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HASAN KALYONCU UNIVERSITY

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FORECASTING OF TURKEY'S LONG-TERM ENERGY CONSUMPTION BY USING METAHEURISTIC ALGORITHMS

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MERVE BABAOĞLU

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“Forecasting of Turkey’s Long-Term Energy Consumption By Using Metaheuristic Algorithms”

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Supervisor

Asst. Prof. Dr. Bülent HAZNEDAR

by

Merve BABAOĞLU

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I report that I have obtained all the information in this dissertation in accordance with ethical behavior and academic rules, and in this study, prepared in accordance with the rules of writing the dissertation, I have made a complete reference to the source of all kinds of statements and information that do not belong to me. And when it turns out otherwise, I declare that I accept all legal consequences.

…./…./….

Merve BABAOĞLU

ABSTRACT

FORECASTING OF TURKEY'S LONG-TERM ENERGY CONSUMPTION BY USING METAHEURISTIC ALGORITHMS

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Energy is one of the most important topics for the sustainable development of countries. Due to the fact that the energy used can be depleted, it imports many energy sources, and environmental factors, it is of great importance for Turkey to forecast how much energy needs may be in the future. In this study, whale optimization algorithm (WOA) was preferred from metaheuristic algorithms in order to forecast the amount of energy consumption of Turkey until 2040. A genetic algorithm (GA) and an artificial bee colony algorithm (ABC) were used to measure the performance of the WOA. These heuristic algorithms are increasingly preferred by the high forecasting performance obtained from the models they create. All models are arranged linear and quadratic and the result is obtained. Data for independent variables such as gross domestic product (GDP), population, imports and exports affecting energy consumption were used between 1990 and 2019. These data are taken from TUIK (Turkish Statistical Institute), BP World Energy Statistics Report, World Bank and IEA (International Energy Agency). Modeling of the past 30 years has been provided to determine the equation that gives the closest result to the actual value. For the next 20 years, calculations were made according to 4 different scenarios. According to these calculations, it was observed that the ABC linear model works better than the other two models with values of 99% R^2 and 4.35% MAPE.

Keywords: Whale Optimization Algorithm, Genetic Algorithm, Artificial Bee Colony Algorithm, Energy Consumption Forecasting, Turkey

ÖZET

TÜRKİYE'NİN UZUN VADELİ ENERJİ TÜKETİMİNİN METASEZGİSEL ALGORİTMALARLA TAHMİNİ

MERVE BABAOĞLU

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Enerji, ülkelerin sürdürülebilir kalkınmaları için en önemli konu başlıklarından biridir. Kullanılan enerjinin tükenebilir olması, birçok enerji kaynağını ithal ediyor olması ve çevresel faktörlerden dolayı Türkiye için ileride enerji ihtiyacının ne kadar olabileceğinin tahmin edilebilmesi büyük önem taşımaktadır. Bu çalışmada Türkiye'nin 2040 yılına kadarki enerji tüketim miktarını tahmin edebilmek adına, metasezgisel algoritmalardan balina optimizasyon algoritması (BOA) tercih edilmiştir. Balina algoritmasının performansını ölçebilmek için genetik algoritma (GA) ve yapay arı kolonisi algoritması (YAK) kullanılmıştır. Bu sezgisel algoritmalar, oluşturdukları modellerle elde edilen yüksek tahmin performansları ile gün geçtikçe daha çok tercih edilmektedirler. Tüm modeller lineer ve karesel olarak düzenlenip sonuç alınmıştır. Enerji tüketimini etkileyen gayri safi yurtiçi hasıla (GSYH), nüfus, ithalat ve ihracat gibi bağımsız değişkenlerin 1990-2019 yılları arasındaki verileri kullanılmıştır. Bu veriler, TÜİK (Türkiye İstatistik Kurumu), BP Dünya Enerji İstatistikleri Raporu, Dünya Bankası ve IEA (Uluslararası Enerji Ajansı)'dan alınmıştır. Gerçek değere en yakın sonucu veren denklemin belirlenebilmesi için geçmiş 30 yılın modellenmesi sağlanmıştır. Gelecek 20 yıl için ise öngörülen 4 farklı senaryoya göre hesaplamalar yapılmıştır. Bu hesaplamalara göre YAK lineer modelinin %99′luk R^2 ve %4,35'lik MAPE (ortalama mutlak yüzdesel hata) değerleri ile diğer iki modele göre daha iyi sonuç verdiği gözlenmiştir.

Anahtar Kelimeler: Balina Optimizasyon Algoritması, Genetik Algoritma, Yapay Arı Kolonisi Algoritması, Enerji Tüketim Tahmini, Türkiye

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Merve BABAOĞLU

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LIST OF ABBREVIATIONS

GA	Genetic Algorithm
WOA	Whale Optimization Algorithm
ABC	Artificial Bee Colony
PSO	Particle Swarm Optimization
IWO	Invasive Weed Optimization Algorithm
GWO	Gray Wolf Optimizer
GDP	Gross Domestic Product
ANN	Artificial Neural Network
MAPE	Mean Absolute Percentage Error
MAD	Mean Absolute Deviation
ANFIS	Adaptive Neural-Fuzzy Inference Systems
ARIMA	Autoregressive Integrated Moving Average
SARIMA	Seasonal Autoregressive Integrated Moving Average
VS	Vortex Search
KT	Kilo Ton
TOE	Tone of Oil Equivalent
MTOE	Millions of Tons of Oil Equivalent

CHAPTER I

INTRODUCTION

Energy is one of the indispensable strategic elements of daily life and industrialization. The growing population, industrialization and prosperity levels in the world increase energy consumption. In order to achieve sustainable economic growth, to meet the energy needed by the population and to maintain competitiveness with other countries of the world, the creation of new energy policies is mandatory.

The universe is made up of an emerging energy. After that, human beings needed to obtain nutrients that would energize their bodies in order to survive, work and move. For a long time, people have tried to get all the energy they need through their own metabolism. After a while, human beings began to search to reduce the energy they would need, to do their work with a force other than their own, so that they could minimize the energy they would spend, and by exploring nature, they used the power of fire, wind, water and domesticated animals. The people of the period tried to meet their primary needs, such as carrying loads with the power of animals, plowing fields, inflating sails with the power of wind and water, grinding grain with the power of stone, in order to live their lives.

People have needed energy for centuries to make their lives easier and more sustainable. (Yavuzaslan & Çetin, 2017).

As the population increased in the following years, the application of thought in the field of science and technology, the endless existence of expectations, desires and needs led people to seek more useful, different and stronger sources of energy. Wars between countries have also shown the need to seek and find different energy sources in order for combat power to be at advanced levels (Yazalan, 1983).

The energy needed and used in almost every aspect of daily life can be found in different ways in nature and can be transformed into each other with the help of various techniques. In this way, it is possible to meet the increasing energy demand due to factors such as population growth, economic growth, urbanization and industrialization (Koç & Şenel, 2013).

Global energy consumption growth increased by 0.6% in 2019 compared to the previous year and by an average of 2% each year in 2000-2018. Energy consumption has increased by an average of 3.2% in China, the world's largest consumer since 2009, 1.8% in Russia and 0.8% in India (Enerdata, 2020).

In Turkey, primary energy consumption rates were 47.7 Mtoe in 1990 and reached 155.2 Mtoe levels in 2019. That's nearly, a 3% increase per year (BP World Energy Statistics Report, 2019).

Turkey is a country that aims to develop itself in the field of industry and technology, to increase the welfare level of the country's people and not to stay away from international competition. As part of these goals, it is expected that GDP, industry and urbanization will increase, which is an indicator that the level of prosperity of the country's people is increasing. Therefore, it is forecasted that the amount of energy consumption will increase. Turkey meets most of the energy it needs from deplorable energy sources and has to import many of them. Because of this, Turkey needs to invest more in renewable energy sources using the potential it has, increase its use, and establish a good balance of supply and demand.

Most of the energy used in the world is derived from primary energy sources. According to 2019 data, the resources that have the largest share in primary energy use in the world are oil 52%, natural gas 21% and coal 13%, respectively.

It is necessary to observe the interests of society at the stages of production, transmission and distribution, starting from the evaluation of energy sources, and to minimize the negative effects on the environment, climate and nature in all these processes. This criterion should apply to all energy-related activities. Providing energy to all consumers in an adequate, high-quality, continuous, low-cost and reliable way to this point of view should be a basic energy policy. Electrical energy, in particular, is an essential need of human life, an indispensable element of social structure as a common requirement (TMMOB, 2019).

Lund (2007), conducted a study to investigate whether a country can get all the energy it needs from renewable energy sources. He chose Denmark as an example in his article, where he discussed the perspective of renewable energy (wind, biomass, wave and solar) in creating a strategy for sustainable development.

It found that strategies for this perspective include three technological changes; increased efficiency in energy supply, energy conservation on the side of energy demand, and the use of renewable energy sources instead of fossil fuels. According to the results of Lund's study, a country can obtain 100% of its energy needs from renewable energy sources (Önal, 2020).

Unfortunately, as an energy source in our country, fossil resources that are depleted as they are used and cause environmental pollution are used in large quantities. But more investment in renewable energy sources, where it has great potential, and planning to increase efficiency will solve the energy resource problem that may face in the future.

1.1 Problem Definition and Goal

In this study, I aimed to be able to forecast the energy consumption that our country may need in order to develop in all areas, increase its level of prosperity, have a say in the global world, develop industry and technology, using metaheuristic algorithm methods, and to shed light on the future of these forecastings. For this purpose, data from the last 30 years of GDP, population, import and export variables affecting energy consumption were used. Different scenarios in which future values of independent variables were forecasted and included in linear and quadratic equations with optimal coefficients generated by algorithms, and an attempt was made to forecast Turkey's energy consumption. When we put these models in place in the objective function, we obtained different equations in each algorithm. After these equations, the coefficients to be applied to each variable were determined and energy consumption for the future were forecasted. The performance level of each algorithm's modeling with past data and the error percentages of the results are shown in the application section.

1.2 Sections of the Thesis

In the first chapter, the general objectives of the study, the methods used and which variables are selected to make consumption forecasting are mentioned.

In the second part of the study, a literature review was conducted, citing some studies that attempt to realize energy consumption forecasting.

In the literature review, information was mentioned, such as which methods are used when estimating energy consumption in the World and Turkey, and which data is preferred as an independent variable.

In the third chapter, general information about artificial neural networks. The definition, history and structure of the artificial neural network have been mentioned. After that, the definition of heuristic algorithms was made. It is mentioned why it is necessary and what the amenities it provides are.

Heuristic algorithms are mentioned in the genetic algorithm and artificial neural networks that we use for this study. Explanations have been made about the working principle of the genetic algorithm, the basic steps and what factors affect its performance. After that, it was mentioned who developed the artificial bee colony, what was the logic of the study, what were its basic steps, and the types of selection mechanisms.

In the fourth chapter, some general narratives are made about the whale algorithm. Explanations have been made about the flow chart of the algorithm, what the inspiration is, and how its mathematical model was created.

In chapter fifth, energy and energy types are mentioned and information about energy use in the World and Turkey is given. Classification of energy, renewable and non-renewable energy sources are given general information.

The final chapter, consumption forecasting was attempted by creating linear and quadratic models with the methods of genetic algorithm, whale algorithm and artificial bee colony algorithm to the suitability function used to perform energy consumption forecasting. Evaluation of the results of the models, calculation of their performance and comparison of the results were made. In the last part, the results and suggestions are given.

CHAPTER II

LITERATURE REVIEW

2.1 Studies for Energy Consumption\Demand Forecasting in Turkey

In Turkey, which is among the developing countries, many studies have been conducted to forecast the energy that may be needed in the next period. While mathematical or statistical forecasting methods were widely used in the past, artificial intelligence methods (YSA), which have greater reliability and performance, are at the forefront today. Some of the studies conducted in this area are as follows:

Toksarı (2007), developed the energy demand estimate using the ant optimization algorithm using population, gross domestic product (GDP), import and export variables. According to three scenarios, Turkey's net electricity production and demand were estimated by 2025.

Uzlu (2019), estimated Turkey's energy consumption using the gray wolf optimization (GWO) algorithm. In order to see the accuracy of this model, ANN models trained with the artificial bee colony (ABC) algorithm and the back were used. As a result, the ANN-GWO model was superior to the ANN-ABC and ANN-back propagation algorithm models.

Boğar & Boğar (2017), in their work, they modeled net electrical energy consumption in Turkey using the particle swarm optimization (PSO) algorithm. For the best modeling of electrical energy consumption, models connected to different base functions were proposed, the best result was given by the Chebyshev polynomial regression model, and particle swarm optimization (PSO) was also an effective method of optimizing the coefficients of these functions.

Bayramoğlu et al. (2017), estimated primary energy demand using the ANFIS model. Energy prices were also included in the study variable, and the primary energy source requirement was estimated for 2016-2030.

Es et al. (2014), used artificial neural networks to realize Turkey's net energy forecast. He compared his results with the multiple linear regression technique.

Ediger & Akar (2007), estimated how much turkey's primary energy demand will be by 2020 using the ARIMA method.

Koç et al. (2018), estimated energy demand based on economic indicators. Gravitational search algorithm (GSA) and invasive weed optimization algorithm (IWO) were used for this. Turkey's energy demand has been estimated from 2012 to 2030 using 3 different scenarios.

Demirel et al. (2010), estimated the load of electrical energy using ANFIS and ARMA models. According to the errors received, the best result could be found using the ANFIS model.

Durğun (2018), has realized Turkey's long-term energy demand forecast with artificial intelligence techniques. In this study, Turkey's between 1980 – 2017 years' annual electricity consumption, GDP, population, meteorological data taken from TUIK and General Directorate of Meteorology and were made 2018-2023.

Ekinci (2019), using the YSA and ANFIS models, he conducted an energy consumption estimation study. It has shown that the performance of the anfis model predicts electrical consumption more accurately than the YSA method.

Binici (2019), estimated Turkey's 10-year demand using a mathematical model. As a result, it is predicted that Turkey's electricity needs will increase 1.5 times over 10 years.

Hamzaçebi & Kutay (2004), estimated Turkey's electricity consumption by 2010. The results showed that artificial neural networks were a good predictor of electrical energy consumption.

Özkan (2018), aimed to predict Turkey's energy demand by 2050 using particle swarm optimization (PSO) and genetic algorithm (GA) models. It was observed that PSO model provides better forecast results than GA.

Ceylan et al. (2005), estimated Turkey's demand for electricity by 2020 using a genetic algorithm.

Uzlu & Dede (2020), aimed to create a trained artificial neural network (YSA) model using the Jaya algorithm to predict Turkey's future electrical energy consumption. The results show that electric power consumption estimation can be accurately modeled using YSA-Jaya, and this optimization method is advantageous for predicting future electricity consumption.

Özkış (2020), a new linear regression model based on the Vortex Search (VS) algorithm has been developed to predict Turkey's energy demand. With the VS model, Turkey's energy demand between 2012-2030 years was estimated through 3 different scenarios.

The energy demand estimates of the VS model have been compared with those of the IWO and GSA models in the literature. After all, the VS model predicted that there would be more energy demand in all year. Information about some studies on energy demand forecasting in Turkey is shown in Table 2.1.

Table 2.1: Studies for energy consumption\demand forecasting in Turkey.

Author (Year)	**Method**	**Arguments**	**The Data That Is Used**	**Predicted**
Bayramoğlu et al. (2017)	ANFIS	GDP, population and energy prices	1990-2013	Primary energy demand forecasting
Uzlu (2019)	GWA	GDP, population, import, export	1980-2014	Energy consumption forecast
Es (2020)	Gray forecasting models	GDP, population, import, export	1995-2018	2019-2025 Energy demand forecasting
Durğun (2019)	ANN	GDP, population and meteorological data	1980-2017	2018-2023 Energy demand forecasting
Binici (2019)	Mathematical modeling	GDP, population	1995-2018	2017-2028 Energy consumption forecast
Ekinci (2019)	YSA and ANFIS	Electrical energy data of past years, population	1970-2015	1970-2015 Energy consumption forecast
ES et al. (2014)	YSA	GDP, population, import, export, building face measurement and the number of vehicles	1970-2010	Energy demand forecasting
Demirel et al. (2010)	ANFIS and ARMA	GDP, population, generated energy, installed power	1970-2007	2006-2010 Electric power load estimation
Hamzaçebi & Kutay (2004)	ANN	Population	1970-2002	Electric power consumption forecast
Canyurt et al. (2005)	GA	GDP, population, import, export	1970-2001	2002-2025 Energy demand forecasting
Kavaklıoğlu (2011)	Support vector regression (SVR)	GDP, population, import, export	1975-2006	Modeling and estimation of electrical energy
Ediger & Akar (2007)	ARIMA	-	1950-2004	2005-2020 Primary energy demand forecasting
Haklı (2013)	ABC, PSO	GDP, population, import, export	1979-2005	2006-2015 Energy demand forecasting
Özkış (2020)	VS	GDP, population, import, export	1979-2011	2012-2030 Energy demand forecasting

2.2 Studies for Energy Consumption\Demand Forecasting in the World

Mohamed & Bodger (2003), estimate New Zealand's long-term electricity consumption using multiple linear regression analysis. In their study, they used for the period 1965-1999 the country's gross domestic product, average electricity price and population data as variables.

Ekonomou (2010), used artificial neural networks (ANN) to estimate Greece's long-term energy consumption. The developed ANN model is used for the prediction of Greek energy consumption in 2005-2008, 2010, 2012 and 2015. As a result, it has been observed that artificial neural networks provide effective results for energy consumption forecasting.

Azadeh et al. (2007), estimated the electricity consumption data needed in the Iranian agricultural sector using a genetic algorithm and an artificial neural network. Data from 1981-2005 were used in their studies.

