human intelligence.”
- “Artificial Intelligence is the ability to do things that require a lot of knowledge to do by human beings but easily by the machine.”

Alan Turing definition of discipline, he is the founding father of AI:

- “AI is the engineering and science of making intelligent computer programs and smart machines.”

In these definitions, intelligence explained in a concept that refers to reasoning and learning, to communicate in natural language, to planning, construct knowledge and the ability to sense.

Figure 2.12: AI explanation.

Actually, this is about working with a specific topic. The computer can win human in playing chess, but that same computer may not solve a complex math problem. So meaning it can only do what it created to do is. Currently AI design for narrow areas. In this case, it means that a special algorithm must be designed for each problem to solve it. Being Narrow for AI is to be more successful on focused task, and are mostly much better than humans: for example translation, calculus, face recognition, chess computers. General AI is The holy grail for AI, that the only one system that can be trained and can earn the ability to solve any problem is presented. This is exactly the same as human behavior: we can specialize in a particular subject from metaphysics to abstract mathematics and from art to sports. We can also specialize in all of them.

An AI system uses a combination of data analysis methods and machine learning to obtain AI capabilities. [20]

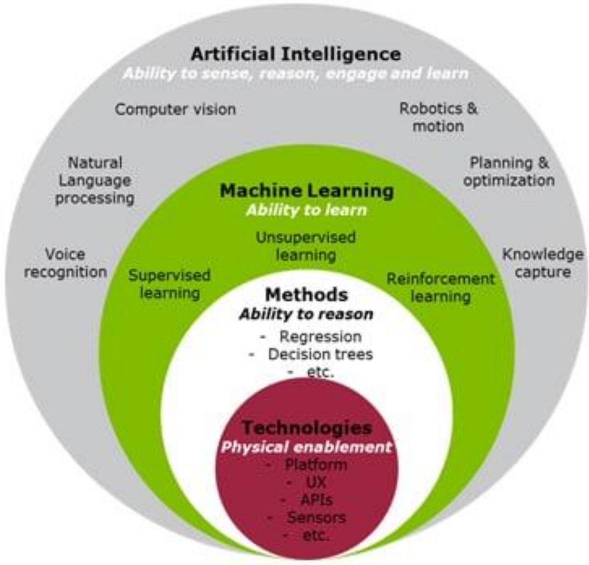


Figure 2.13: AI topics.

In many applications for demand estimates, Artificial Intelligence techniques are increasingly used instead of more classical techniques. Two of them which applied in this study reviewed in the next section.

2.2.1. Artificial Neural Network

Animals also have a brain, and they use it to process information from their environment and to decide how to adapt to changing conditions. Of course this ability to perform come from their nervous system. Scientific studies show simulation and modelization of the nervous system is possible. In artificial systems also possible to obtain similar behavior and to reproduce it. ANN (Artificial Neural Networks) is the network that is used to process modeled as a sample of the neural structure of a brain. Honestly, human or animal brains number of the neural structure is billions, but ANN might have only thousands of neurons still.

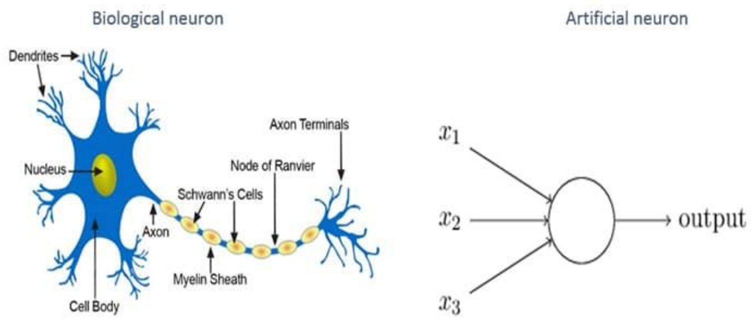


Figure 2.14: Neuron cell.

The basic principle is about the connection between each neuron, that called the neural structure and each connection line has a specific strength. The output of a neuron produced from the data obtained from the weight of the inputs from all the other neurons. This output can also be used as input to another neuron. This easy technique modeled in the structure of ANN, each connection strength represented with weights between neurons. This is the beginning of the cycle. First every neuron request data as input from the neurons which is connected, and using a mathematical function on the data, an output will be calculated. Then this output is used for another neuron's input.

In the biological human brain, the learning process can be explaine with changing of connection strength between neurons. Similar to this, ANN changes the weights of connection between the neurons. So using enough training dataset, with the right features, the neural network can calculate the weighs between the artificial neurons. This can be named recognization of features for the neural network.

Mainly every network has three part of neurons. First is the input layer which is attendant to collect every input data and deliver them to the next layer. Second is named hidden layer, this part of the network can contain more than one layer. According to the complexity of the network. This part is the decision part, every output data from the first layer processed with their weigh, in the hidden layer. A third one is the output layer which receives all output data from the hidden layer and converts this to the result.

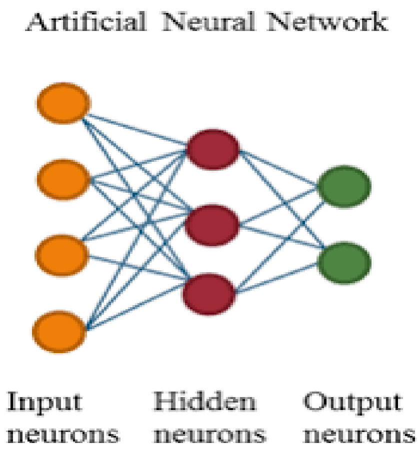


Figure 2.15: Artificial neural network.

The figure shows a sample structure of a neural network, the network connects all neurons from one layer to another layer. This is the type of fully-connected network. Connection models can be design many different ways depending on the solution that searched for. For example, Convolutional networks generally are used for image recognition. In this type only specific groups of neurons connected to particular groups of neurons from the next layer. And Recurrent networks generally preferable for speech recognition task. Thus, possible to make loops between next layer neurons and back layer neurons.

2.2.2. Support Vector Machine

There are many classification problems in daily life, such as email checking, it is spam or not. As a purpose of these problems is to determine specific class that separates data whether is true or not. This process called classification and to do this; the model should be trained. When finished first training, with a set of data (e.g., set of emails given status is spam or not) to build classifier model on target. The model now ready to classify new, unseen data. SVM (Support Vector Machines) is a powerful technique for such types of issue.