Camara et al. (2016), aimed to estimate energy consumption in the United States using two approaches: the statistical approach (SARIMA) and the neural networks approach (ANN), and compared them to find the best model for forecasting. According to the results obtained, the artificial neural network model gave better results than the statistical method.

Yu et al. (2012), in order to estimate China's energy demand, PSO–GA was applied to obtain results by using factors such as GDP, population, economic structure, urbanization rate and energy consumption structure that affect demand. It is shown in the forecast results that there will be 6.91, 5.03 and 6.11 billion Tce (“standard” ton coal equivalent) in three different scenarios for 2020.

Geem & Roper (2009), used artificial neural networks to estimate energy demand for South Korea. South Korea's industry largely imported energy resources (the world's fifth largest oil importer and the world's second-largest liquefied natural gas importer) because energy policy is critical for accurately forecasting of energy demand. As a validation, the country's gross domestic product (GDP), population, import and export data were used.

Behrang et al. (2011), offered the application of the BA technique to estimate the total energy demand in Iran based on socioeconomic indicators. The study used data on the country's energy consumption between 1981-2005 years.

Rodriguez et al. (2019), used particle swarm algorithm to forecast energy demand in Spain and France. The study used separate annual data from each country.

Zahedi et al. (2013), in their study, modeled electricity demand in Ontario-Canada, from 1976-2005 using ANFIS. Inputs for the Model include the number of jobs, GDP, population, number of dwellings, and the two meteorological parameters related to the annual air temperature.

AbuAl-Foul (2012), aimed to forecast energy use in one of the Mena countries in Jordan. In the study, data for the period 1976-2008 were used. The methodology used in this study follows the analysis of artificial neural networks. Four independent variables are used to estimate energy use: the country's GDP, population, exports and imports. In this region, the projected energy use in 2015, 2020 and 2025 respectively, will reach 8349, 9269 and 10189 KT.

Table 2.2: Studies for energy consumption\demand forecasting on Earth

Author (Year)	**Method**	**The Data That Is Used**	**Country**
Geem & Roper (2009)	ANN	GDP, population, imports and exports	South Korea
Ekonomou (2010)	ANN	GDP, annual energy consumption, annual temperatures, installed power capacity	Greece
Assareh et al. (2010)	PSO-GA	GDP, population, imports and exports	İran
Mohamed & Bodger (2003)	Multiple linear regression analysis	GDP, average electricity price and population	New Zealand
Behrang et al. (2010)	ABC	GDP, population, imports and exports	Iran
Camara et al. (2016)	ANN-SARIMA	Population, GDP, weather caprices, storage capacity	US
Yu et al. (2012)	PSO-GA	GDP, population, economic structure, urbanization rate and energy consumption structure	China
AbuAl-Foul (2012)	ANN	GDP, population, imports and exports	Jordan
Rodriguez et al. (2019)	PSO	Energy production, population, GDP, CO2 emissions, electricity generation, electricity consumption, unemployment rate, renewable energy use, oil demand	Spain and France
Zahedi et al. (2013)	ANFIS	GDP, number of jobs, population, number of Housing and annual air temperature	Canada

CHAPTER III

3.1 ARTIFICIAL NEURAL NETWORKS

3.1.1 Artificial Neural Network

Artificial intelligence, a computer, a machine or computer-aided, usually human qualities, solution finding, understanding, meaning extraction, generalization, and learning from past experiences, as well as high in relation to the process logic is defined as the ability to perform tasks in the world of science (Nabiyev, 2012).

The most obvious and remarkable feature of artificial neural networks, one of the sub-branches of artificial intelligence, is that the human brain tries to model and simulate the working principle (Karaatlı et al., 2005).

The person is the only being capable of thinking. It analyzes the resulting situation, makes sense and compares it with past situations, trying to reach a conclusion with the experience he has achieved. It is our brain system that provides all this. The brain system is quite complex.

ANN is inspired by the human brain developed, each with its own memory and processing elements connected through weighted connections of parallel and distributed information processing structure; in other words, are computer programs that mimic biological neural networks (Elmas, 2003).

In the past times, human beings have imagined machines that think like their own and have human behavior. At that time, could a structure similar to the human brain be created? Can a robot be created that can behave like a human? Can computers think? Can they act like us? Can they find out? Can they come to a conclusion based on what they've learned? And the answers to similar questions had not yet been found. Even, this situation has been the subject of many books, films and documentaries. However, today some of these questions are partially answered. Such thoughts are no longer imagined thanks to artificial neural networks. Because the artificial neural network offers us a structure that learns like a human, gain experience as it learns, and predicts the unknown based on what it has learned with a situation it has never encountered before. Science is very advanced in this sense.

Artificial neural networks have become the preferred method for prediction problems because they can use past knowledge and the accumulation and learn complex relationships (Bayrakçı-1997).

ANN has an adaptive nature based on learning with examples, rather than traditional programming methods in solving problems. However, ANN also has internal parallelism, which allows for fast calculations. YSA incorporates computational models that serve quick and consistent purposes of generalization, learning, and forecasting over other forecasting models (Sönmez et al., 2015).

In making predictions about the future, different models have been used in the past. As the years have passed and the technology has progressed, more comprehensive analyses and more realistic predictions have been made in this area. Like the human brain, it can be said that analysis of artificial neural network models can have a smaller margin of error (Sarıkaya, 2019).

It is vital for a country to be able to predict the energy that may be needed in the future. Forecasting studies, using existing resources correctly, finding new alternatives instead of depleted resources and in order to meet the growing need in parallel with the growing population, it provides guidance on issues such as how much investment should be made in renewable energy sources. In the field of energy, there are many studies conducted with ANN in the world and in our country. Some of these studies have been shared under the title literature review.

The reason why the interest in ANN systems is so intense and has found a wide place in engineering applications is that it has been successfully applied to problems that cannot be solved by classical methods or are very complex to solve, creating an alternative to classical methods (Canan, 2006).

The ANN can change their behavior according to ambient conditions. In other words, in the face of changes that will occur in the problem, the ANN can re-train and adjust its weight again. If the parameters of the problem are constantly changing, the ANN can be constantly trained. This feature of ANN has found effective use in adaptive control systems (Simpson, 1990).

Artificial neural networks are used for prediction, function approximation, pattern classification, data Association, clustering, data filtering, optimization and control through their nonlinear structure and continuity. It is preferred in almost all areas of financial fields, medical field, defense industry, automation and control fields (Bayır, 2006).

3.1.2 History of Artificial Neural Network

The first artificial neuron was produced in 1943 by neuropsychiatrist Warren McCulloch and scientist Walter Pits. Because of the fact that technology did not develop much during these periods and limited opportunities, the model of artificial neural networks did not develop much (Pekel, 2008).

Early research on the topic of artificial intelligence was conducted by McCulloch and Pitts, who worked on the physiology of artificial neural networks and the logic of propositions using Turing's computational model. They tried to model functions using only the “and” “or” logical operators, showing that with neuron logic, artificial nerve cells can acquire learning abilities (Saraç, 2004).

Bernand Widrow and Marcian Hoff developed artificial neural network models called Adaline (ADAptive LInear NEuron) and MADALINE at Stanford University in 1959 (Widrow &Hoff, 1960).

In 1969, Misky and Papert, in their book “Perceptron”, showed that the network of single-layer perseptrons cannot solve very simple operations (for example: the XOR problem) and claimed that there are difficult obstacles to overcome in calculations. Based on this, Minsky and Papert emphasized that YSA is not an interesting topic, and they almost brought the work on YSA to a halt (Minsky & Papert, 1969).

Looking at the historical development of artificial neural networks, it seems that 1970 was a turning point. After 1970, interest in artificial neural networks was rekindled as a result of a limited number of researchers continuing their work and solving the XOR problem. In the following 10 years, around 30 new models were developed. At the same time, studies have come out of laboratories and become systems used in everyday life. These studies have also been supported by advances in both artificial intelligence and hardware technology. Everyone now accepts that they can learn about their computers and wants to take advantage of this technology (Öztemel, 2003).

Parallel Distributed Processing (McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986, 1988), which was important in the emergence of multilayer sensors and was a revolutionary invention for artificial neural networks, was published in 2 volumes (Rumelhart et al., 1986).

The interest in ANN is increasing day by day because it is understood more clearly, gives more accurate results compared to mathematical systems, and its development in parallel with technological developments.

3.1.3 Artificial Neural Network Structure

Our brain coordinates our emotions, movement system and senses. It is the billions of nerve cells in its structure and their extensions that provide us with these properties. The artificial neural network system has made this structure, its own working principle.

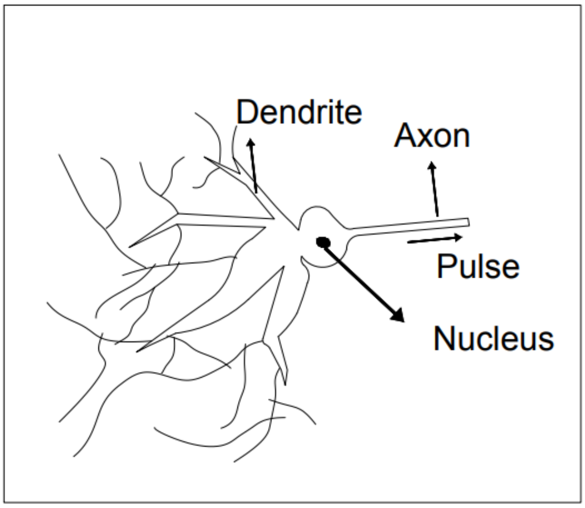

Figure 3.1: Structure of biological neuron.

The basic elements of a nerve cell are the cell body, dendrite and axon (Harvey, 1994). There are synapses between biological nerve cells, and thanks to these structures, they communicate with each other. Axons are used when information is transferred from one cell to another. The differences between ANN and biological nerve cells are shown in Table 3.1.

Table 3.1: Biological neural structure and artificial neural network equivalents.

Biological Nervous System	**Artificial Neural System**
Neuron	Processing Element
Dendrite	Input
Cell Nucleus (Soma)	Node
Axons	Output
Synapses	Weights (Interconnections)

Artificial neural networks consist of a combination of multiple horizontal nerve cells, just as billions of biological nerve cells combine to form the brain. Nerve cells usually line up in several layers to form an artificial neural network. The first layer is usually the input layer. The output layer is the last layer. The other layers are called the middle layer or hidden layer. A network can have more than one hidden layer (Yıldız, 2006).

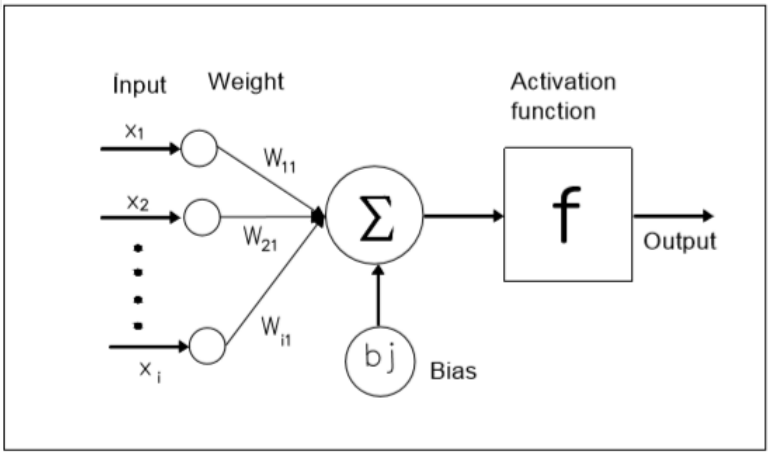

Figure 3.2: Artificial neural network modeling.

Similarly, artificial nerve cells collect information from outside with a collection function and pass it through the activation function, producing output and sending it over the connections of the network to other cells (process elements). There are different collection and activation functions. The values of the connections that connect artificial neural networks to each other are called weight values. Information is transmitted to the network from the input layer. They are processed in intermediate layers and sent to the output layer from there. Information given from outside to an artificial nerve cell is called input. Weight values, on the other hand, show the importance of the information given as input to the cell and its effect on the cell. One of the commonly used preprocessing functions is the addition function. The addition function calculates the net input coming into the cell and is usually the sum of the multiplication of the incoming inputs by their own weight (Öztemel, 2003). This function is shown in Equation 3.1.

$$sum = x_1w_1 + x_2w_2 + x_3w_3 + \cdots + w_nx_n + x_0\, b = \sum_{i=0}^{n} w_ix_i + x_0b \qquad (3.1)$$

$$y = f(sum)$$

The inputs (x_i), are multiplied by the links between them (w_i) and applied to the aggregate function ($\sum$) together with the bias value $x_0 * b$. The Bias value is a default value applied externally to the neural network. And finally, in this structure, the result is obtained by applying the activation function f to the output of the addition function.

The activation function processes the net input that comes into the cell, determining the output that the cell will produce in response to this input. Today, the most widely used "multilayer sensor" model generally uses the "sigmoid function" as its activation function. Activation functions are shown in Table 3.2.

Table 3.2: Activation functions.

Function Name	**Formula of The Function**
Linear	$y = x$
Sigmoid	$y = \frac{1}{1 + e^{-x}}$
Rational Sigmoid	$y = \frac{x}{1 + \sqrt{1 + x^2}}$
Gaussian	$y = e^{-x^2}$
Tangent Hyperbolic	$y = \frac{1 - e^{-x^2}}{1 + e^{2x}}$

3.2 HEURISTIC ALGORITHMS

Heuristic algorithms are techniques in computer science that can yield convergent results to solve problems by drawing inspiration from surrounding phenomena. They do not commit to a definitive and provable outcome, but offer a guarantee of solving the most complex problems in an acceptable time and achieving results at the closest level to the best.

The necessity of heuristic algorithms is explained by (Karaboğa, 2011):

• The optimization problem, may have a structure in which the process of finding the exact solution cannot be defined.

• In terms of intelligibility, heuristic algorithms can be much simpler in terms of the decision maker.

• Heuristic algorithms can be used for learning purposes and as part of the process of finding the exact solution.

• In definitions made with mathematical formulas, the most difficult aspects of real-world problems (what purposes and what limitations should be used, what alternatives should be tested, how problem data should be collected) are often omitted. Incorrect data used at the stage of determining the model parameters can cause errors larger than the sub-optimal solution that the heuristic approach can produce.

General-purpose heuristic methods are evaluated in six different groups: biology-based, physics-based, swarm-based, social-based, music-based, and chemistry-based. There are also hybrid methods that are a combination of them. Algorithms such as the genetic algorithm, differential growth algorithm, ant colony algorithms, bee colony algorithms and artificial immune systems are bio-based algorithms. The imperialist contestant algorithm, the parliamentary optimization algorithm, and the taboo search algorithm are social-based algorithms. The artificial chemical reaction algorithm based on chemistry; harmony search algorithm based on music; heat treatment, big bang big jump, gravitational search algorithm, central force optimization, intelligent water droplet algorithm and electromagnetism algorithm are physics-based. Particle swarm optimization and cat swarm optimization are swarm-based algorithms and models (Alataş, 2007).

Nature-inspired heuristic algorithms solve optimization problems by mimicking biological or physical events. Heuristic algorithms can be grouped into three main categories: evolution-based, physics-based, and swarm-based methods, as shown in Table 3.3. There are other heuristic methods in the literature that are inspired by human behavior. Evolution-based methods are inspired by the laws of natural evolution. Physics-based methods mimic physical rules in the universe. Swarm-based methods mimic the social behavior of animals (Mirjalili & Lewis, 2016).

Table 3.3: Classification of heuristic algorithms (Mirjalili & Lewis, 2016).

Method	**Algorithm**
Evolution-Based	Genetic Algorithm Evolution Strategy Genetic Programming Biogeography Based Optimization
Human-Based	Taboo Search Harmony Search Group Search Optimization Learning-Based Teaching
Physics-Based	Simulated Annealing Big Bang – Big Crunch Gravity Search Algorithm Black Hole
Swarm-Based	Particle Swarm Optimization Ant Colony Optimization FA-Firefily Algorithm Cuckoo Optimization Algorithm Artificial Bee Colony Whale Optimization Algorithm

In this study, in order to forecast the total energy consumption of Turkey, WOA, which was not used before in the studies in this field, was preferred. For the performance analysis of the WOA, the GA and the ABC algorithm were preferred.

General information about GA and ABC algorithms used in comparison will be given at the next stage.

3.2.1 GENETIC ALGORITHM

A genetic algorithm is a computational model inspired by evolution designed to optimize a particular data set or obtain results closest to a solution from that data set.

For the first time in the twentieth century, studies on evolutionary computation began to be conducted in the United States and Germany. The genetic algorithm was first described by John Holland in the 1960s. It was later further developed by Holland and his students and colleagues at the University of Michigan. Holland's goal was to understand the phenomenon of “adaptation” occurring in nature and to develop ways in which natural adaptation mechanisms could be transferred to computer systems (Mitchell, 1995).

In order to solve a problem in the algorithm, random initial solutions are determined first. Then these solutions can be matched with each other and produce high-performance solutions. The basic elements of a genetic algorithm are chromosome and gene, solution, crossover, mutation, fitness function and reproduction. (Öztemel, 2003).

GA can be applied quite easily, even to complex problems consisting of multidimensional functions, where the search space is too large, constraints are not specific or cannot be fully defined, the number of variables is too large, and meaningful results can be obtained. Instead of searching the entire space in its search space, it can usually produce reasonable results for short periods of time as a result of the tendency to avoid values that may result in bad results or try values that may be better. Due to the mutation operator, which has similar applications in other population-based algorithms, the tendency to obsess over local (local) minimum values is low. Since GA can be applied in both discrete and continuous functions, it has a wide range of applications (Kevran, 2009).

GA is the most preferred method of evolutionary-based heuristic algorithms. Many studies are carried out using this algorithm, and many books are written and conferences are held on this topic.

In the field of engineering, it is mainly used for optimization purposes and gives better results than other classic methods (Bolat et al., 2004).

Some studies using genetic algorithm are given below:

So & Chan (1997), applied a genetic algorithm to the elevator control system and reduced the average waiting time by this method.

In the study by Tsujimura et al. (1995), the solution of the target function, which aims to minimize the total processing time on each workstation, was performed together using a genetic algorithm and fuzzy set logic.

Güler (2018), attempted to perform aircraft parking optimization using a genetic algorithm.

Wang & Lin (2007), used a genetic algorithm for assigning resources, sorting and editing in an ordered factory. In their work, they also made the distribution of resources by order using fuzzy logic.

Tozan (2007), used genetic algorithms (GA) and particle swarm optimization (PSO) methods to maximize sensor coverage and concluded that GA showed better results with fewer trials.

In addition, genetic algorithm has been used in the various fields such as; finance, marketing, mechanical, learning, production, assignment, system security, transportation problems, traveling salesman problem, vehicle routing, assembly line balancing problems.

3.2.1.1 How the Genetic Algorithm Works?

Goldberg noted that a genetic algorithm can be considered a computer simulation that uses chromosomes, called abstract representations, in optimization problems. In general, analysis consists of chains consisting of 0 and 1. Evolution starts from random individuals and manifests itself in generations. In each generation, various individuals are selected from the existing population, modified to form a new population (mutated and re-copied) and this population is used in the next iteration of the algorithm. As can be seen, the structure of genetic algorithms is quite easy and understandable. Because of this, it can be easily applied to problems. By creating a fitness (objective) function to report what is good to the genetic algorithm and encoding the variables of the problem, all kinds of complex problems can be solved thanks to genetic algorithms (Goldberg, 1989).

GA consists mainly of a population of candidate solutions and an objective function. Candidate solutions (chromosomes) are sequential sequences that hold variables with discrete or continuous values belonging to the solution they represent. The conformance function is the function that measures the “quality” of candidate solutions (Kevran, 2009).

Genetic algorithms are divided into four basic points from classical optimization algorithms: (Oğuz & Akbaş, 1997):

- GA does not deal with the parameters themselves, but with an encoded form of the parameter set.
- GA, start the search, not at a single point, but from a family of points. So, it can work without being stuck in a local optimum.
- GA does, not uses the derivatives of the objective function and any additional information, but the direct goal function itself.
- In GA, random pass rules are used, not deterministic.

3.2.1.2 Basic Steps of Genetic Algorithm

Genetic algorithms that have application opportunities in many areas the process steps can be explained as follows (Engin, 2001):

- ✓ All possible solutions in the search space are encoded arrays.
- ✓ Usually, a random set of solutions is chosen and considered the initial population.
- ✓ A fitness value is calculated for each array, and the fitness values found indicate the solution quality of the arrays.
- ✓ A group of arrays is randomly selected and replicated according to a certain probability value.
- ✓ By calculating the fitness values of new individuals, they are subjected to crossover and mutation procedures.
- ✓ The above operations are continued during the predetermined number of iterations.
- ✓ The iteration is then terminated when the specified number of generations is reached. According to the objective function, the most appropriate array is selected.

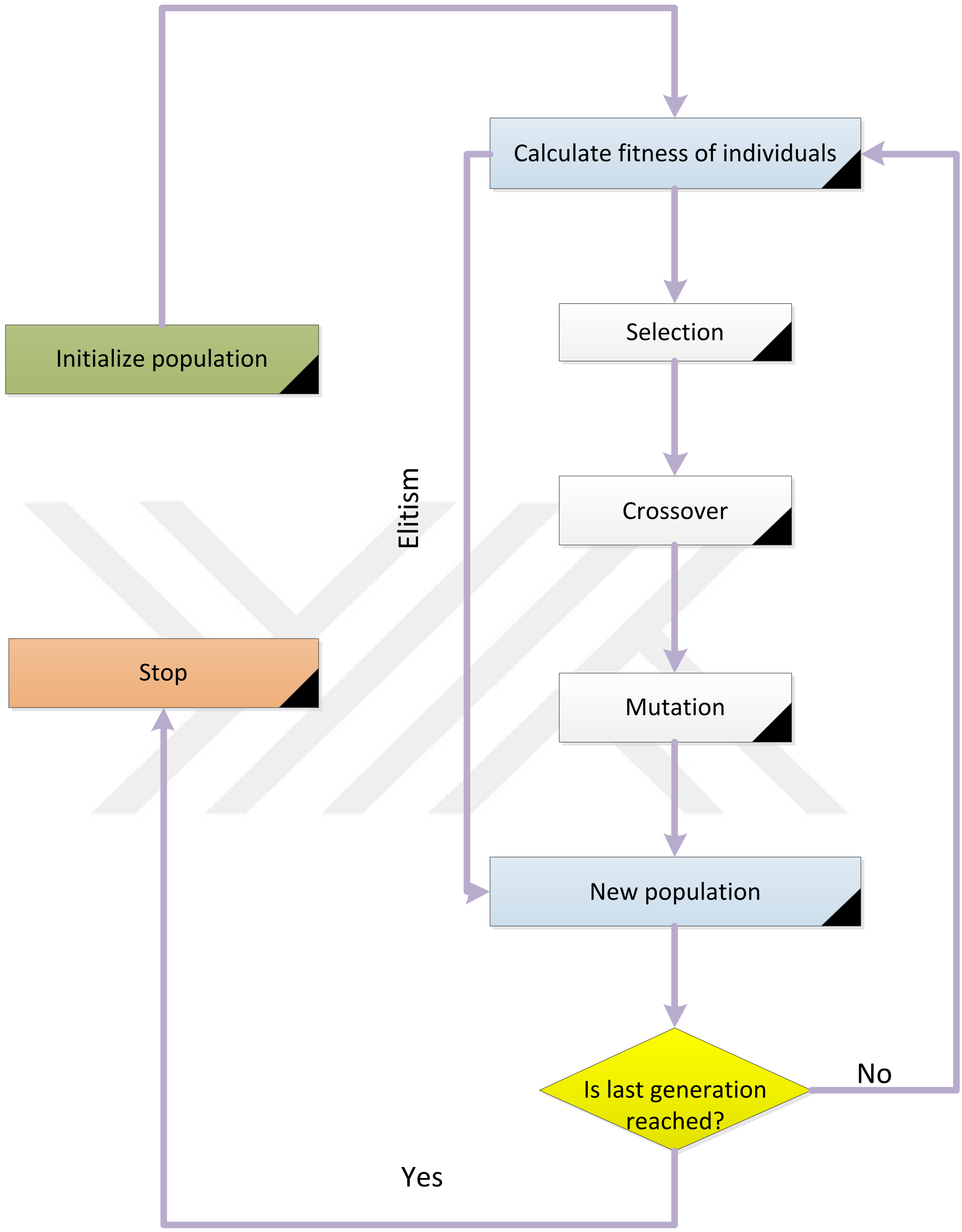

Figure 3.3: The flow chart of GA.

A-) Coding Solutions

Encoding parameters allow the translation of problem-specific information into the form that the genetic algorithm will use (Jang, 1997). Genetic algorithms use chromosomes instead of parameters. In genetic algorithm applications, it is first necessary to create an encoding that will represent the entire algorithm (Altıparmak, 1996).

According to the type of problems, there are applications such as binary coding, integer or sequential permutation coding, real number coding and tree coding.

Binary Coding

It occurs by converting values in the solution space into a binary counting system. The advantage of the binary coding technique is that it facilitates crossover and conversion, which will be described in the future (Vural, 2005). For example, 4 is indicated by 0100 in code space, while 6 is indicated by 0110 in code space. The notation format is as follows:

Chromosome A	1 1 0 1 0 0 0 1 1 0 1 0
Chromosome B	0 1 1 1 1 1 1 1 1 1 0 0
Chromosome C	1 0 1 1 0 1 1 0 1 1 0 0

Figure 3.4: Binary coding.

Permutation Coding

This coding is used in sorting problems such as the traveling salesman and job sorting problems. Sequences consist of sequentially ordered numbers.

Chromosome A	7 8 5 3 1 4 7 8 9 6 2 1
Chromosome B	2 3 6 8 1 2 3 9 8 7 4 2
Chromosome C	8 5 1 3 6 9 8 4 2 3 6 7

Figure 3.5: Permutation coding.

Real Coding

This encoding is used in problems involving complex numbers such as real. In value encoding, each chromosome consists of a sequence of values, and these values are also numbers associated with the problem, real numbers, or some special characters specific to the problem, etc. it can be any format. For some specific problems, this type of encoding produces the best results. Another point of view, it is often necessary to develop genetic operators specific to the problem. This encoding can be used for problems that use complex data, such as real numbers. Binary coding is very difficult to use in such problems. The notation format is as follows (Sivanandam & Deepa, 2008):

Chromosome A	2.5 3.2 7.5 8.9 8.8 2.3 7.5
Chromosome B	SMFJRODXJSGSJUFHD
Chromosome C	(back), (back), (right), (forward), (left)

Figure 3.6: Real coding.

Tree Coding

In this structure, each chromosome is shaped like a tree of some objects, such as commands or functions of the programming language (Sivanandam & Deepa, 2008). It is used for evolving programs or values that change.

B-) Creation of the Initial Population

Individuals (chromosomes) that make up the initial population consist of a randomly generated gene pool. A random set is considered to most accurately reflect the natural process.

When creating a population, a large number of selected individuals increases the quality of the solution, but the steps of the algorithm take more time.

Population size should be determined according to the structure of the problem. In order for subsequent steps to be more efficient in the study of a genetic algorithm, it is necessary that the initial population is large enough to accommodate different solutions to cover a significant portion of possible solutions (Drake et al., 2000).

An initial population created by the binary encoding method is as shown in Figure 3.7.

Chromosome	Chromosome Sequence	Fitness
A	10001110	4
B	11101110	6
C	00100000	1
D	00110100	3

Figure 3.7: Randomly generated initial population.

C-) Calculation of Fitness Value

Fitness value is a tool used to identify individuals who will move into the new population. Therefore, the fitness values of individuals in the current population are calculated in each cycle of the algorithm (Dengiz & Altıparmak, 1998).

Fitness value is necessary for comparing different solutions (chromosomes) and choosing the best ones. The fitness function makes these different solutions into the parameters of the problem and calculates accordingly. This function is the brain of the genetic algorithm, and the success of the algorithm depends on the precision and efficiency of the fitness function. The better the result, the better the representation rate in other generations increases at this rate. After the population is created, the fitness function is calculated and the solution that gives the best result is taken as the best solution.

According to Figure 3.8, function f (x2) that gives the best solution.

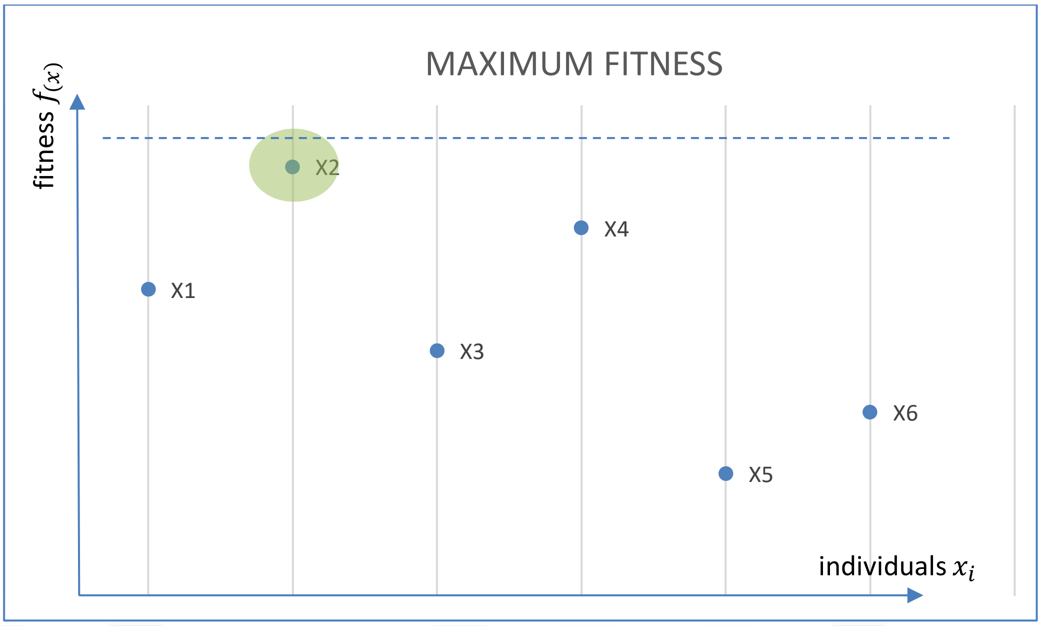

Figure 3.8: Calculate the maximum fitness value.

D-) Genetic Processes

The generation that occurs after the genetic algorithm runs is obtained by applying the following steps to the previous generation:

- Selection
- Crossover
- Mutation

The examples given in Figure 3.9 show selection, crossover and mutation processes (Konak et al., 2006):

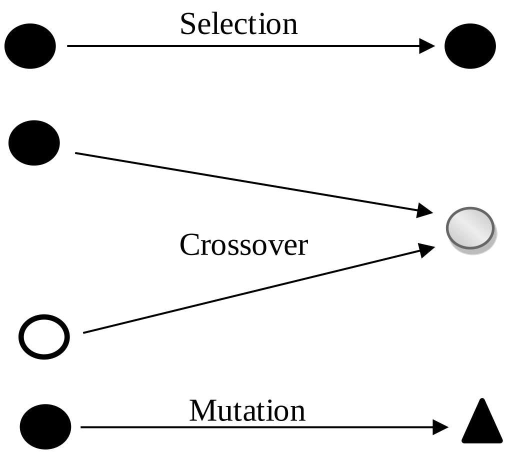

Figure 3.9: Genetic algorithm operations (Konak et al., 2006).

I) Reproduction / Selection

The fitness function of individuals in the population is calculated, and some of them are selected to produce a new generation. Although there are many methods developed as a selection method, roulette circle, tournament and elitist selection methods are mainly used as genetic algorithm selection methods.

As the re-reproduction (selection) operator, the most commonly used roulette wheel method was chosen (Goldberg, 1989). This method is the most common method in the literature (Gen & Cheng, 1997).

<u>Roulette Wheel Method:</u>

The basic logic of the roulette wheel method selection strategy is that chromosomes with a high fitness value are more likely to be selected as parent chromosomes than chromosomes with a relatively low fitness value.

The roulette wheel selection method was first revealed by Holland (Holland, 1975). Here, the fitness values of all individuals are written in a chart and these values are collected. The fitness values of all individuals are obtained by dividing the collection into numbers in the range (0,1), and the numbers are all collected in a chart. The numbers in the chart are added to each other and randomly advance to a number, and when this number is reached, the solution to which the last added number belongs is selected (Bolat et al., 2004).

This method is applied in the following format (Sivanandam & Deepa, 2008):

1. Sum total expected value of individuals in the population. This value is T.

2. Repeat it N times:

   I. Select a random ‘r’ number between 0 and T.

   II. Start rotating individuals in the population. Sum expected values until the total equals or exceeds ‘r'. Select the individual whose expected value exceeds this limit.

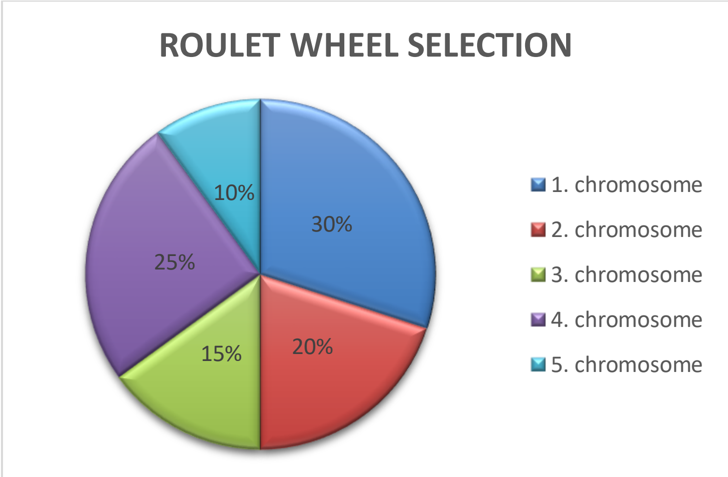

Figure 3.10: The roulette wheel selection.

According to the data in Figure 3.10, chromosome 1 has the highest fitness value and chromosome 5 has the lowest fitness value.

<u>Tournament Method:</u>

In the selection of the tournament, two or more candidates are selected first from the current population, and the candidate whose performance is best is selected from the group formed by the selected candidates. The basis of this method is based on the survival of the fittest principle. In this way, the worst individual of the current population is prevented from being the ancestor of the next generation (Goldberg, 1994).

In this method, chromosomes are matched by throwing them into a match pool. The individual who wins these matches is defined as the strong individual and is asked to pass on to the next generation. Probability p is determined for this. The p value is selected in the range [0.5 – 1]. Best in tournament method;

1. Individual passes with probability p, on to the other generation.
2. Individual passes with probability p $(1-p)$, on to the other generation.
3. Individual passes with probability p$(1-p)^2$, on to the other generation.

n. Individual passes with probability p$(1-p)^{n-1}$, on to the other generation (Miller & Goldberg, 1995).

Elitist Method of Selection:

Some of the best can be lost in crossover and mutation steps when processing a genetic algorithm in its natural process. Elitist selection protects these best so that they can be passed on to the next generation.

This can be done by keeping the chromosome ratio to be crossed low, or by storing the best value in a separate variable if the entire population is to be crossed and mutated (Kevran, 2009).

If, after crossover and mutation, the strongest individual is not among the next generation, the weakest individual in the next generation is killed and replaced by the strongest individual of the previous generation (Vural, 2005).