Basically, the purpose of the SVM is that decide the borderline which is paralleled to each other to provide max gap between the classes of the dataset. An easy explanation is below to understand this:

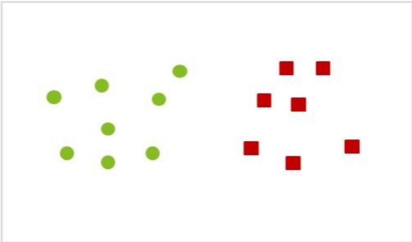


Figure 2.16: Data set.

In this example, customer segments in a whole set of customers, represented in two different shapes with red squares and green circles (e.g., low risk and high risk). For each customer can be considered all kinds of properties. To solve the classification problem, need to find Valid boundary line, should be checked to separate to be all red squares in one side and all green circles another side. Of course, there are many drawn lines can be found for this condition. Four different examples can be seen as sample of these lines below:

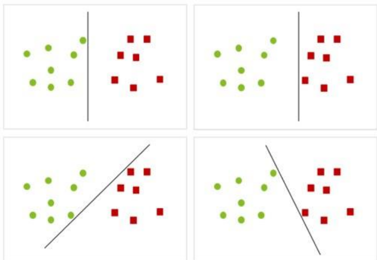


Figure 2.17: Data divison.

As mentioned before, SVM tries to maximize the area between boundary lines; these separate the two classes. As follows this can be shown:

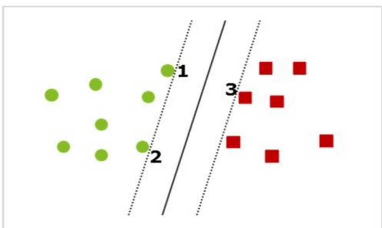


Figure 2.18: SVM boundaries.

In order to separate the data, parallel two lines must be selected between mentioned examples which divides dataset with maximum gap.

Supporting vectors from data points in any of the lines between the data, the name SVM comes from here. In this example (Figure 2.18), there can be seen three supporting vectors.

If one of data point that is not a supporting vector moved a bit, it does not affect boundary lines. However, if supporting vectors (e.g., points showed with 1,2 and 3 in Figure 2.18) position changed even slightly, it means boundary lines will change. In this case, the classification line will also change.

In this example shown simplified data, but in real life, it is more complicated. Usually, need to work with three or more dimensions. SVM technique draws not only straight separation lines but also certain types of non-linear boundaries, using mathematical formulation and some kernel structure.

SVM can use in many applications, for example, face recognition, image recognition, or handwriting recognition.

2.3. WEKA

Weka is a library of machine learning algorithms with work area. Programmed in java for data mining studies. Also, it has extensions and preparation tools for data. (For association rules mining, clustering, regression, classification, and visualization). Weka licensed by GNU (General Public License), so this means open source software can be used or distributed by anyone.

Weka has many regression algorithms on the platform. Also one of the advantages is having many machine learning algorithms in the platform. It makes easily possible to model using machine learning.

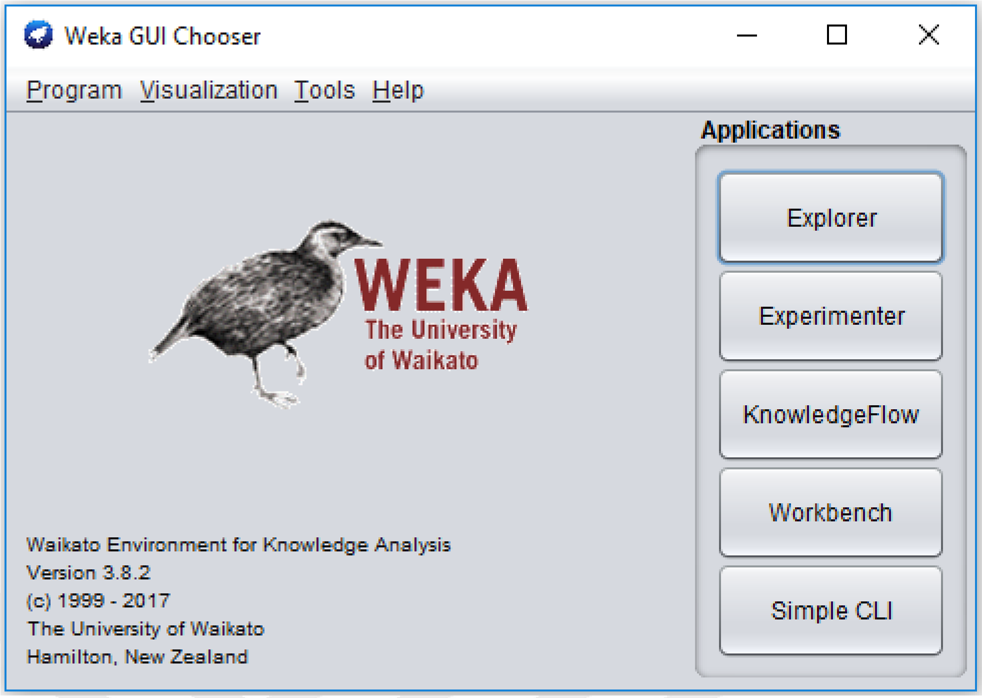
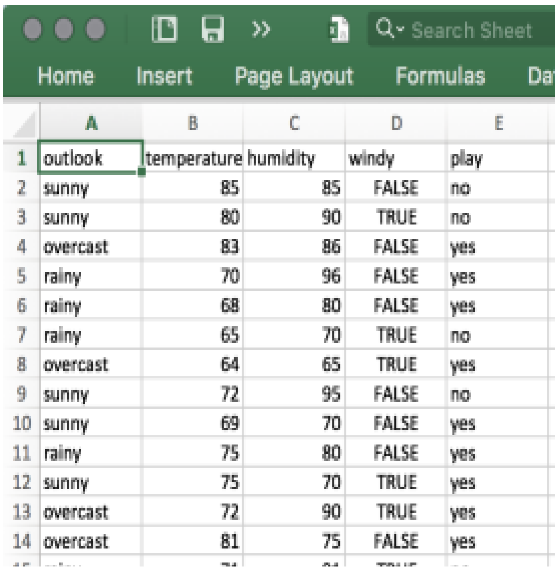


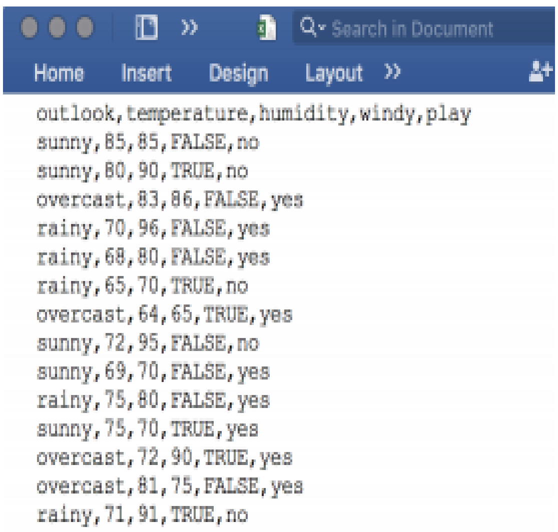
Figure 2.19: Weka gui chooser.