There are two genetic operators called crossover and mutation that are applied after the selection method to obtain new solutions.

II) Crossover

Crossover processes select genes in the parent individual to, create new offspring. The simplest form of this is to select a random breakpoint (Cross Point) and take everything before that point from the first ancestor and everything after that from the second ancestor and combine it to form the offspring (Fığlalı & Engin, 2002).

Crossover is the most important step in the genetic algorithm to ensure diversity. If the chromosomes are not crossed, individuals occur exactly the same as their ancestors. In the crossover process, individuals who have been cloned after the selection process are crossed and a richer population is created. In the selection step, new individuals are not created, good ones are cloned and used in the crossover process.

The crossover process can usually be performed in 3 different ways. These are single-point cross, double-point cross, and uniform cross.

Single-Point Crossover:

A fixed point on two genes is randomly selected in a point-crossing and the genes that remain on the right side of this point are replaced (Deb, 2001). It is also called simple crossover.

Chromosome 1: 1001|**0100011010**   Chromosome 2: **1110**|1000001110

Child 1: 1001|1000001110   Child 2: **1110**|**0100011010**

Figure 3.11: Single-point crossover.

Double-Point Crossover:

During single-point crossover, the first gene does not change and remains constant in all cases. The number of ‘n’ is increased to allow the first gene to change. In this way, diversity is increased. This cross method is used in 0-1 binary encoded individuals, while other cross methods are used in individuals encoded by other methods (Vural, 2005).

In single-point crossover, the head and tail or final part of the sequence cannot be copied together. If both the head and tail contain good genetic information, this information cannot be transferred to the offspring by a single-point crossover. Two-point cross eliminates this problem and usually gives better results than single-point cross (Sivanandam & Deepa, 2008).

Chromosome 1: 1001|**01000**|11010   Chromosome 2: 1110|**10000**|01110

Child 1: 1001|**10000**|11010   Child 2: 1110|**01000**|01110

Figure 3.12: Double-point crossover.

Uniform Crossover:

Given two parents, each gene in new individuals is created by copying the corresponding gene from one of their parents. The gene of first parent is transferred to the first new person, and gene of the second parent is transferred to the second person (Affenzeller et al., 2009; Magalhaes-Mendes, 2013).

In uniform crossover, the cross mask is randomly generated. It is created by copying the gene corresponding to the first and second chromosomes. In the crossover mask, 1 means that this gene will be copied from the first chromosome, and 0 means that this gene will be copied from the second chromosome (Bolat et al., 2004). In the second child, the opposite is applied.

Chromosome 1:	10010100011010	Chromosome 2:	11101000001110
	Mask: 01001010100010		
Child 1:	10100000001110	Child 2:	11011000011010

Figure 3.13: Uniform crossover.

III) Mutation

In artificial genetic systems, the mutation operator protects against the loss of a good solution that may never be achieved again (Goldberg, 1989).

It processes bits on a chromosome by turning them randomly. For binary encryption, variety is provided by making several randomly selected 0 to 1 or 1 to 0 changes. In systems that do not use binary coding, displacement, placement and mutual exchange methods are used according to the need.

Chromosome 1:	10010100011010	Chromosome 2:	11101000001110
Child 1:	10111000101111	Child 2:	01000011010010

Figure 3.14: Mutation formation.

3.2.1.3. Factors Affecting Performance in Genetic Algorithm

In a genetic algorithm, the components that affect the performance are as follow;

1. Population size
2. Cross probability
3. Probability of mutation
4. Electoral strategy
5. Generational range
6. Function scaling

The values of these parameters affect the performance of the GA, that is, the finding of the optimal or closest optimal solution of the GA. Therefore, the most important decision in GA applications is to determine GA control parameters (Emel & Taşkın, 2002; Yeniay, 2001).

A-) Population Size:

When creating the first population, two decisions need to be made; population size and where the initial estimates in the solution come from. Choosing the large population size will increase the chances of the initial solution achieving a high fitness and optimal solution (Devillers, 1996; Çetin, 2006).

B-) Crossover Probability:

The goal of crossover is to create more suitable chromosomes by combining the characteristics of existing good chromosomes (Patriksson & Labbé, 2002). In the crossover operator, the basic parameter is the crossover probability. The probability of crossover is a parameter that defines how often the crossover will occur. If there is no crossover, the offspring becomes a direct copy of the parents. But that doesn't mean the next generation is the same as the previous. In the case of crossover, the progeny consists of parts of the chromosomes of both parents. Crossover is done with the expectation that the new chromosomes will carry good parts of the old ones (Sivanandam & Deepa, 2008).

C-) Probability of Mutation:

The purpose of the mutation is to preserve the genetic diversity in the population. Mutation can occur in every bit on a chromosome with the possibility of P (m). If the probability of mutation increases, the genetic search turns into a random search. But it also helps to find the lost genetic generation again (Emel & Taşkın, 2002).

D-) Electoral Strategy:

Various methods of renewing the old generation are available. In generational strategy, chromosomes in the current population are completely replaced by offspring, but cannot be transferred to the next generation because the best chromosome of the population is also renewed. In order to transfer good qualities to the next generation, this strategy is used in conjunction with the most appropriate (elitist) strategy. In its optimal strategy, the best chromosomes in the population are never renewed. In a fixed-state strategy, only a few chromosomes are renewed in each generation. Usually, the worst chromosomes are regenerated when new chromosomes join the population (Emel & Taşkın, 2002).

E-) Generational Range:

The ratio of chromosomes formed in each new generation is called the range of generations. The higher this ratio, the more chromosomes are displaced.

F-) Function Scaling:

Methods such as linear scaling, exponential scaling are available. Choosing the most appropriate scaling method according to the problem is important for effective processing of the genetic algorithm (Holland, 1992).

3.2.2. ARTIFICIAL BEE COLONY ALGORITHM

3.2.2.1 General Information

Artificial bee colony optimization algorithm was developed by Derviş Karaboğa in 2005, inspired by the foraging behavior of bees in nature.

One of the most interesting flocks in nature is the swarm of honeybees, who can dynamically distribute their work with their community intelligence. In addition, honey bees have the ability to decide as a group when choosing new nests. Bees living in colonies have a navigation system, visual memory and comprehension abilities (Yiğitbaşı, 2014).

Colonies of social creatures such as bees, fish, and ants behave instinctively to solve problems, with the help of the abilities of individuals. This ability is called swarm intelligence. Food sources discovered by individuals or various threats spread quickly within the swarm through interaction with individuals. A common reaction in this way will be an example of the colony's intelligent behavior (Karaboğa, 2009).

Bees, from determining the best food source, due to inform each other of the location of this food source with their unique communication skills, because they bring as much nectar as necessary from this source, they must process it, to be kept intact, and as a result they do produce the best honey has a surprising degree of this cycle have been performed flawlessly and communities as they are the most noticeable. Exactly how bees carry out this cycle so flawlessly and have such an order within themselves is still being studied. For this reason, new information can be obtained from bees every day.

Onlooker bees can't find their own food resources. Most of these bees are located in sources, according to the information they receive from other bees. Bees are deaf. For this reason, they carry out the transfer of information to each other through dance. While the bee bringing information with dancing, it tries to get the information about the taste and smell of the nectar by touching the dancing bee with its antennae. The more bees dance this way, the more resources it will turn to (Akay, 2009).

To learn how bees make honey, researchers put a glass hive in a natural environment. But before the honey went into construction, the bees first closed the interior of the glass hive, which they adopted as their home, so that the outside environment could not be seen with honeycombs. This behavior that bees exhibit shows that their intelligence is superior (Başaran, 2018).

According to Tereshko, there are three basic components in the minimal foraging model that enable this intelligence to emerge. These components are;

1) Food sources,

2) Employed bees on duty

3) Onlooker bees

Also, this minimal model works in two ways (Tereshko, 2000):

1) Turning to a food source,

2) Leaving the food source

Some studies with artificial bee colony algorithm are as follows:

Banharnsakun et al. (2010), proposed a distributed version of ABC for large-sized problems.

Karaboğa & Baştürk (2008), used ABC for optimization of multidimensional numerical functions and compared the success of the method with differential development, PSO and evolutionary algorithms.

Karaboğa & Görkemli (2011), adapted the ABC algorithm to solve the traveler salesman problem, a discrete problem with a mutation operator-based update method.

Aderhold et al. (2010), investigated the effects of population size on ABC's work, incorporated knowledge of the global best solution into ABC's research strategy, and made the selection based on distance.

Suthiwong & Sodanil (2016), improved the performance of the ABC algorithm's exploitation mechanism at the worker bee stage, the PSO proposed an ABC algorithm inspired by the advantage of sharing the best solution information to guide the algorithm to search.

Sulaiman et al. (2015), applied the methodologies what they developed by applying different modifications to the ABC algorithm to solve optimization problems with different constraints and showed that they achieved more effective results.

Alvarado-Iniesta et al. (2013), conducted a study on the distribution of raw materials to different production lines. They used the ABC algorithm to solve the optimization problem, which is similar to the vehicle routing problem, and found appropriate results.

Pamuk (2013), created by ABC using the PowerWorld simulation program control parameters for minimize transmission line losses under load flow equations.

Yiğitbaşı (2014), introduced a program that aims and develops the process of finding edges in an image, which is one of the important areas of image processing, using the ABC.

The ABC algorithm has been preferred for many other studies and will continue to be in demand in terms of its convenience, flexibility and results closest to the result.

Some key features of the ABC algorithm are as follows:

- It is an algorithm based on swarm intelligence.
- Flexible and simple.
- Has quite few control parameters.
- True foraging is inspired by the behavior of bees.
- Developed for numerical problems, but can be used in discrete problems.

It has global research capability performed by scout bees; regional research capability performed by attendant and onlooker bees. These local and global research processes are carried out in parallel (Karaboğa, 2014).

The flow chart of the ABC algorithm is as shown in Figure 3.15.

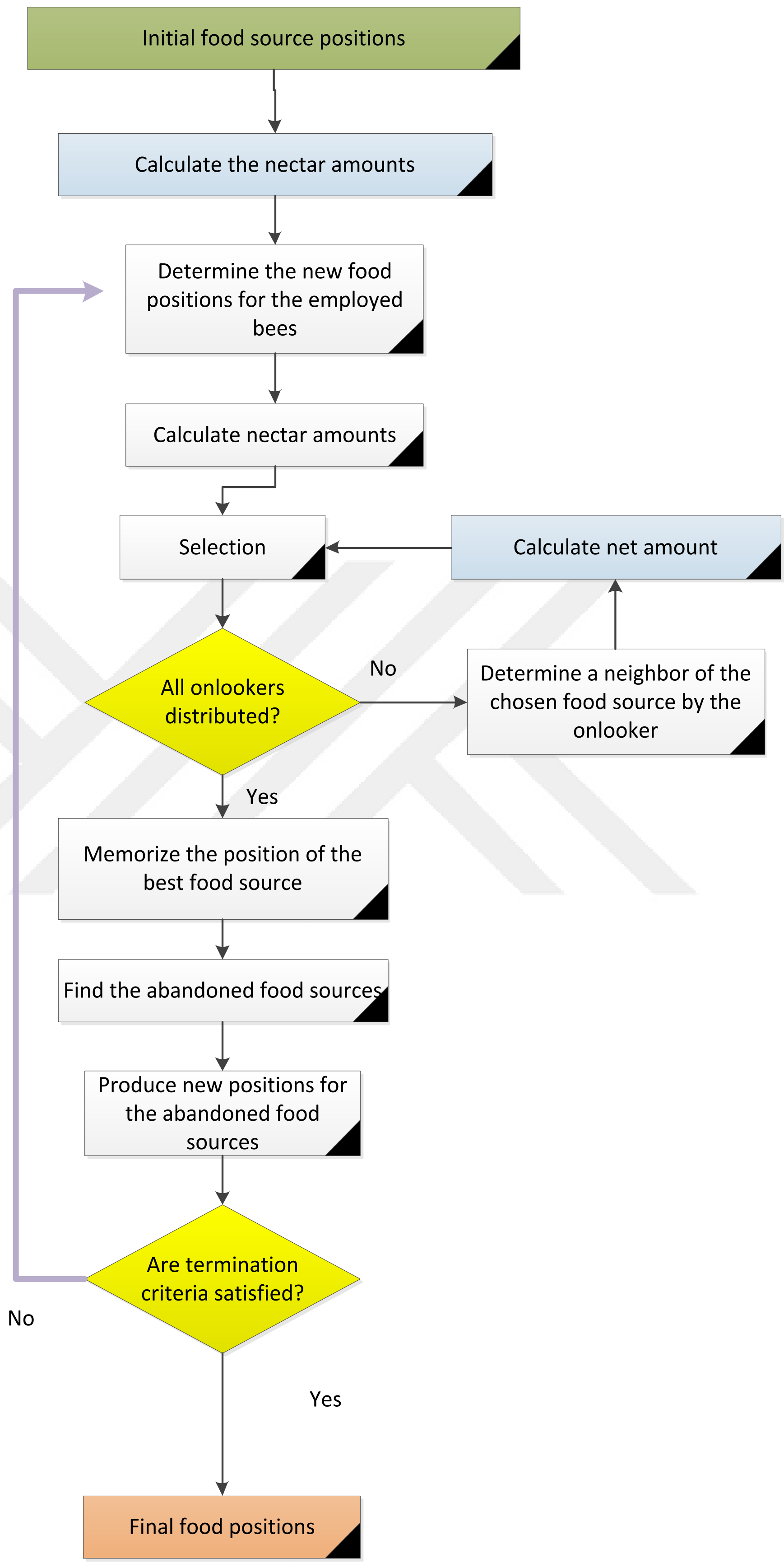

Figure 3.15: The flowchart of ABC.

3.2.2.2 Basic Steps of ABC Algorithm

In the ABC model, the colony consists of three groups of bees: employed bees, onlookers and scouts. Each employed bee is responsible for a food source. The number of employee bees is equal to the number of onlooker bees. In the event of depletion of resources, employee bees turn into onlooker bees, and employee bees begin to look for new resources. Therefore, as a result of depletion of resources, the abandonment of these resources by employed bees provides negative feedback and the search for new resources by onlooker bees provides random oscillation (Karaboğa & Baştürk, 2007).

Worker bees are called employed bees, while onlooker and scout bees are called unemployed bees. (Figure 3.16)

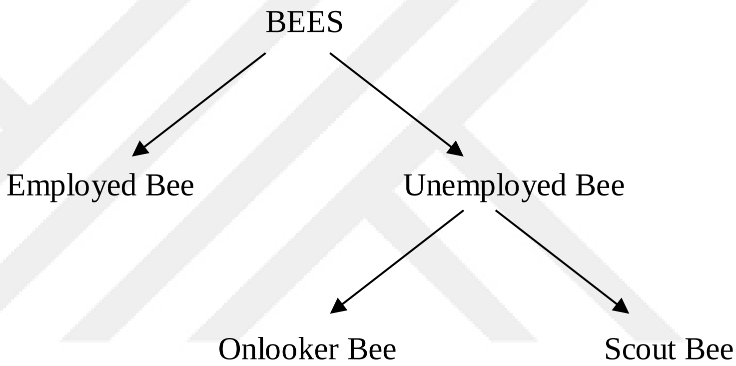

Figure 3.16: ABC algorithm elements.

A bee that carries nutrients from a specific source is called an employee bee. If the bees find a food source, they dance to the other bees in the hive. Bees that wait in the dance zone and choose the food source according to the information received are called onlooker bees. A bee that looks for food by wandering randomly is called a scout bee. Half of the colony consists of employee bees and half of the onlooker bees. In all food sources, there is only one employee bee. Therefore, the number of employee bees or onlooker bees in the colony is equivalent to the number of solutions. Each bee that ends up with a food source turns into a scout bee and looks for a new food source. The location of the food source represents only one of the solutions to the optimized problem. The amount of nutrients in the source is a selection criterion for the suitability of the solution (Erkol, 2017).

Bees find their food source by randomly searching the environment. They pass information about the source they find to the hive. They transmit information such as the distance of the source, the quality of the nectar, and the direction of the source to the bees waiting in the hive. As good as the quality of the nectar found in the source is, the attendant bee will perform its dance accordingly. According to this information, the onlooker bee chooses the source. The number of bees on employee is the number of resources (Karaboğa, 2005).

Employee bees are responsible for bringing nectar into the hive from certain previously discovered sources. These bees share information about the quality and location of the food source they go to with other bees (Figure 3.17). They demonstrate this exchange of information with their dance called "bee dance". According to this dance, information about the distance of the food source to the hive and its location relative to the sun is transmitted to the onlooker bees (Barth, 1982).

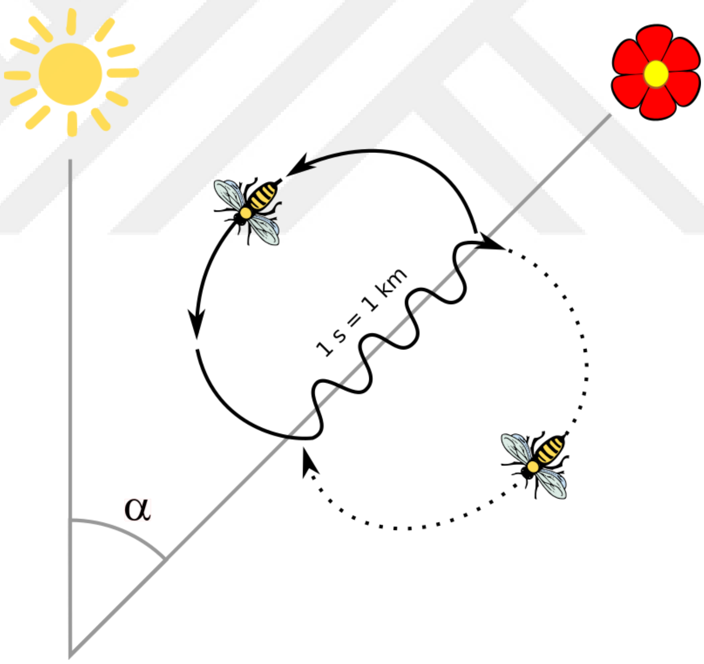

Figure 3.17: Bee dance and food location information transfer. (Wikipedia, 2020).

(https://en.wikipedia.org/wiki/Waggle_dance#/media/File:Bee_dance.svg)

The duration of the dance performed is directly proportional to the quality of the food source. In other words, the longer the duration of the dance performed, the better the food source found (Özdemir, 2012).

By watching this dance, the onlooker bees understand the positions of the last food source that the employee bees found, and by visiting places close to there, they try to find better food sources. Employee bees, which cannot find a more suitable new food source at the end of the experiment until a certain iteration number limit, also leave the food source in which they are located, turning into a scout bee and randomly moving to another location in the search space. Regardless of whether the amount of nutrients (fitness value) of this new location is better or worse, the change in location occurs, and nearby places around it continue to be scanned. Which of the food sources that the onlooker bees will want to go to, shown by the employee bees, is determined by a probability-based selection process? Food sources with high fitness value are more likely to be selected by onlooker bees (Tunçbilek, 2018).

The employed bee, whose resource has run out, is now the scout bee. It starts looking for resources by wandering around randomly.

Every bee has the ability to organize itself. This ability they have is in the form of taking information from other individuals and evaluating it in a unique way and shaping the system.

Bonabeau et al. (1999), characterized being organized on his own by four characteristics: positive feedback, negative feedback, fluctuation and multiple interactions.

Positive feedback: As the quality of the food source increases, the number of onlooker bees that choose this source increases.

Negative feedback: It is left when the food source begins to run out.

Fluctuation: Scout bees search randomly to find a food source. In this way, they improve the quality of what they do.

Multiple interactions: Information sharing takes place in the dance space.

In the ABC, initial parameters must be determined first. One of the advantages of the algorithm is that the number of parameters is small (Gözde, 2010).

The summary of the steps of the ABC algorithm is as follows (Akay, 2009):

1. First, scout bees randomly disperse in search space, starting the process of searching for food.

2. After food sources are found, scout bees become employee bees and carry food from their own sources to the hive. After the employee bees empty their nutrients into the hive, they dance in the dance area to transmit information about the source they are working with to the onlooker bees waiting in the hive. If nectar is depleted in the studied source, the employee bees turn into scout bees and randomly search for new sources in the search space.

3. Onlooker bees monitor the dances of the on-duty bees and select a source depending on the frequency of the dances. In other words, the higher the dance frequency, the stronger the probability of selecting a source.

Generating Source Locations for Startup

The hive environment where the bee swarm is located is determined as the search space for the optimization problem. The algorithm starts working by generating random values at the source locations in the search space. The process of generating random places occurs by generating random values between the lower and upper limits of each parameter (Karaboğa, 2014).

In this step, random numbers are generated and the position values of the sources are determined using the following formula 3.2.

$$x_{ij} = x_{minj} + rand(0,1) * (x_{maxj} - x_{minj}) \quad (3.2)$$

$i \in \{1, \ldots, SN\}$ $\qquad$ $j \in \{1, \ldots, D\}$

Terms here;

SN: Number of food sources

D: Number of parameters to optimize

xij: Position values of the source

$xj\ max$: The upper limit of the parameter j

$xj\ min$: The lower limit of the parameter j

At the initial stage of the algorithm, $failure_i$ counters are also reset, which refers to the number of times each resource cannot be developed. After the initial stage, food sources are passed through the processes of the employed bee, the onlooker bee and the scout bee to try to find the best (Aslan, 2012).

Sending Employee Bees to Food Supply Areas

Every time an employee bee goes to its source food, wants to check whether there is a better source of food around that source. If he finds a source with better nectar, he records it in his memory. The employed bee searches for new sources in the neighborhood of its source according to Equation 3.3.

$$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) \tag{3.3}$$

v_{ij}, represents a new source in the neighborhood of x_{ij}. Φ, is a random value in the range [-1.1], ensuring that the displacement in the neighborhood is random.

The generated v_{ij} value should not exceed the previously determined maximum and minimum values. Equation 3.4 is used to control this.

$$v_{ij} = \begin{cases} x_j^{min} & , v_{ij} < x_j^{min} \\ v_{ij}, & x_j^{min} \leq v_{ij} \leq x_j^{max} \\ x_j^{max}, & v_{ij} > x_j^{max} \end{cases} \tag{3.4}$$

Using Equation 3.4, possible boundary violations are eliminated and v_i resource is obtained within the limits. Fitness value is calculated according to Equation 3.5 according to the quality of the resulting v_i source (Akay, 2009).

$$fitness_i = \begin{cases} \frac{1}{(1+f_i)} & , f_i \geq 0 \\ 1 + abs(f_i) & , f_i \leq 0 \end{cases} \tag{3.5}$$

f, shown in Equation 3.5, is the cost value of a resource and the abs absolute value function. This process is performed to select the best source. If the new found resource is better, the employed bee deletes the old resource from its memory and heads to the new resource.

Onlooker Bees

Employed bees, which receive the necessary data from many sources that they can reach, share what they know with the onlooker bees waiting in the hive. After this process, the onlooker bees choose a food source for themselves using a probabilistic calculation based on the location and nectar information that the employee bees share with them. The selection process is done by using the fitness values made by the employed bees. For this purpose, the roulette wheel selection method was used in the algorithm. This is given in Equation 3.6.

$$p_i = 1/\sum_{i=1}^{SN} fitness_i \qquad (3.6)$$

$fitness_i$, quality of the source of i, SN, shows the number of employed bees. According to this calculation process, as the amount of fitness of a resource increases, the number of scout bees that will select this resource region will also increase. This property corresponds to the positive feedback property of the ABC.

When selecting a food source by each onlooker bee, a random number between 0 and 1 is generated. After all food sources are examined in order, if the probability of one food source is greater than the other value, that food source is selected by the onlooker bee. If it is small, the probability value of the food source is subtracted from the random number, with the remaining value looking at the next food source. In this way, the processes continue until all onlooker bees choose a food source to go to (Karaboğa 2005, Karaboğa & Baştürk, 2007).

Scout Bees

In order for scout bees to start searching, it is checked whether they have exceeded the limit value specified in the model. If the set limit value is exceeded, a new population is created. As in previous stages, searches for a loop are completed by calculating the availability value.

The recommended values in the literature on the control parameters of the ABC algorithm are as follows:

Value of 20-50 is usually proposed for colony size, and a value of around $(SN \times D)$ multiplied by the number of parameters (D) and colony size (SN) for "limit" (Karaboğa & Akay, 2011).

3.2.2.3 Selection Mechanisms

The ABC algorithm uses 4 different selection processes. These:

- A global probability-based selection process in which probability values are calculated using Equation 3.6 to determine potential good sources,
- Regional probability-based selection process, which is instrumental in finding the source in a region using visual information that allows the employee and onlooker bees to determine the type of nectar source, such as color, shape, smell (Equation 3.3),
- Greedy selection, which employee and onlooker bees use to determine the best source,
- Random selection performed by scout bees through Equation 3.2. By using all these selection methods together, the ABC algorithm can do both good global research and regional research (Akay, 2009).

CHAPTER IV

WHALE OPTIMIZATION ALGORITHM

Whales are creatures of the high seas; they feed at sea, mate, give birth, breastfeed and raise their young at sea. Their lives have adapted so much to living at sea that they cannot survive on land. Its dimensions range from the dwarf sperm whale, which weighs 2.6 m and 135 kg, to the blue whale, which weighs 29.9 m and 190 tons and is the largest living animal in the world (Wikipedia, 2021).

There are 7 species: killer, minke, northern, humpback, glacier, slotted and blue whale. Whales never sleep because they have to breathe from ocean surfaces. Only half their brains sleep. Another fact about whales is that they have feelings (Tanyıldızı & Cigal, 2017).

4.1 WOA Inspiration

The WOA is one of the meta-heuristic algorithms inspired by the hunting method of humpback whales. Humpback whales have their own hunting methods. According to this method, also called an air bubble, the whale detects the location of the prey and makes a loud sound, causing the prey to be afraid. It then gets its prey confused by the water bubbles they remove under the water and prevents it from escaping by not finding its direction. They draw circular movements that shrink upward as they try to reach prey.

Although WOA, one of the swarm-based algorithms, is a very new algorithm, research has shown that WOA is applied to many optimization problems and successful results have been obtained.

The WOA is an algorithm developed by Mirjalili and Lewis in 2016 using whale hunting strategies. In particular, the behavior of humpback whales was inspired by the way they guide the fish swarm with air bubbles that they remove. This method is as shown in Figure 4.1 (Mirjalili & Lewis, 2016):

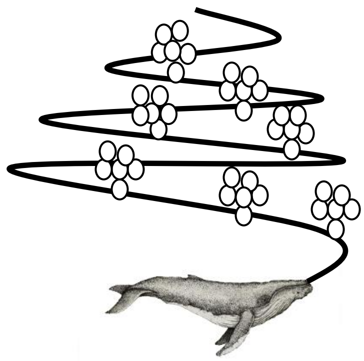

Figure 4.1: The humpback whale's hunting method.

The search pattern of humpback whales is called bubble web feeding, in which whales form bubbles in an upward spiral swimming path around the fish (Watkins & Schewill, 1979).

4.2 Mathematical Model of the WOA

The mathematical model of the WOA is shaped according to the instinctive behavior that the whale exhibits when hunting. These behaviors are discussed in three parts: surrounding the prey, moving towards the prey, and searching for prey.

4.2.1 Surrounding the Hunt

Humpback whales can predict the location of their prey. The prey to be reached is considered the optimum point in the whale algorithm. Since the optimal solution is not known in optimization problems, an attempt is made to obtain the optimal solution using local or global search spaces. The search continues until certain criteria are met. The optimal solution is considered the best solution reached or a point around it. After determining the best solution, the locations of the other solutions are updated using the best solution. The mathematical model of the behavior of surrounding prey is shown in Equation 4.1 and Equation 4.2 (Mirjalili & Lewis, 2016).

$$\vec{D} = |\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)| \quad (4.1)$$

$$\vec{X}(t+1) = |\overrightarrow{X^*}(t) - \vec{A}.\vec{D}| \quad (4.2)$$

The terms in the equations are respectively; t, the current iteration, $\vec{A}$ and $\vec{C}$, convergence vectors, $\overrightarrow{X^*}$, the best obtained solution vector, ".", denotes matrix multiplication.
The values $\vec{A}$ and $\vec{C}$, which are the convergence vectors, are calculated as shown in Equation 4.3 and Equation 4.4.

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \qquad (4.3)$$

$$\vec{C} = 2.\vec{r} \qquad (4.4)$$

r , random vector, a, refers to a vector that decreases from 2 to 0 during iterations (Mirjalili & Lewis, 2016).

Figure 4.2 (a) shows the justification for Equation 4.2 for the 2-dimensional problem. Any search agent (X, Y) can determine its position according to the best search agent (X^*, Y^*). Points around the best agent can be reached by setting constants A and C. Figure 4.2 (b) shows the 3-dimensional search space in the same way.

a) b)

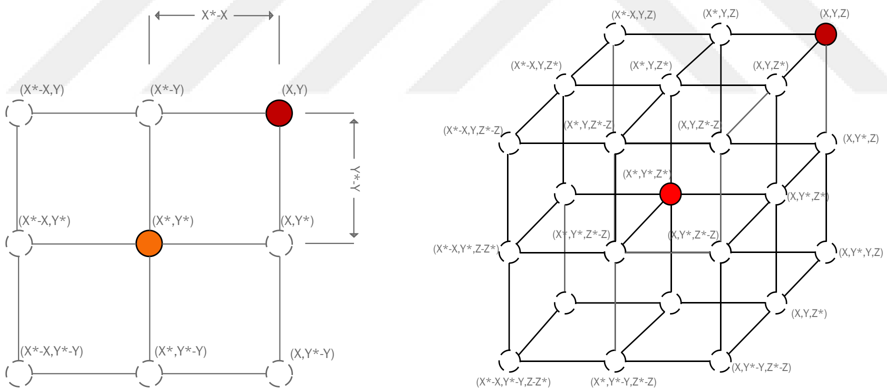

Figure 4.2: 2 and 3-dimensional position vectors and possible positions of search agents. (Mirjalili & Lewis, 2016)

4.2.2 Progress towards the Hunt

This process has been considered in 2 different cases, taking into account the fact that the whale creates a spiral movement as it moves towards the hunt, and this circle gradually shrinks.

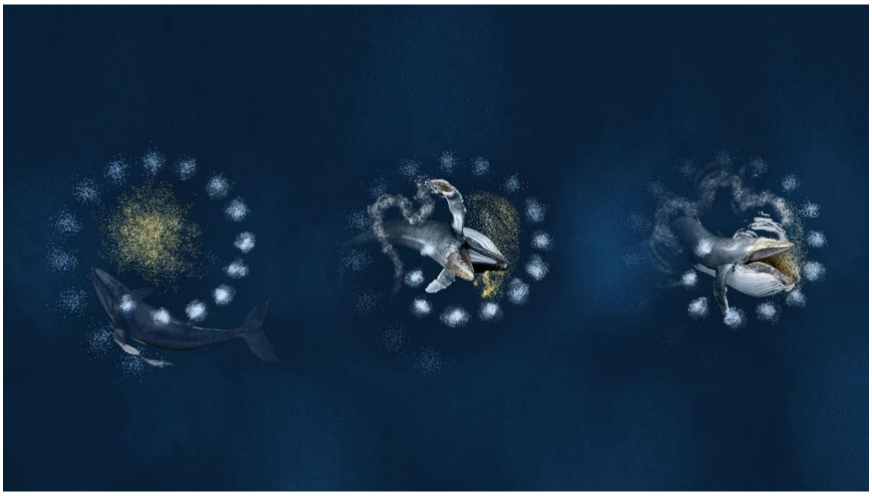

Figure 4.3: A spiral shape formed by a humpback whale.
https://www.sciencenews.org/article/humpback-whales-bubble-nets
(Kosma / Royal Society Open Science 2019)

Narrowing the circle around the prey is possible by reducing the $\vec{a}$ value in Equation 4.3. Figure 4.4 shows the best search agent's location and the spiral movement it made. Based on this, the correlation between the best search agent and the other search agent is formulated with Equation 4.5.

$$\vec{X}(t+1) = \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) \quad (4.5)$$

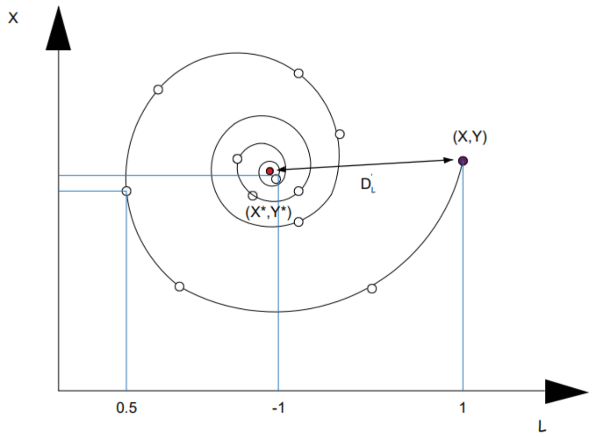

Figure 4.4: Spiral movement (Mirjalili & Lewis, 2016).

In Equation 4.5, $\overrightarrow{D'} = \overrightarrow{X^*} - \vec{X}(t)$. This expression gives the distance between the search agent and the best-known point. The terms in this equation are respectively; b logarithmic spiral constant, l is a random number between [-1.1] (Tanyıldızı & Cigal, 2017).

In the algorithm, which of the spiral motion and linear motion will be made is determined with ½ probability, as shown in Equation 4.6. The p value is a random number in the range [0, 1], in Equation 4.6.

$$\vec{X}(t+1) = \begin{cases} |\overrightarrow{X^*}(t) - \vec{A}.\vec{D}| & , \; p < 0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t), & p \geq 0.5 \end{cases} \tag{4.6}$$

4.2.3 Hunting Search

Humpback whales can hunt their prey at random, except for the bubble method. In order to move away from the reference whale in random hunt search, random values of vector $\vec{A}$, greater than 1 or less than -1 are used. In the hunting search mechanism, unlike the bubble mechanism, when updating the search agent's position, a randomly selected search agent is used instead of the best search agent ever found. $|\vec{A}| > 1$ causes the whale optimization algorithm to be searched globally because it is a random search tool (Doğan, 2019).

The mathematical equations used in such a case are as follows:

$$\vec{D} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}| \tag{4.7}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \tag{4.8}$$

In Equations 4.7 and 4.8 , $\overrightarrow{X_{rand}}$ shows a randomly selected search agent.

In WOA's mathematical model, the humpback whale's circle of prey expressed the situation with vectors.

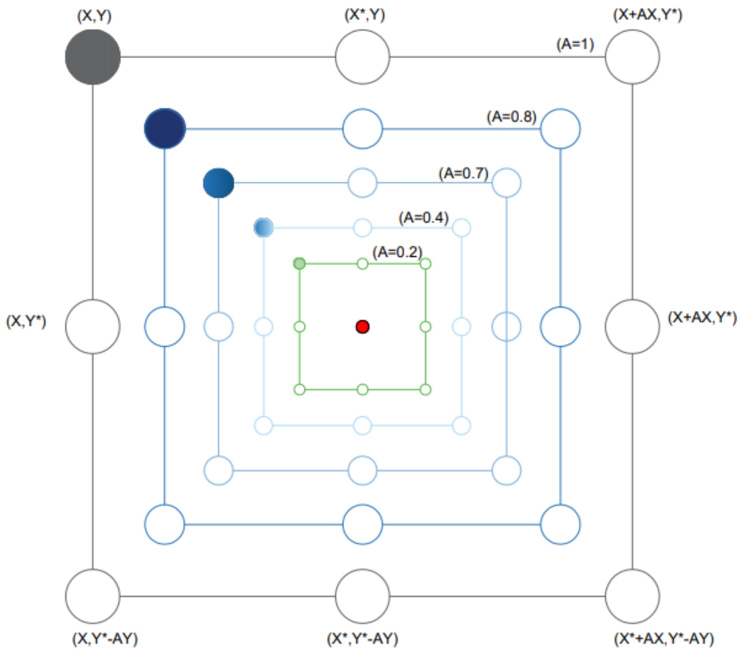

Figure 4.5: WOA's global search behavior (Mirjalili & Lewis, 2016).