The latest version of WEKA available on the WEKA web page, and can be downloaded freely, it works on both Windows or Linux. For a newcomer, many helpful documents and resources can be found in the documentation, also enough alone WEKA manual.



	A	B	C	D	E
1	outlook	temperature	humidity	windy	play
2	sunny	85	85	FALSE	no
3	sunny	80	90	TRUE	no
4	overcast	83	86	FALSE	yes
5	rainy	70	96	FALSE	yes
6	rainy	68	80	FALSE	yes
7	rainy	65	70	TRUE	no
8	overcast	64	65	TRUE	yes
9	sunny	72	95	FALSE	no
10	sunny	69	70	FALSE	yes
11	rainy	75	80	FALSE	yes
12	sunny	75	70	TRUE	yes
13	overcast	72	90	TRUE	yes
14	overcast	81	75	FALSE	yes

Figure 2.20: Sample dataset.

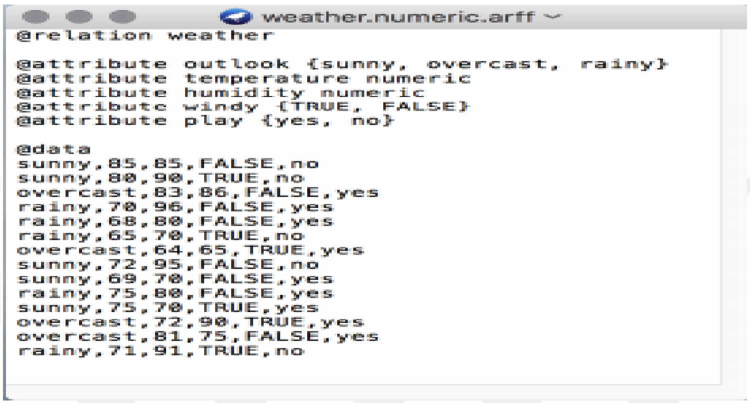


```
outlook,temperature,humidity,windy,play
sunny,85,85,FALSE,no
sunny,80,90,TRUE,no
overcast,83,86,FALSE,yes
rainy,70,96,FALSE,yes
rainy,68,80,FALSE,yes
rainy,65,70,TRUE,no
overcast,64,65,TRUE,yes
sunny,72,95,FALSE,no
sunny,69,70,FALSE,yes
rainy,75,80,FALSE,yes
sunny,75,70,TRUE,yes
overcast,72,90,TRUE,yes
overcast,81,75,FALSE,yes
rainy,71,91,TRUE,no
```

Figure 2.21: Csv format.

At the begin, inputting dataset into WEKA is the first step. It usually, work with a .arff file format but also .csv file format acceptable. The format is about labeling data.

Format creation is easy as be can, labeling starts with a definition of data (@relation ...), then needed to define enough features for data using (@attribute ...). After this first part, (@data) information series have to be entered into the file. There is no limitation for data set. Mostly .csv file or .data file formats will use. They can be convertible to .arff also.



```
weather.numeric.arff
@relation weather

@attribute outlook {sunny, overcast, rainy}
@attribute temperature numeric
@attribute humidity numeric
@attribute windy {TRUE, FALSE}
@attribute play {yes, no}

@data
sunny,85,85,FALSE,no
sunny,80,90,TRUE,no
overcast,83,86,FALSE,yes
rainy,70,96,FALSE,yes
rainy,68,80,FALSE,yes
rainy,65,70,TRUE,no
overcast,64,65,TRUE,yes
sunny,72,95,FALSE,no
sunny,69,70,FALSE,yes
rainy,75,80,FALSE,yes
sunny,75,70,TRUE,yes
overcast,72,90,TRUE,yes
overcast,81,75,FALSE,yes
rainy,71,91,TRUE,no
```

Figure 2.22: arff format.

Generally encountered datasets file formats are various. Therefore it may be better to learn how to create files a .arff format. Even so, it is possible to import a .csv format.

2.3.1 Building a Model

Many model evaluation techniques can be chosen from, and the Weka machine learning workbench offers them.

2.3.1.1 Class Multilayer Perceptron

This is a classifier that uses backpropagation to learn a multi-layer perceptron to classify instances. The network can be built by hand or set up using a simple heuristic. The network parameters can also be monitored and modified during training time. The nodes in this network are all sigmoid (except for when the class is numeric, in which case the output nodes become un-thresholded linear units).

2.3.1.2 Class SMOreg

SMOreg implements the SVM for regression. The parameters can be learned using various algorithms. The algorithm selected by setting the RegOptimizer. The most popular algorithm (RegSMOImproved) is due to Shevade, Keerthi et al. and this is the default RegOptimizer.

Kernel structure performance is essential for this class. About the kernel, Jean-Baptiste Fiot and Francesco Dinuzzo design kernels specifically tailored to capture the seasonal effects present in electricity load data, to define suitable kernels.

Also demonstrated in the study that kernels with a multiplicative structure yield superior predictive performance with respect to the widely adopted (generalized) additive models. [6]

2.3.1.3 Train – Test Split Method

This is rather important concepts in data science and data analysis and is used as tools to prevent (or at least minimize) overfitting. Method explained in figure 2.23.

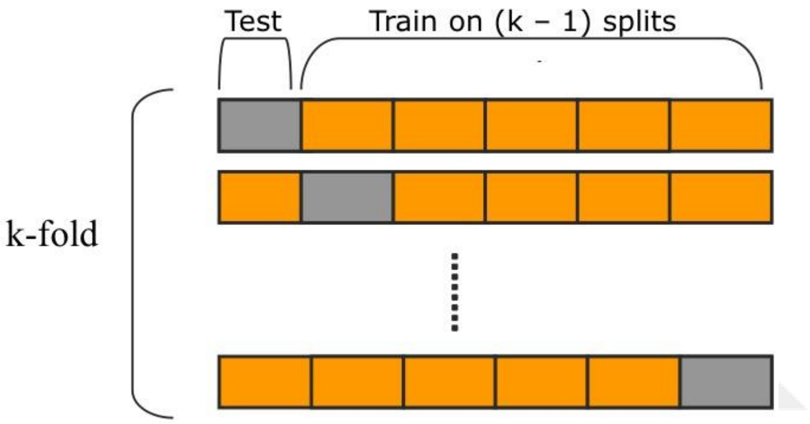


Figure 2.23: Split method.