In summary, hunting in the WOA algorithm is considered the optimum point to be reached. Since the optimal solution to this problem is unknown, the optimal point is considered the best solution reached or the point closest to it around it. In the surrounding phase of the hunt, the best search agent is determined, and in subsequent steps, the positions of the other search agents are updated using this search agent. After updates are made, the phase of surrounding the prey ends and the phase of moving towards the prey begins. At this stage, the circle around the prey, that is, the optimal point, is narrowed. As humpback whales rise towards prey, they simultaneously continue the spiral movement. In the algorithm, it is determined which of these moves will be made with a 50% probability. Finally, in the hunt search phase, the new locations of search agents for the global search are determined around a randomly selected search agent, rather than the best-known point (Eröz & Tanyıldızı, 2018).

4.3 Whale Algorithm Pseudo Code and Flow Chart

The pseudo-code of the whale algorithm Table 4.1's is like (Tanyıldızı & Cigal, 2017):

Table 4.1: The pseudo code of WOA (Tanyıldızı & Cigal, 2017).

```
Initialize the whale population Xi (i = 1, 2, . . ., n)
Calculate the fitness value of each search agent
X* = Best known search agent

while (t < maximum number of iterations)

for (for each search agent)
    Update a, A, C, l ve p

        if (p < 0.5)
            if (|A| ≥ 1)
                Update search agent location with Equation 4.1
            else if (|A| < 1)
                Choose a random search agent ( X_rand )
                Update search agent with Equation 4.8
            end if
        else if (p ≥ 0.5)
                Update search agent location with Equation 4.5
        end if

end for

Give limit value to individuals who are out of constraint,
Calculate objective function values,
Update the best agent if a better solution is found.

t = t + 1
end while
Return X *
```

The flow chart of the whale algorithm is as in Figure 4.6.

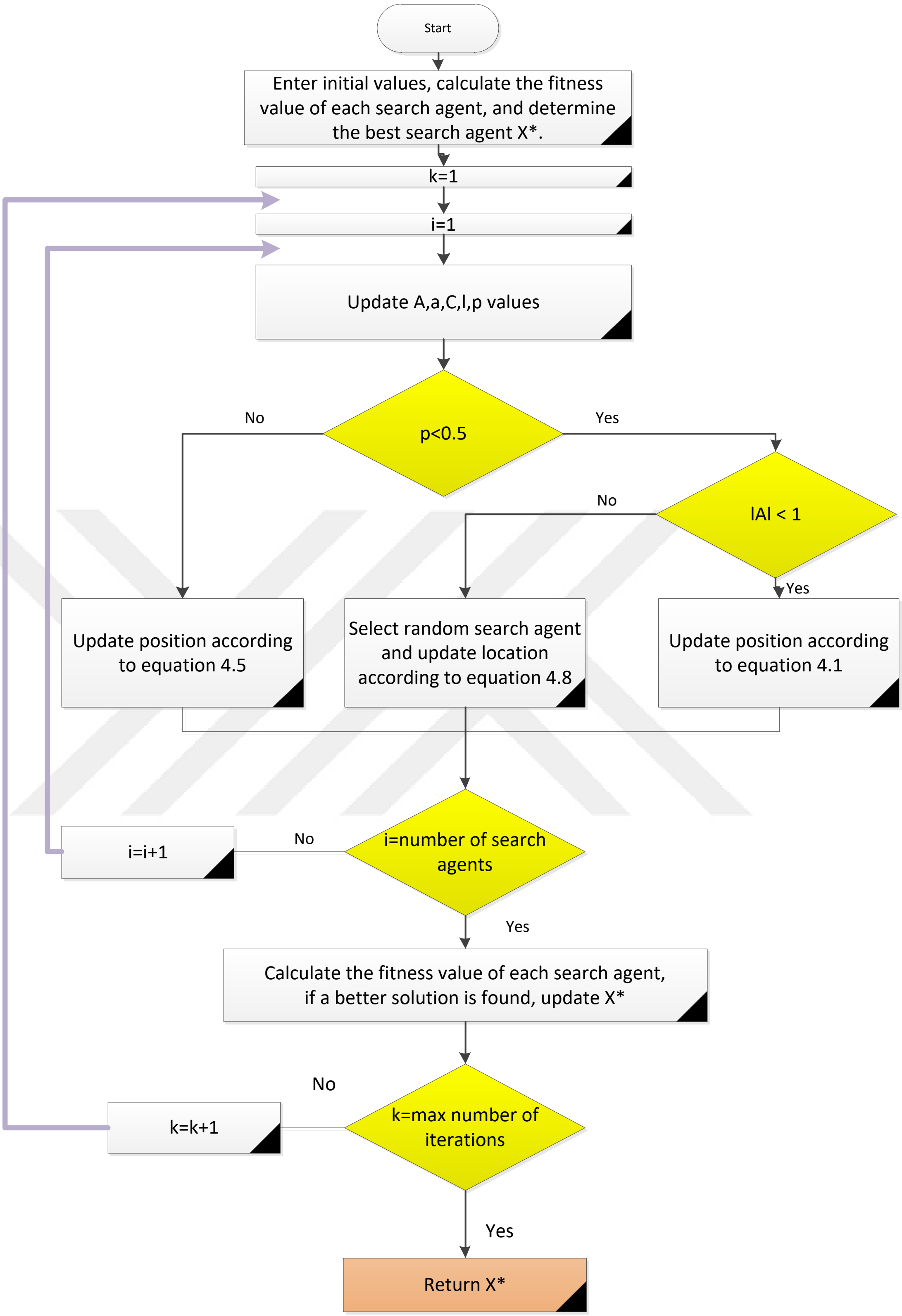

Figure 4.6: The flow chart of WOA (Doğan, 2019).

CHAPTER V

ENERGY AND ENERGY TYPES

Humanity, which used its own power intensively as a source of energy in the early periods of history, has developed methods that can benefit from nature and the powers and energies of animals by exploring its surroundings over time. Fire was discovered, and used with wood and then with coal, fire energy was used, over time, steam energy was added to the energy sources in order to facilitate its life by finding steam power (Günen, 2017).

In nature, energy can be found in forms such as mechanical, chemical, nuclear, hydraulic, solar energy. These energy sources can be converted into other energy. The definition of energy is mostly used instead of the term electric energy. The energy provided to consumers by converting mechanical or thermal energy into electricity is called electrical energy (Uğurlu, 2006).

<table>
<tr><th colspan="4">ENERGY SOURCES</th></tr>
<tr><th colspan="3">PRIMARY ENERGY SOURCES</th><th rowspan="2">SECONDARY ENERGY SOURCES</th></tr>
<tr><th>RENEWABLE ENERGY RESOURCES</th><th colspan="2">NON-RENEWABLE ENERGY RESOURCES</th></tr>
<tr><td>Sun</td><td rowspan="3">FOSSIL ORIGIN</td><td>Coal</td><td>Electrical</td></tr>
<tr><td>Wind</td><td>Oil</td><td>Gasoline, diesel</td></tr>
<tr><td>Wave</td><td>Natural gas</td><td>Kok, Petrokok</td></tr>
<tr><td>Geothermal</td><td rowspan="4">NUCLEAR</td><td>Uranium</td><td>Air gas, liquefied petroleum gas</td></tr>
<tr><td>Hydraulic</td><td></td><td></td></tr>
<tr><td>Biomass</td><td>Thorium</td><td rowspan="2">These sources are energy sources obtained by converting primary energy sources.</td></tr>
<tr><td>Hydrogen</td><td></td></tr>
</table>

Figure 5.1: Classification of energy sources.

Energy sources can be grouped into two main groups according to their convertibility. The raw state of the source that has not been converted is called primary energy, the energy obtained by converting primary energy is called secondary energy (Figure 5.1).

5.1 Primary Energy Sources

Oil, natural gas, coal, solar, wind, uranium, etc. the non-converted state of fossil, natural and nuclear energy sources, which we can increase samples of, is called primary energy. A large part of the energy used today is provided from primary energy sources.

The Toe (Tone of Oil Equivalent) measurement unit is used to compare energy sources (Table 5.1).

Table 5.1: Ton equivalent oil equivalents.

Tonne of Oil Equivalent (TOE)	**TEP**
Ktep (Ktoe)	1.000 TEP
Mtep (Mtoe)	1.000.000 TEP
Gtep (Gtoe)	1.000.000.000 TEP

A unit of energy called Toe refers to the energy released when 1 ton of crude oil is burned. Although it is expressed in Turkish sources as Tep (Ton equivalent Oil), national sources are also shown as Toe (Tone of Oil Equivalent). The values of 1-ton equivalent oil corresponding to other energy units are shown in Table 5.2.

Table 5.2: Conversions of 1 TOE oil to other energy units.

1 Toe	11630 kWh
1 Toe	41868 MJ
1 Toe	10.000.000 kcal
1 Toe	7,14 boe (barrel oil equivalent)
1 Toe	1.1111111111111E-6 Gm ^{3} NG

Primary energy supply in the World by year are shown in Figure 5.2.

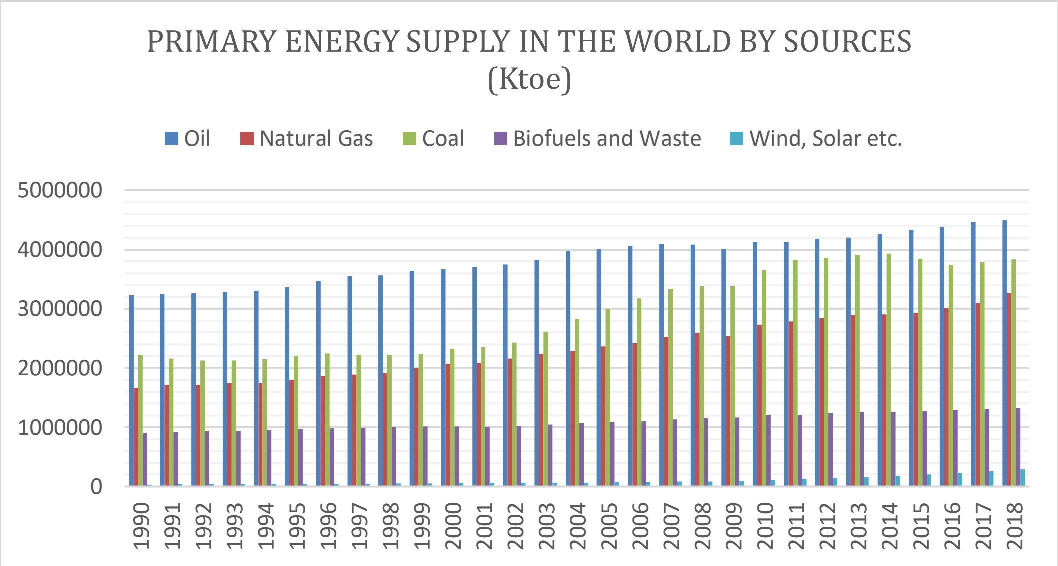

Figure 5.2: Primary energy supply in the World by year. (IEA, 2020).

Primary energy consumption in the World by year is shown in Figure 5.3.

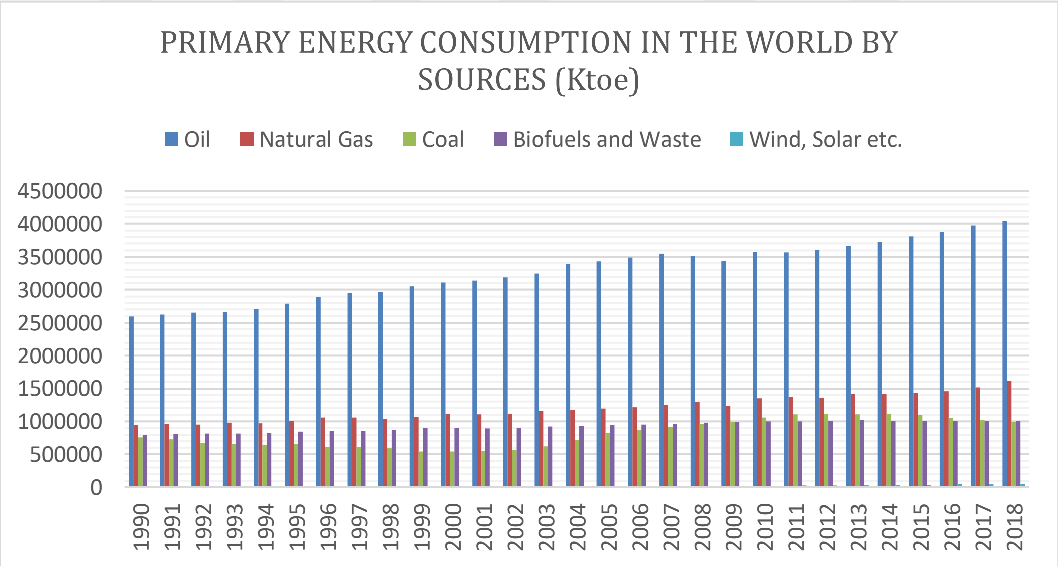

Figure 5.3: Primary energy consumption in the World by year (IEA, 2020)

As can be seen from the charts above, the consumption of oil in the world in 2018 was 4496998 KTOE, natural gas 3261595 KTOE, coal 3838326 KTOE, biofuel and waste 1327127 KTOE and renewable energy sources 286377 KTOE.

Primary energy supply in Turkey by year are shown in Figure 5.4.

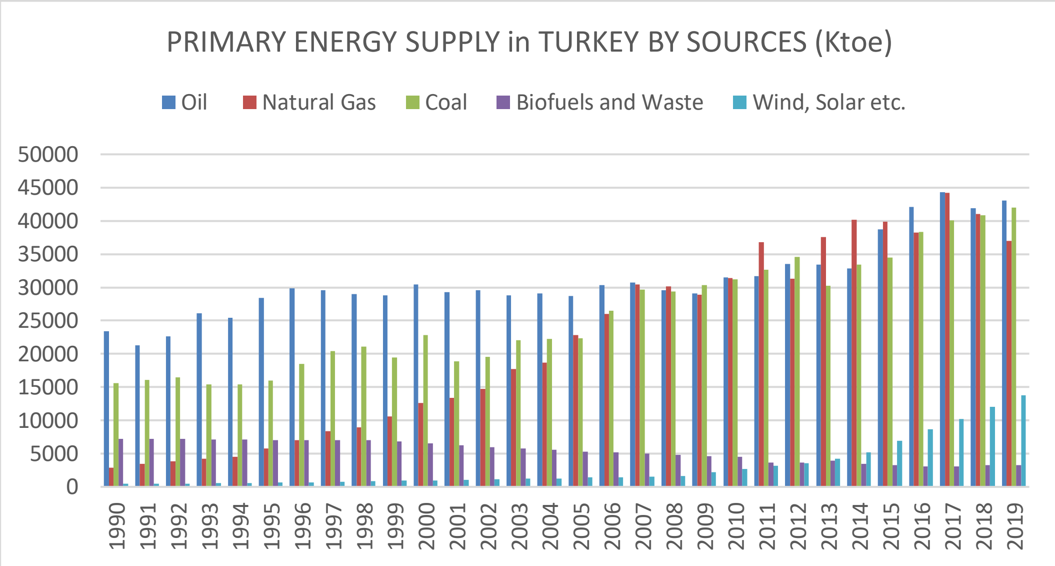

Figure 5.4: **P**rimary energy supply in Turkey by year (IEA, 2020)

Primary energy consumption in Turkey by year are shown in Figure 5.5.

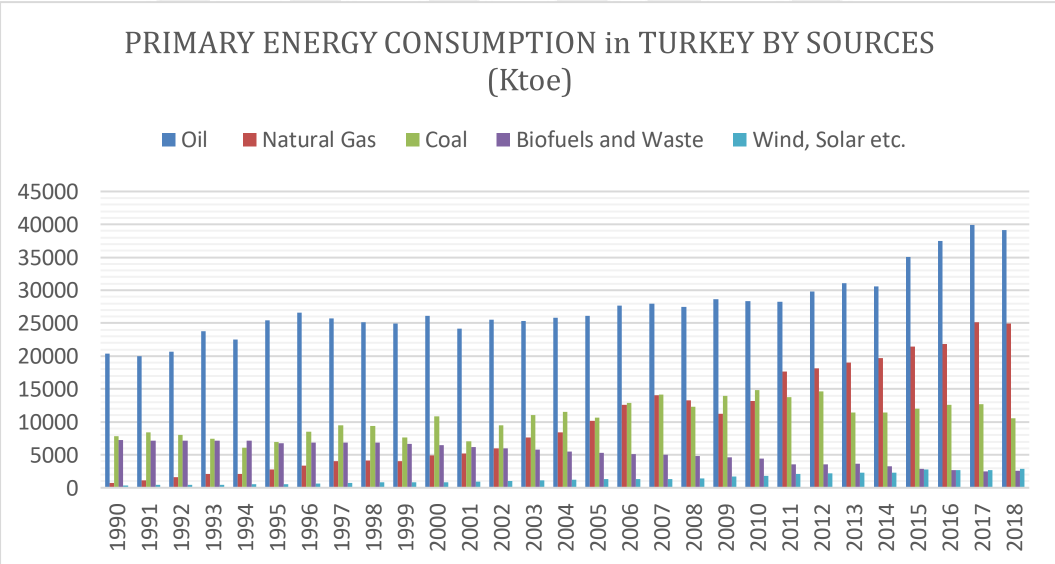

Figure 5.5: **P**rimary energy consumption in Turkey by year (IEA, 2020)

As can be seen from the charts above, the consumption of oil in Turkey in 2018 was 39154 KTOE, natural gas 24950 KTOE, coal 10571 KTOE, biofuel and waste 2540 KTOE and renewable energy sources 2831 KTOE. Primary energy sources are divided into 2 as renewable and non-renewable energy sources.