2.3.1.4 Cross Validation Method

Cross-validation method is one of the evaluation techniques; it helps to run model systematically with percentage splits data. Each dataset will divide into ten pieces ("folds"), then for every stage hold out one piece to turn the testing data and the remaining nine for training. This makes it ten times and gives an average of ten evaluation results. In "stratified" cross-validation, when making the first distribution, we make sure that each layer contains the approximate correct ratio of class values. After having ten times the cross-validation and calculating the evaluation results, Weka calls the learning algorithm last (11th) time in the entire data set to obtain the model it prints.

3. RESULTS

Analyzes were carried out in three stages:

a) Data preparation – data received is filtered and prepared for analysis (includes interpolation of small errors). The preliminary exploratory statistical analysis includes correlation and factor analysis.

b) Preparation of models and training of models with data. Proper coefficients determination by the program.

c) Reporting of results and comparison of models, evaluation according to success percentages.

In this section, the experiment results of the chosen models were shown, with an explanation. Before starting to prediction, data divided into two as training and test data. Both the normalized and the raw data from the 17520 line, divided 14592 line (83%) as educational data, the remaining 2928 line (17%) as test data.

Analyzes were made entirely using weka application. The prediction started after selecting the appropriate coefficients and making the settings for the specified models. Class multilayer perceptron and class smoreg used. For each class, the training test method runs first; then the cross-validation method was used again.

3.1 CLASS MULTILAYER PERCEPTRON

The multilayer perceptron algorithms can help with the classification and regression problems.

It also referred to as neural networks or as artificial neural networks.

Neural networks are complex structures use for prediction modeling, and there are several configuration parameters that managed intuitively and are decided by many tests and corrections.

Artificial neural networks is an algorithm created by taking the model of biological neural networks. One small part of brain is the neurons, they are small processing units. ANN designed with the thought that, if configured, they have the ability to reach the desired point for the intended purpose. In classification, we try to approach the underlying function to make the best separation between the data sheets. In regression problems, we try to formulate the function that best suits the actual value output.

Choosing Multi-Layer Perceptron algorithm:

1. To select “MultilayerPerceptron” click the “Choose” button and find it under the “function” tab.
2. If click on the algorithm`s name, review of the algorithm will appear.

It can manually specify the structure of the neural network used by the model, but it recommended for beginners to select automatically.

When the default is selected, the design of the network will be done automatically and will be trained in the target dataset. By the way for default settings, the hidden layer network will be created only one. The number of hidden layers can be set from hidden layers parameter, and the default is set to "a" automatically.

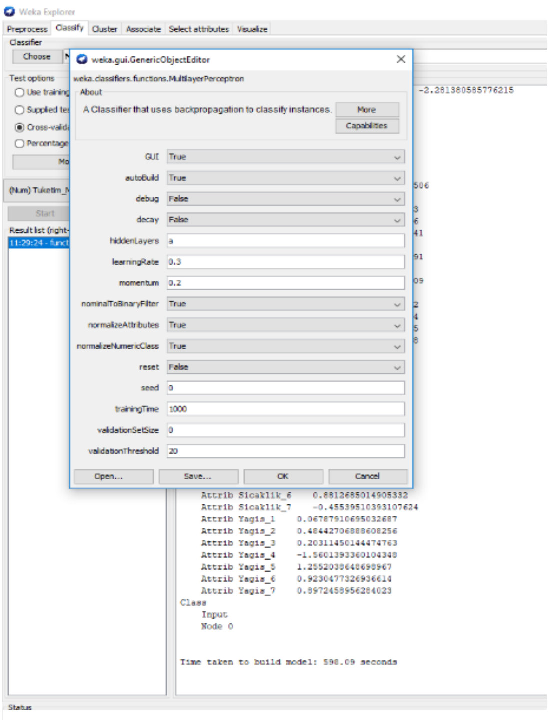


Figure 3.1: Weka object editor.

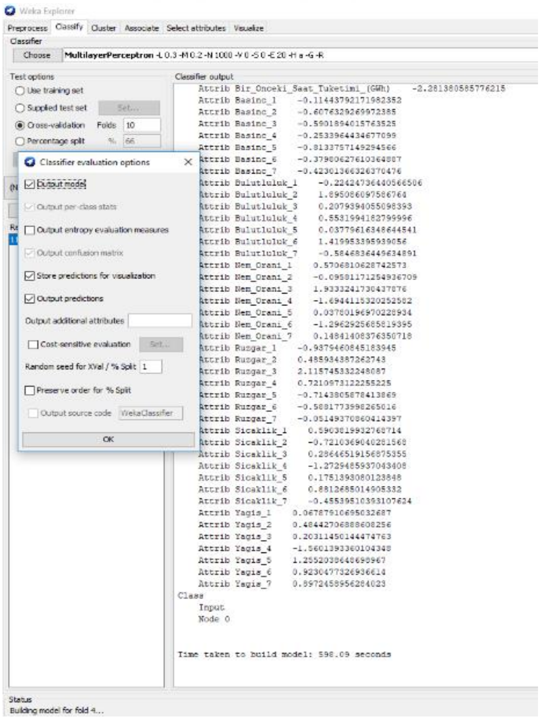


Figure 3.2: Weka classifier evaluation opt.