5.1.1 Renewable Energy Sources

Renewability means that nature can somehow provide reinforcements obtained from nature and when it is reduced. Worldwide, especially increasing population, living standards, industrialization and unconscious consumption of scarce resources increase the importance of renewable energy sources many times.

Renewable energy is energy that is replaced in a short time. Non-renewable energy is defined as energy used but not re-formed in a short period of time (Satman, 2007).

The reason we turn to renewable energy sources is not only because the reserve life of non-renewable energy sources ends, but also because environmental pollution caused by the use of these non-renewable energy sources threatens our lives (Cengiz, 2017).

Consumption is inevitable, although negative effects on the ecological balance, unlike fossil fuels, among clean sources of energy, hydro energy, solar energy, biomass energy, wind energy, geothermal energy, hydrogen energy and wave energy are located (Oktik, 2000).

Table 5.3: Types and sources of renewable energy (Tiftikçigil & Yesevi, 2015).

Types of Renewable Energy	**Source**
Solar Energy	Sun
Wind Power	Wind
Hydraulic Energy	Stream, River
Biomass Energy	Biological Waste
Geothermal Energy	Groundwater
Wave Energy Ocean	Sea
Hydrogen Energy	Water

Turkey's renewable energy supply and consumption graph is as shown in Figure 5.6.

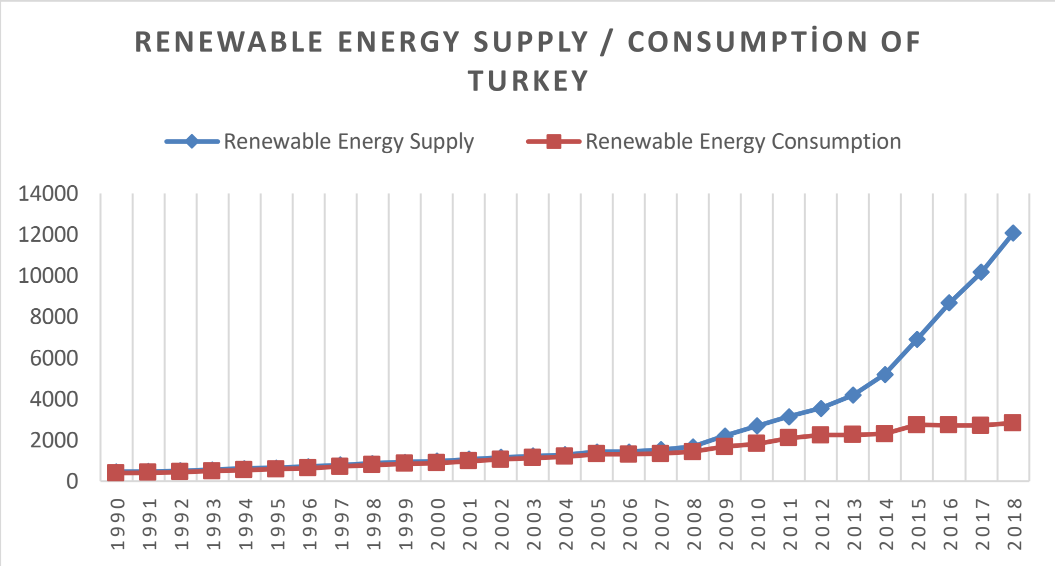

Figure 5.6: Renewable energy supply / consumption graph of Turkey by year (IEA, 2020).

As can be seen from the chart, the amount of supply to renewable energy sources in Turkey was calculated as 12067 ktoe in 2018 and the amount of consumption was calculated as 2831 ktoe.

Renewable energy sources are solar, wind, geothermal, hydraulic (hydroelectric) biomass energies.

5.1.1.1 Solar Energy

Most of the energy that exists on earth is directly or indirectly based on solar energy. Because of the generation in which our country is located and the solar energy potential it has, it is more preferred than other renewable energy sources.

Solar energy is a kind of radiation energy. This energy is generated by the fusion process in the solar core. Although solar energy is a renewable energy source that can be found in sufficient quantities, it is environmentally friendly and does not contain harmful emissions (Karataş, 2009).

Different technologies have been developed to make use of the sun's rays. Some technologies use energy directly, such as heat or light energy, while other technologies use solar energy to generate electricity (Aydın, 2014).

5.1.1.2 Wind Energy

The main source of wind energy is wind. It is an immaculate and endless energy like solar energy.

The sun's rays cause different temperatures, pressures and humidity to form on the Earth. These, in turn, cause uneven warming and cooling of the Earth. The forces that arise when the Earth warms and cools in different ways form air movements. If an air mass warms more than its current state, it rises above the atmosphere, and a cold air mass of the same volume settles in the place that is empty as this air mass rises. The displacement of these air masses is called wind. Wind energy is the energy of motion that the air flow that makes up the wind has. The source of wind energy is the sun. 1-2% of solar energy is converted into wind energy (Energy Portal-Küçükkaya, 2019).

Realizing the potential of wind energy as an inexhaustible resource leads to an increasing rate of use in the world. The International Energy Agency (IEA) is trying to determine the potential of Earth wind energy by conducting various research. Regions/continents with high wind energy potential respectively; 1. North America, 2. Eastern Europe and Russia, 3. Africa, 4. South America, 5. Western Europe, 6. Asia and 7. Oceania-shaped. (Şenel & Koç, 2015).

Turkey's wind energy potential has been determined as 48,000 MW. The total area corresponding to this potential is 1.30% of Turkey's face measurement (Ministry of Energy and Natural Resources of Turkey, 2021).

5.1.1.3 Geothermal Energy

Geothermal energy is the energy generated by the heat accumulated at various depths of the Earth's crust, the temperature of which is above atmospheric temperature and can contain more molten minerals, salts and gases than the normal underground and above-ground waters around it (Kaymakçıoğlu & Çirkin, 2005).

Geothermal energy is divided into three groups according to the high, medium and low heat level it has. If it is greater than 150°C, it is used in electricity production, and if it is at medium and low temperature, it is mainly used for heating purposes (DPT, 1996).

According to fossil sources, geothermal reserves can be counted at an infinite level. Because our country has its own natural resource, it does not create external dependence. But initial investment costs can be a little high.

In 2008, with the entry into force of the law on Geothermal Resources and Natural Mineral Waters and the Work of Geothermal Exploration, development and investment of the private sector, our country's total geothermal heat capacity (visible heat amount) reached 35,500 MWT. Turkey's potential geothermal heat potential is estimated at 31500 MWT and the potential for electricity generation is estimated at 2000 MWe. (Ministry of Energy and Natural Resources of Turkey, 2021).

5.1.1.4 Hydraulic (Hydroelectric) Energy

Hydraulic energy is the energy generated by obtaining electricity by taking advantage of the power of water accumulated in dams, the height of the fall and the speed of flow (Yaman, 2007).

Hydroelectric power plants are one of the methods of electricity generation that is widely used in our country and in developed world countries. In fact, we meet a significant proportion of the energy we produce, such as about 25%, from hydroelectric power plants (Dinçer et al., 2017).

It is also possible to obtain a high amount of energy by releasing the deposited water from a very high point. In both methods, water from the water flow route or deposited and directed into a certain channel travels quickly towards the turbines, allowing the turbines with propeller-like arms to rotate rapidly for electricity generation. Turbines convert mechanical energy in this process into electrical energy through generators (Kanat, 2019). Hydraulics has an important place in the renewable energy potential of our country. With our theoretical hydroelectric potential of 433 billion kWh and our hydroelectric potential, our economic potential can technically be evaluated as 160 216 billion kWh billion kWh/year. In 2018, 59.9 billion kWh of electricity was generated from hydropower. As of the end of August 2019, hydraulic power generation has reached 68,452 GWh (Ministry of Energy and Natural Resources of Turkey, 2021).

5.1.1.5 Biomass Energy

Biomass is generated by all organic matter-derived plants, trees, and crops collecting and storing solar energy through photosynthesis (Ellabban et al., 2014).

Biomass is mainly used in the traditional way as fuel for households and small businesses, while it has become increasingly used for commercial purposes in modern industrial-scale applications. Therefore, biomass is transformed into modern energy with various energy conversion technologies and makes significant contributions to the global energy mix (Johansson et al., 2004).

The use of biomass energy is divided into two categories as classical and modern methods. In classical use, energy is provided by direct burning of biomass material such as wood, plant and animal waste, and is widely used, especially in underdeveloped countries. In modern usage, animal and agricultural wastes, organic content, domestic, urban and industrial wastes/waste water, energy crops, forestry energy products, forestry wastes, seaweed and algae that grow in aquatic ecosystems the conversion of biomass materials with methods such as process heat, electricity and fuel, it is possible to obtain liquid or gas (İlleez, 2020).

The utilization rates of renewable energy sources in Turkey are as shown in Figure 5.7.

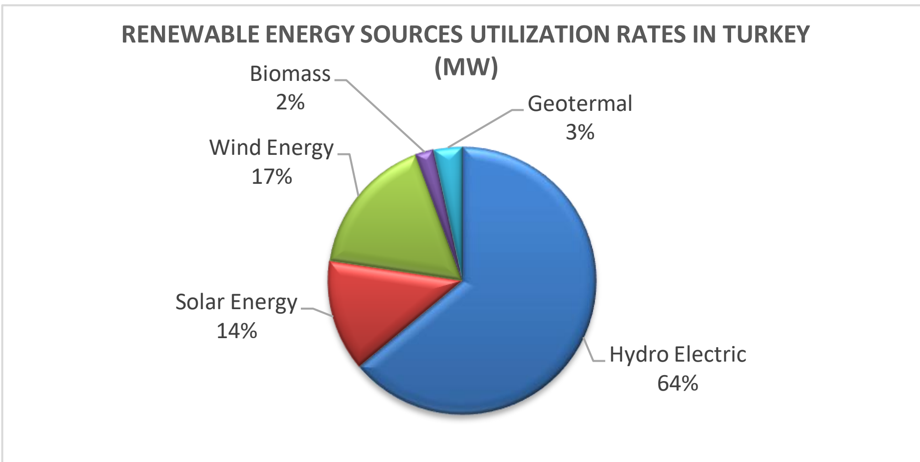

Figure 5.7: In 2019, renewable energy production rates in Turkey.
(Source: https://temizenerji.org)

According to 2019 capacity data, hydroelectric capacity in Turkey is 28503 MW, wind energy is 7591 MW, solar energy is 5996 MW, bioenergy is 983 MW, biogas is 534 MW, and geothermal is 1515 MW (Temiz Enerji, IRENA Yenilenebilir Enerji İstatistikleri, 2020-https://temizenerji.org/2020/07/22/irena-yenilenebilir-enerji-istatistikleri-2020raporunu-yayimladi/).

5.1.2 Non-Renewable Energy Sources

A resource that cannot be replaced as its reserve is consumed is called an irreplaceable energy source. Energy consumption in our country is steadily increasing. Accordingly, imports of non-renewable energy sources are increasing.

As of its location, there are plenty of oil and natural gas resources around it in Turkey, unfortunately these resources are insufficient. But in terms of lignite coal reserves, it can meet its needs from its own reserves. Non-renewable energy sources are divided into 2 as fossil and nuclear energy sources.

5.1.2.1 Fossil Energy Sources

Coal:

As a result of the plants that started to appear on land in very old years, they were buried and stuck in sedimentary rocks over time and changed and came to the consistency of coal. The most important feature of coal is that it is the first fossil energy source used among mineral fuels (Şen, 2002).

It is an organic rock with the ability to burn, consisting of elements such as carbon, hydrogen and oxygen (Tugal, 2014).

The coal supply and demand chart for 2018 in our country is as shown in Figure 5.8.

As can be seen from the Figure 5.8, as of 2018, the amount of coal supply was measured as 40833 ktoe and the amount of demand was measured as 10571 ktoe.

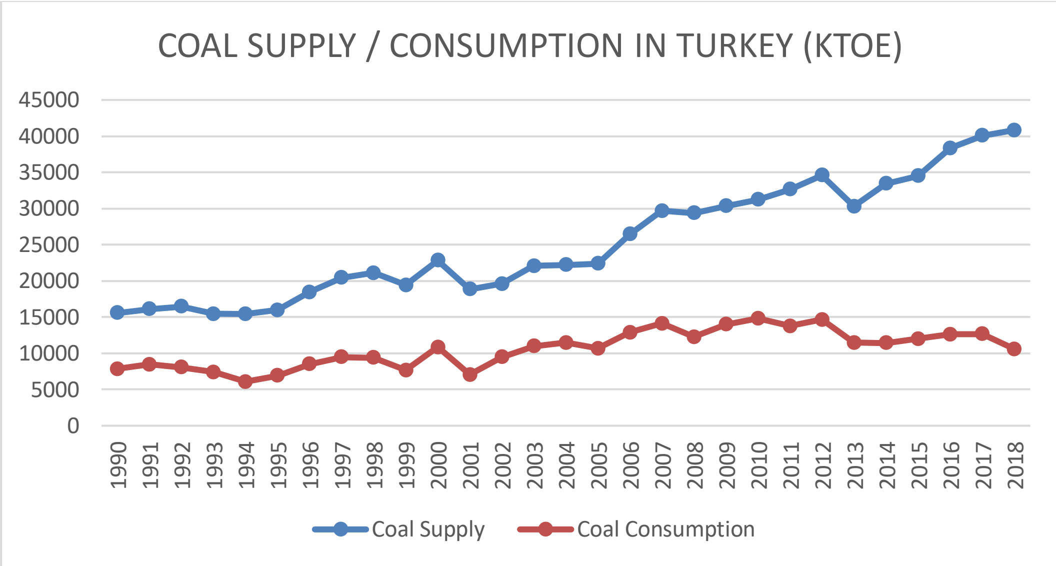

Figure 5.8: Coal supply and consumption rates in Turkey until 2018 (IEA, 2020).

Oil:

Oil occurs when organic substances are degraded and exposed to pressure and heat. Hydrogen and carbon are present in its composition and contain a small amount of nitrogen, oxygen and sulfur. Oil in unrefined liquid state is called crude oil, oil in semi-solid and solid state, consisting of heavy hydrocarbons and tar, asphalt, pitch, tar and similar names. Because the main components of crude oil are hydrogen and carbon, it is also called hydrocarbon. The worldwide proven oil reserves in 2019 were 1,733.9 billion barrels. 833.8 billion barrels of oil reserves are in Middle Eastern countries, 324.1 billion barrels are in South and Central American countries, and 244.4 billion barrels are in North American countries (Ministry of Energy and Natural Resources of Turkey, 2021).

Oil can be found in solid, liquid or gaseous form due to its chemical properties and the temperature and pressure conditions in which it is located. Liquid hydrocarbons are called crude oil; solid hydrocarbons are called bitumen, asphalt or paraffin according to their content; gaseous hydrocarbons are called natural gas (Erdem, 2010).

Some statistical data obtained on oil in Turkey are as in Table 5.5 (Petform, 2020):

Table 5.5: Turkey's oil production statistics (Petform, 2020).

Oil Production (2019)	2.9 million tons
Average Daily Production (2018)	54,386 barrels / day
Consumption Satisfaction Rate of Production (2018)	%8
Total Producible Reserve	209.6 million tons
Cumulative Production (1954-2018)	158.6 million tons
Remaining Producible Reserve (2018)	51.0 million tons

Turkey's oil supply and consumption chart, created according to IEA data, is as follows in Figure 5.9. According to these data, Turkey's oil supply in 2018 was 41495 KTOE and oil consumption was 39154 KTOE.

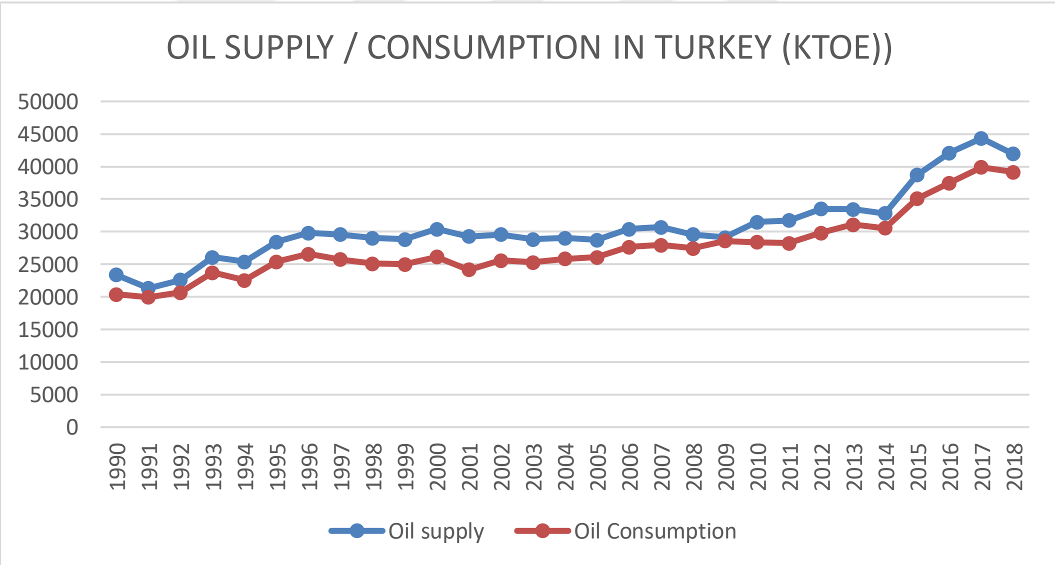

Figure 5.9: Oil supply and consumption rates in Turkey until 2018 (IEA, 2020).