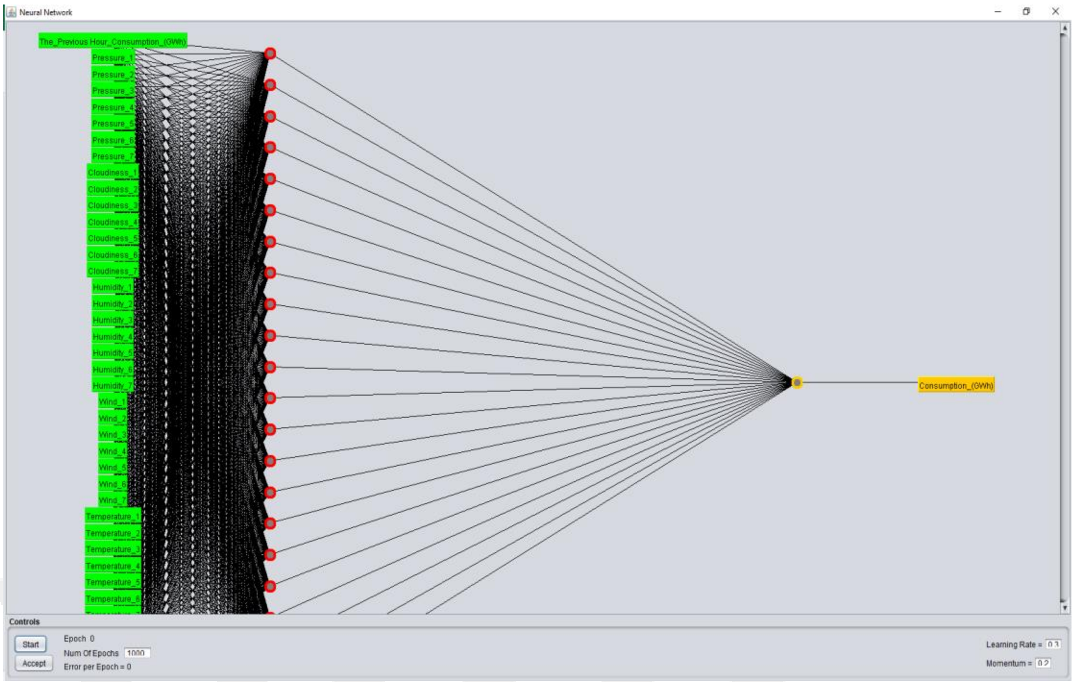


Figure 3.3: ANN stracture of model.

GUI is a beautiful tool for designing the network structure. It may be fun, but it is better to use the GUI with a training test method. When you select cross-validation, you will be asked to design a network for each layer of ten steps.

By setting the learning rate, it can configure the learning process by specifying how much time the model will update each period. Generally used small values are between 0.1 and 0.3(default).

In the learning process, the momentum (default 0.2) set to update the weights, even if no changes made, and decay used to reduce the speed of learning (fixing to actual value). It performs more learning at the early stage of training and diminishing towards the end.

1. Algorithm configuration close after clicking to the “OK”.
2. On the target dataset, to run the algorithm, click the “Start” button.

At the default configuration, Multi-Layer Perceptron algorithm gives an RMSE value that reported at the output section.

Estimates were made with the settings shown on the screenshot in the weka application, hidden layer selection was automatically assigned to the ANN structure, learning rate was 0.3, momentum was 0.2, and the number of iterations was 1000. Output predictions were checked to see the output values.

3.2 CLASS SMO_REG

SMOreg Class is selected to forecast using SVM, the complexity constant C is set to 1.0 and polykernel -c250007 -E 1.0 was preferred in the kernel structure.

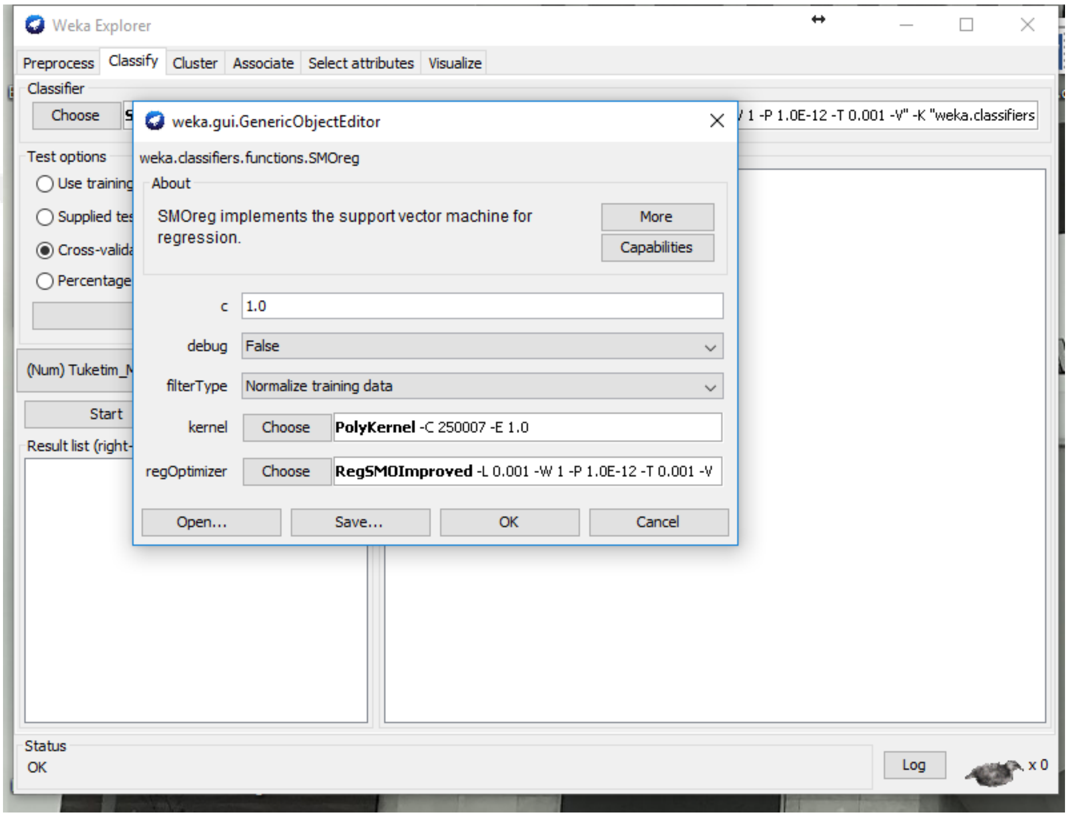


Figure 3.4: Class smo_reg object editor**.**

There have been many technical extensions to support regression and multi-class classification problems, Support Vector Machines is a tool developed for binary classification problems. SVR (Support Vector Regression) is the adaptation tool of SVM for regression.

Chooseing the SVR algorithm:

1. Push the “Choose” button, go “function” group and select “SMOreg” under the tab.
2. If click on the algorithm`s name, review of the algorithm will appear.

One of the parameters in weka is the complexity parameter; it is called C. Weka checks the gap between data when drawing a separation line, to control all possibilities, and select the best one. To understant this, if the given value of C is equal zero, then margin violation is forbidden. And value 1 is selected defaultly.

Choosing kernel type is the critical step for SVM. The linear kernel is the simplest kernel that uses hyperplane or straight line to separates data. Default selected kernel is Polynomial Kernel in Weka. The kernel uses high degree functions and a curved line to separate classes better than linear separation. Exponential value increases if the function is more wiggly or higher polynomial.

A linear kernel is the default of The Polynomial Kernel tool, and the exponent value is 1. Radial Basis Function Kernel acceptable the most useful and powerful, shortly it is called RBF kernel. That kernel has a capacity of solving closed polygons and difficult types of shapes.

To see what works best, need to try different C (complexity) values and suite of different kernels on the problem.

1. Algorithm configuration close after clicking to the “OK”.
2. On the target dataset, to run the algorithm, click the “Start” button.

At the default configuration, SVR algorithm gives an RMSE value that reported at the output section. [39]

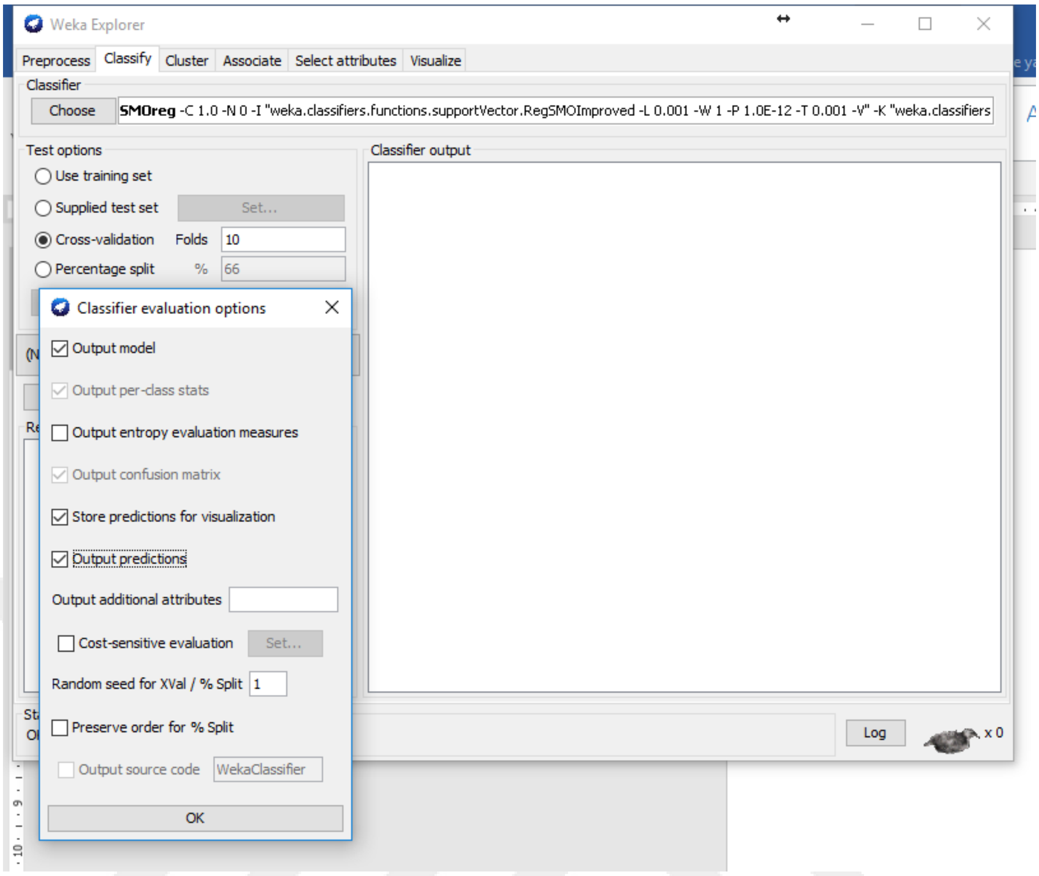


Figure 3.5: Class smo_reg evaluation opt**.**

First the model was trained with the training data, then the test data was tested in the trained network. Finally, all of the data was used for re-modeled with the cross validation method, ten fold was selected at the end results were saved.

3.3 PERFORMANCE of MODELS and METHODS

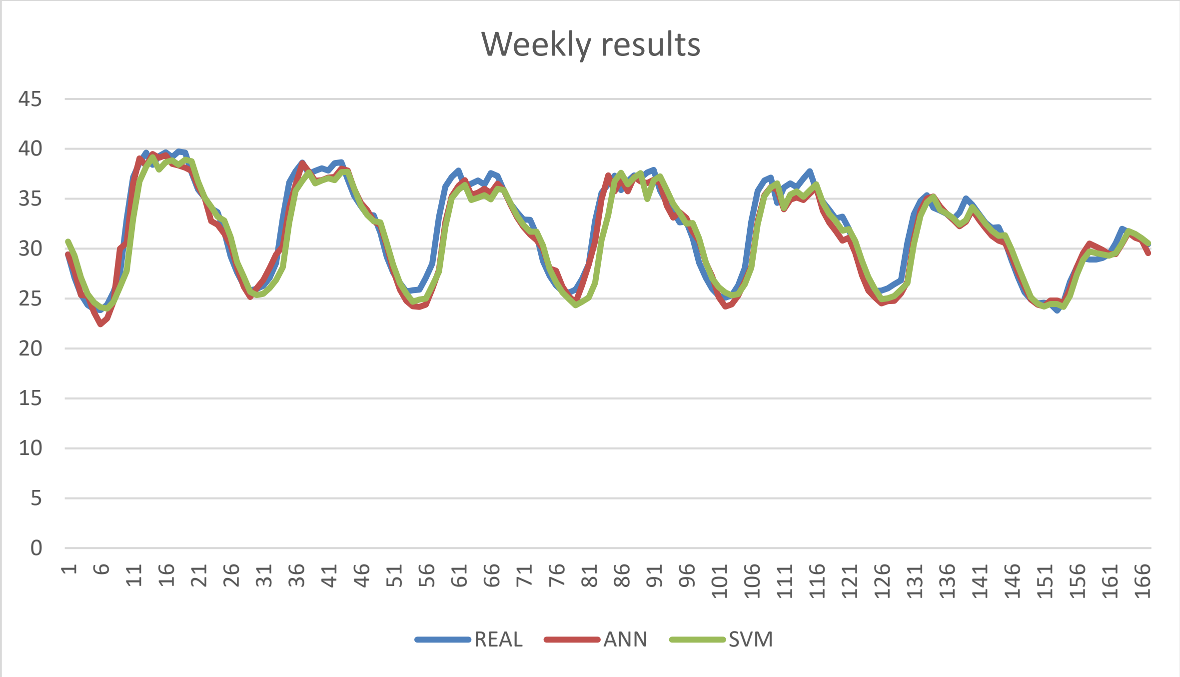


Figure 3.6: Graph of weekly results.

Electricity consumption is not linear naturally, yet there is daily and weekly periodic similarity. Estimates made to take advantage of this similarity in the literature are evaluated in parts, as weekdays, weekend, summer, winter.

The graph above shows the one-week portion of the analysis. The daily movement pattern can be seen. It shows that energy consumption reached its highest value on Monday. The weekend falls sharply compared to business days. And, it reaches its lowest value on Sunday.

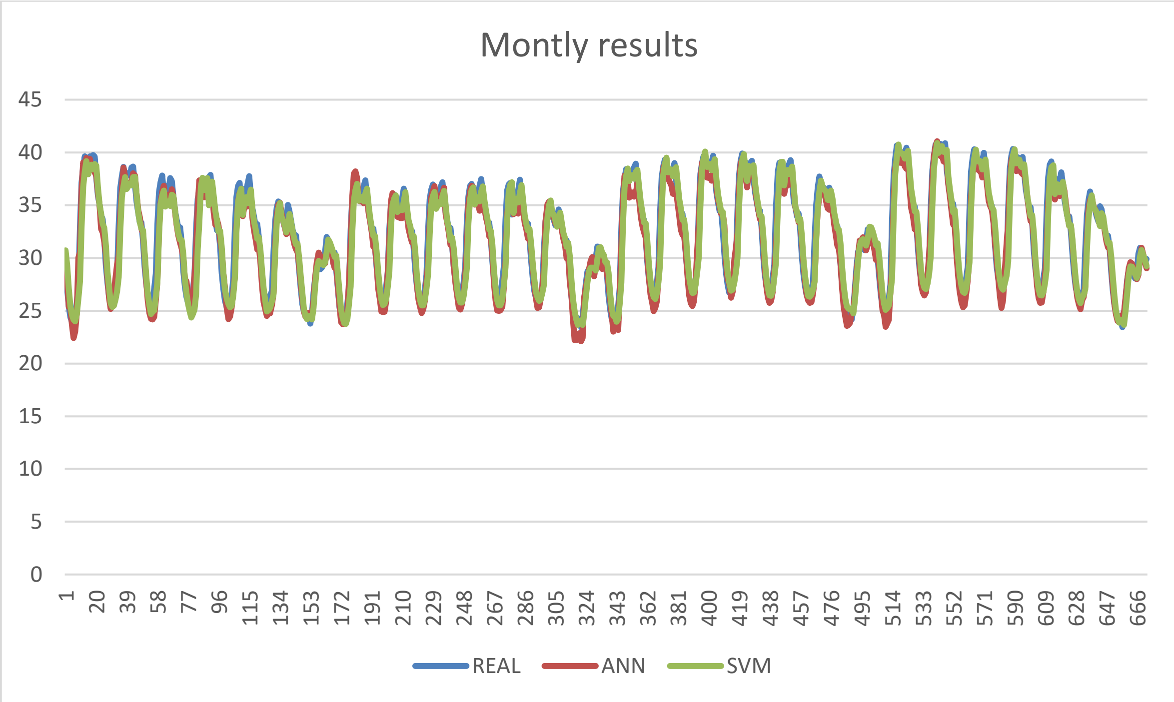


Figure 3.7: Graph of montly results**.**

This chart shows a monthly section from the results of the performed work. The similarities in consumption can be seen in weekly harmony. However, it is clear that there are differences in electricity consumption for every day.

We used the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Correlation Coefficient(figure 3.8) to compare model performance, these techniques are used widely by energy forecasting community.

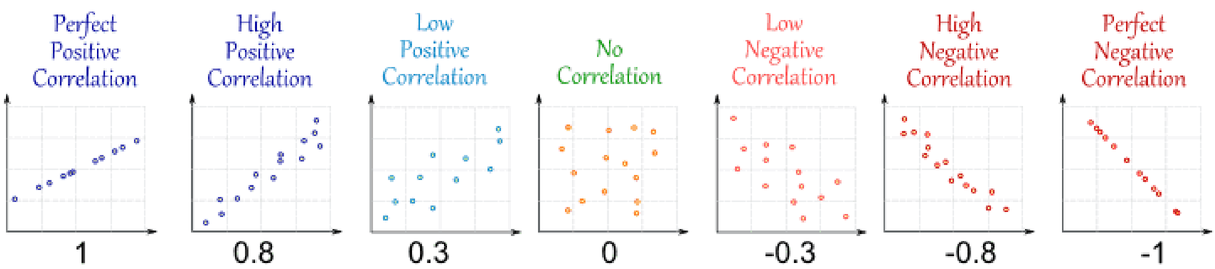


Figure 3.8: Correlation coefficient explanation.

(address: http://www.mathsisfun.com/data/correlation.html)

Mean absolute error formula is:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \|\hat{\theta}_i - \theta_1\| \tag{3.2}$$

Root mean square error fomula is:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (\hat{\theta}_i - \theta_i)^2} \tag{3.3}$$

Correlation coefficient fomula is:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{3.4}$$

3.3.1 Analyzes with Normalized Data

Table 3.1: Train results with normalized data.

Normalized Data - Train	ANN	SVM
Correlation coefficient	0.9785	0.9663
Mean absolute error	0.8679	0.9048
Root mean squared error	1.1511	1.3156
Total Number of Instances	14592	14592

When we train the model with normalized data, in the model established using ANN, 0.9785 accuracy achieved. And the model established with SVM an accuracy 0.9663 was obtained. MAE was 0.86 for ANN, and 0.90 for SVM. According to the results of the analysis made with this data set, we can see that ANN results are better.

Table 3.2: Test results with normalized data.

Normalized Data – Test	ANN	SVM
Correlation coefficient	0.9618	0.9596
Mean absolute error	1.0954	0.9281
Root mean squared error	1.4492	1.3248
Total Number of Instances	2928	2928

When we tested the data that we have separated from the normalized data for the test, it observed that the rate of education slightly lowered according to the training data. Although the MAE error rate was higher in ANN, it observed that the model established with ANN yielded better than 0.95 accuracy with a 0.96 accuracy ratio. Here too, the model established with ANN was more successful.

Table 3.3: Cross validation results with normalized data.

Normalized Data – Cross Validation	ANN	SVM
Correlation coefficient	0.9602	0.9623
Mean absolute error	1.0435	0.914
Root mean squared error	1.4247	1.3745
Total Number of Instances	17520	17520

The analysis of the normalized data set with the cross-validation method revealed that the accuracy of 0.96 and ANN and SVM were very close to each other. The MAE ratio was 1.04 in the ANN and 0.91 in the SVM.

3.3.2 Analysis with Raw Data

Table 3.4: Train results with unprocessed data.

Unprocessed Data - Train	ANN	SVM
Correlation coefficient	0.9803	0.9675
Mean absolute error	0.781	0.8922
Root mean squared error	1.039	1.2909
Total Number of Instances	14592	14592

As a result of the training we did with the data set that we separated from the unprocessed data to train model, the CC was 0.98, and the MAE was 0.78, a better result than the normalized set of the same data set. Analysis of this data set with SVM, CC was 0.96, we can say that it gives slightly better results than normalized data. As a result of this analysis, ANN showed better results.

Table 3.5: Test results with unprocessed data.

Unprocessed Data - Test	ANN	SVM
Correlation coefficient	0.9386	0.9633
Mean absolute error	1.0755	0.8882
Root mean squared error	1.6904	1.2457
Total Number of Instances	2928	2928

In the trained model, the result of the analysis we made with the test set from raw data, CC was 0.93 and MAE was 1.07 for the model established with ANN. The model established with SVM was CC 0.96, MAE 0.88. As a result of this analysis, it observed that the model established with SVM had significantly better results. Subsequent control showed that there were deviations from the climate data deficiencies in the test data. This increased the error rate in the model established with ANN.

Table 3.6: Cross validation results with unprocessed data.

Unprocessed Data – Cross Validation	ANN	SVM
Correlation coefficient	0.9623	0.967
Mean absolute error	1.0555	0.8929
Root mean squared error	1.3905	1.2835
Total Number of Instances	17520	17520

Finally, as a result of the analysis of the raw data by cross-validation method, CC 0.96 and MAE 1.05 were obtained from the model that established with ANN. As a result of the model established with SVM, CC 0.96 and MAE was 0.89. Here, it observed that the model established with SVM yielded better results.

4. DISCUSSION

As it is known, in the case of future estimation, ANN has a problem in predicting the different values due to a regular increase or decrease. Various methods have proposed as a solution to this problem in the literature. In our study, we tried to solve this problem by training the model with the cross-validation method.

Table 3.7: Mean of train results.

Mean	ANN	SVM
Correlation coefficient	0.9794	0.9669
Mean absolute error	0.8244	0.8985
Root mean squared error	1.0950	1.3033

As a result of the training of the model with the training data. The CC of the model established with ANN was up to 0.98. By the way, the model established with SVM was close to 0.97.

Table 3.8: Mean of test results.

Mean	ANN	SVM
Correlation coefficient	0.9502	0.9615
Mean absolute error	1.0855	0.9082
Root mean squared error	1.5698	1.2853

When we tested the model with the test data, CC of the model established with ANN decreased to 0.95. Value decrease of the model built with SVM was lower, and CC value was the same before, 0.96.

Table 3.9: Mean of cross_validation results.

Mean	ANN	SVM
Correlation coefficient	0.9613	0.9647
Mean absolute error	1.0495	0.9035
Root mean squared error	1.4076	1.329

In our prediction study using the cross-validation method, we obtained a better result with ANN at 0.96. The accuracy of the SVM showed a slight increase. In any case, we have seen that the cross-validation method increases the accuracy of the model.

The proposed method gives the ability to design type of a decision support system and can be used for short and long-term decisions by power companies. To make the technique a long-term or a short-term demand profile will be transferred historical demand data to the system. That will make it easy decision-making processes. Also, the system has the ability to implement the demand segregation method. [18]

The demand estimation method in this article can be used by power companies to help their day ahead consumption plan. Also, system operators are very concerned about this information. The system operator looks for short or long-term demand profiles when planning planned outages, production plans, and reserves. Our future work for this study to improve the method produced. [18]

5. CONCLUSION AND RECOMMENDATIONS

In this work, the study on the hourly electricity demand forecasting technique for Turkey explained using ANN and SVM. Meteorological data such as temperature, precipitation, wind speed, relative humidity, cloudiness, and pressure applied as the descriptor variables also used.

In addition, exceptional events affect daily demand. Inputting more information about extraordinary circumstances such as peak temperature values, the world cup, and some events that change our daily life routines necessary to increase forecast accuracy. [18]

Energy demand forecasting is an active research topic in statistics, engineering, and econometrics. A crucial task for the power systems planning and the efficiency in operations is electricity demand forecasting. Prediction of hourly, daily, weekly, and annual values of the system demand and peak demand are the areas of work in demand forecasting. [3]

As a result, lots of work on the demand forecast, it is crucial remembering the difficulties of finding data, and uncertainty will always protect itself, there are many criteria to guess. Achieved accuracy levels over 97%. By reviewing user profiles and collecting the data from them in the following years, it can be possible to reach 99% accuracy. The exact estimate is not possible due to the uncertainty of the future.

As a piece of advice, instead of forecasting consumption, smart grid and other smart systems should be researched for efficient in energy ecosystem. If the use of energy planned, the difference between energy production and consumption can be reduced so that the system works more healthily. This can only be achieved if the consumer and the producer connect around an interconnected network and remain in constant communication, in this way, the planned energy needs can be reported to the system as an instant, and the necessary energy can be produced.

Today, energy transition and energy efficiency are one of the main concerns of the scientific community. Surely, the increase in electronic devices and the expansion of the IoT lead to a considerable increase in energy demand. A finding solution to this phenomenon is essential. Currently, Smart Grid, one of the solutions, to apply the system. It optimizes consumer models by determining consumption patterns adapted to a particular situation, taking into account different parameters such as pricing, user preferences or parameters of household appliances. [40]

It is still difficult to obtain healthy data for estimation. One of the problems we encountered in the data collection phase was the access to consumption data on a provincial basis. For example, for the European side of Istanbul, there are thirty-one transformers (electricity distribution center) centers belonging to TEIAS (Turkish Electricity Transmission Corporation), but some of them also feed other provinces, so central distribution and control of energy makes it difficult to determine the area border of costumers.

This problem can be eliminated with IoT technologies and smart meters instead of the energy system which is distributed and controlled from the center. Using the data collected from the consumer with smart meters at the base, users can be grouped into appropriate groups, and more targeted, more accurate results can be obtained for demand forecasting.

As a result, the possibilities offered by the blockchain method should be evaluated, it is necessary to create a system with a transparent and easy to distribute network structure. As a future work, this study is planned to be used in smart grid systems to model forecasting studies and to assemble them on the blockchain.

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