Natural Gas:

Natural gas, an oil derivative, is a kind of combustible gas mixture of fossil origin inside the Earth's crust. It is composed of methane gas (CH4), ethane (C2H6), propane (C3H8) and butane (c4h10) gases. It also contains a small amount of carbon dioxide (CO2), nitrogen (N2), helium(he) and hydrogen sulfide (H2S). Like oil, natural gas is found in the microscopic pores of rocks and flows through the rock, reaching production wells (Petform, 2021).

In 2019, approximately 45.3 billion m3 of natural gas was consumed in Turkey and a total of 483 million m3 was produced. The remaining producible Reserve is approximately 3.36 billion m3. In our country, with new fields discovered as a result of natural gas drilling in 2018 and 2019, natural gas production has increased in the last two years and production has increased by 20% in 2018 and about 11% in 2019 compared to previous years (Ministry of Energy and Natural Resources of Turkey, 2021).

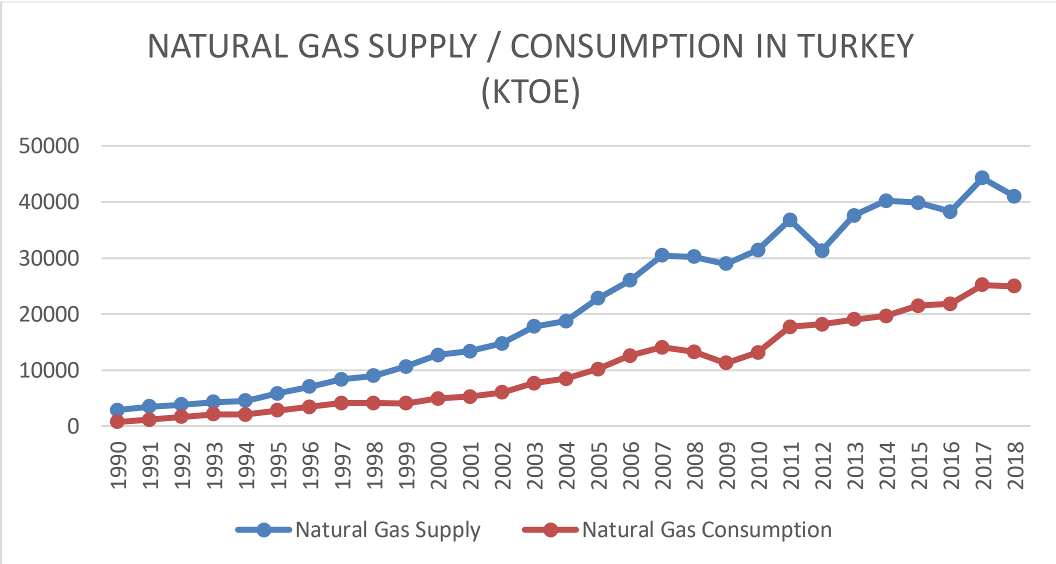

Figure 5.10: Natural gas supply and consumption rates in Turkey until 2018 (IEA, 2020).

Turkey's natural gas supply and consumption chart, created according to data from the IEA, is as shown in Figure 5.10. According to these data, Turkey's oil supply in 2018 was 41018 ktoe and oil consumption was 24950 KTOE.

5.1.2.2 Nuclear Energy

Nuclear energy is a type of energy derived from the nucleus of an atom. Energy generated by the destruction of radioactive elements such as uranium, plutonium and thorium by special methods is used in electricity production. In this way, special measures are taken to minimize the radioactive waste generated in power plants, such as placing it in special hoppers and burying it very deep in the ground. By processing in nuclear energy plants (atomic reactors), they are consumed in the construction of nuclear fuels. They are also used in the production of electrical energy (Energy Portal, Küçükkaya, 2021).

The most feared aspect of nuclear power plants is their ability to pollute the environment in a way that cannot be cleaned after an accident (Gülay, 2008).

As of July 2018, 453 nuclear reactors are in operation in 31 countries and 57 nuclear reactors in 17 countries are under construction. Electricity generated in nuclear power plants is equivalent to 11% of the world's electricity supply. According to the country, France meets about 72% of its electricity demand, Ukraine 55%, Belgium 50%, Sweden 40%, South Korea 27%, the European Union 30% and the United States 20% from nuclear energy (Energy Portal, Küçükkaya, 2021).

5.2 Secondary Energy Sources

The type of energy that occurs when primary energy is physically transformed by containing changes occurs as a secondary energy source. In other words, primary energy sources are needed for secondary energy to occur. It is known that the most important purpose of these energy sources is to store and transport the resulting energy (Gülay, 2008).

CHAPTER VI

SIMULATION STUDIES AND RESULTS

In this study, GDP, population, import and export data between 1990-2019 were used as independent variables in order to make energy consumption forecast of Turkey. These datasets from the World Bank, TUIK and Bp World Energy Statistics Reports are as shown in Table 6.3.

According to historical data in Table 6.3, energy consumption increased from 47.7 MTOE in 1990 to 155.2 MTOE in 2019. It is expected that the import and export rates that will develop depending on GDP, population and industry, which are projected to increase in the coming period, will increase Turkey's energy consumption in parallel. Although there has been an increase in the direction of decreasing in recent years, this increase will continue until it reaches satisfaction. For all these reasons, Turkey has to implement a sustainable growth and development policy and guide its future by acting from the most accurate data. Especially, emphasis should be placed on investment in domestic and renewable energy sources and incentive efforts should be increased.

Algorithm studies were carried out on Matlab 2019 program. Our dependent variable is energy consumption data, and the independent variables are Turkey's past GDP, population, import and export data.

These parameters are popular used in the literature (Toksarı, 2007; Ünler, 2008; Toksarı, 2009).

Table 6.1: General information about the application.

Variables	GDP, Population, Import, Export
Dependent Variable	Energy Consumption
Historical Data	1990-2019 Years
Algorithms Used	GA, WOA and ABC Algorithms

In order to forecast future energy consumption, it is necessary to know the future values of the independent variables that we have used. For this reason, it is necessary to forecast what the conditions will be in the following process and to make forecasting work through these scenarios by derivation some scenarios.

A number of scenario studies have been conducted that forecast the extent to which GDP, population, import and export values, which are known to affect energy consumption, will change in the next years. In this study, the first three scenarios used to make energy consumption forecasting are Ünler (2008) and Kiran et al. (2012).

Scenario 4 will be realized by applying data analysis to the data of the past 30 years in Table 6.3 and forecasting future values. The scenarios used are as in Table 6.2:

Table 6.2: Future scenarios (Ünler, 2008; Kıran, 2012).

Scenarios	GDP	Population	Import	Export
Scenario 1	3,5%	0,1%	7%	5%
Scenario 2	7%	0,12%	3,5%	2,5%
Scenario 3	5%	0,8%	3,5%	4%

In this study, energy consumption forecasting based on the indicators we prefer as independent variables was modeled using linear (Equation 6.1) and quadratic (Equation 6.2) forms in accordance with the scenarios mentioned above.

Linear Model:

$$E_{lineer} = w_1.x_1 + w_2.x_2 + w_3.x_3 + w_4.x_4 + w_5 \qquad (6.1)$$

Quadratic Model:

$$E_{quadratic} = w_1.x_1 + w_2.x_2 + w_3.x_3 + w_4.x_4 + w_5.x_1.x_2 + w_6.x_1.x_3 + w_7.x_1.x_4 + w_8.x_2.x_3 + w_9.x_2.x_4 + w_{10}.x_3.x_4 + w_{11}.x_1^2 + w_{12}.x_2^2 + w_{13}.x_3^2 + w_{14}.x_4^2 + w_{15} \qquad (6.2)$$

In these equations $w_1, w_2, w_3 \ldots\ldots\ldots, w_i$ specifies the design coefficients found appropriate by algorithms. Also, the value x_1 GDP, x_2 population, x_3 imports and x_4 represents the data of exports.

In this section, three metaheuristic algorithm methods were used to determine energy consumption forecasting. These algorithms are genetic algorithm (GA), whale optimization algorithm (WOA), and artificial bee colony (ABC) methods. By comparing the modeling results of these three algorithms, it was desired to determine which one gave the best results. Since the whale algorithm was not previously used when estimating energy consumption, it was preferred specifically for this study.

The main goal in energy consumption forecasting problems is to find the most correct function under certain constraints and the design coefficients of this function (w_i). Through this objective function, the sum of squares of errors is minimized. The objective function of the model is shown in Equation 6.3.

$$\min f(v) = \sum_{i=1}^{m}[E_i^{observed} - E_i^{predicted}]^2 \qquad (6.3)$$

Here m number of observations, $E_i^{observed}$ energy in consumption from 1990-2019, $E_i^{predicted}$ is the forecasted value obtained by the coefficients given by the algorithms.

In addition, stability coefficient (R^2), mean absolute deviation (MAD) and mean absolute percentage error (MAPE) scales were used to test the performance of linear and quadratic models created according to the values given by the algorithms. These error scales are shown in Equation 6.4 and Equations 6.5 and Equation 6.6.

$$R^2 = 1 - \frac{\sum_{i=1}^{T}(E_i - E_t')}{\sum_{i=1}^{T}(E_i - E_i^{ort})} \qquad (6.4)$$

$$MAD = \frac{\sum | E_t - E_t' |}{T} \qquad (6.5)$$

$$MAPE = {}^{1}/_{T}\left(\frac{\sum | E_t - E_t' |}{E_t} * 100\right) \qquad (6.6)$$

$\boldsymbol{E_t}$ **:** Actual observation values

$\boldsymbol{E_t'}$ **:** Estimated values

$\boldsymbol{E_i^{ort}}$**:** Average of actual observation value

T: Number of estimates

Table 6.3: Data sets used 1990-2019.

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	Energy Consumption (Mtoe)
1990	151	53,92	22,3	12,96	47,7
1991	150	54,84	21,05	13,6	48,7
1992	158	55,75	22,87	14,72	51,1
1993	180	56,65	29,43	15,35	55,4
1994	131	57,56	23,27	18,11	53,7
1995	170	58,49	35,71	21,64	60,1
1996	182	59,42	43,63	23,23	65,5
1997	190	60,38	48,56	26,26	68,6
1998	276	61,32	45,92	26,98	70,3
1999	256	62,29	40,67	26,59	68,6
2000	273	63,24	54,5	27,22	73,5
2001	200	64,2	41,4	31,19	66,9
2002	238	65,14	51,55	36,06	73,1
2003	312	66,09	69,34	47,25	77,4
2004	405	67,01	97,54	63,17	82,8
2005	501	67,1	116,77	73,48	84,9
2006	552	68,76	139,58	85,54	94,3
2007	676	69,59	170,63	107,28	100,4
2008	764	70,42	201,96	132,03	100,8
2009	645	71,32	140,93	102,14	102,2
2010	772	72,32	185,54	113,88	107,6
2011	833	73,44	240,55	134,91	115,1
2012	874	74,65	236,55	152,46	122,3
2013	951	76	251,66	151,8	121,5
2014	934	77,23	242,18	157,61	125,4
2015	860	78,52	207,25	143,84	137,2
2016	864	79,82	198,62	142,53	144,6
2017	853	81,1	233,05	156,99	152,7
2018	771	82,32	223	168,1	153,5
2019	754	83,43	202,7	171,53	155,2

MTOE= Million Tonnes of Oil Equivalent

6.1 Turkey's Energy Consumption Forecast by Genetic Algorithm

6.1.1 Linear Equation Modeling

The control parameters selected for linear forecasting using a genetic algorithm are as follows:

- Population Size: 240
- Selection Function: Tournament
- Crossover Fraction: 0.6
- Mutation Function: Constraint Dependent
- Crossover Function: Constraint Dependent
- Number of Generations: 1000

The chromosome forms the values (genes) $w_1, w_2 \dots \dots w_i$ in Equaiton 6.1 and 6.2.

The control parameters given above are the objective function given in equation 6.3 and using the linear model given in equation 6.1, the following equations and values are obtained.

$$Y_{lineer} = -0.04942.X1 + 0.14606.X2 + 0.03025.X3 + 0.79619.X4 + 37.574$$

$$R^2_{lineer} = \%97$$

The modeling of the past 30 years for the GA linear model is shown in Figure 6.1 and Table 6.4.

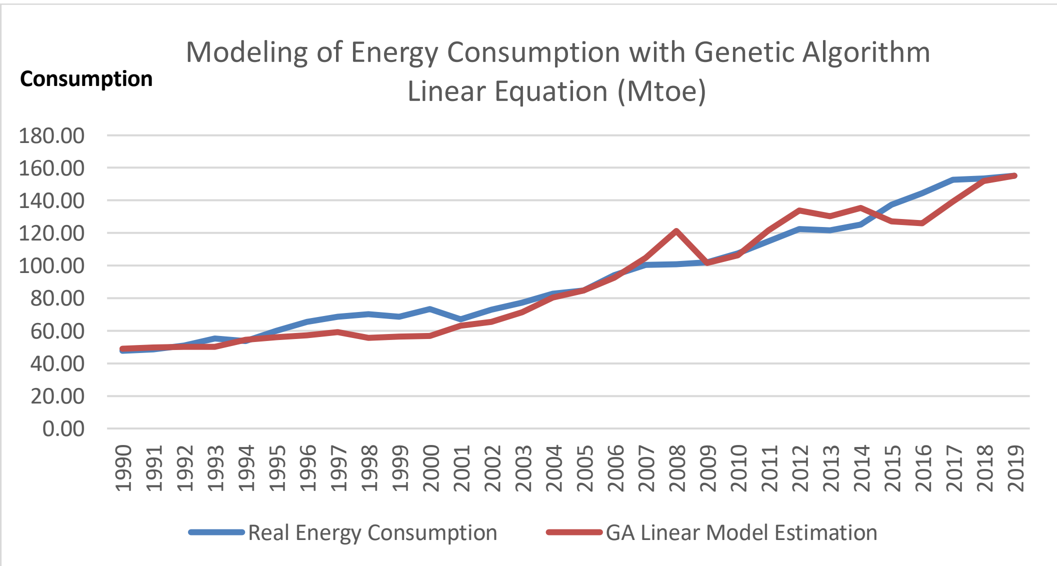

Figure 6.1: Energy consumption modeling with GA linear model.

6.1.2 Quadratic Equation Modeling

The control parameters selected for quadratic forecasting using a genetic algorithm are as follows:

- Population Size: 240
- Selection Function: Tournament
- Crossover Fraction: 0.6
- Mutation Function: Constraint Dependent
- Crossover Function: Constraint Dependent
- Number of Generations: 1000

The control parameters given above are the objective function given in equation 6.3 and using the quadratic model given in equation 6.2, the following equations and values are obtained.

$$Y_{quadratic}=0.16878.X1 + 0.531103.X2 + 0.345932.X3 - 0.162934.X4 + 0.339323.X1.X2 - 0.192926.X1.X3 + 0.277993.X1.X4 - 0.20426.X2.X3 - 0.18908.X2.X4 + 0.309896.X3.X4 + 0.026349.X1^2 + 0.15114.X2^2 - 0.1841.X3^2 + 0.0568.X4^2 + 195{,}345$$

$$R^2_{quadratic}=\%96$$

The modeling of the past 30 years for the GA quadratic model is shown in Figure 6.2 and Table 6.4.

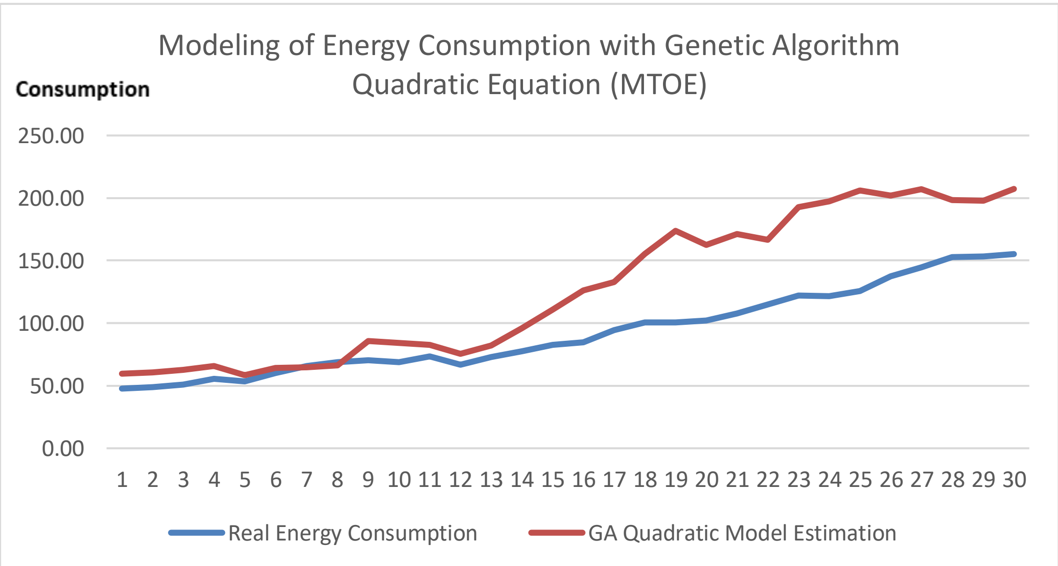

Figure 6.2: Energy consumption modeling with GA quadratic model.

Table 6.4: Energy consumption forecasting and error percentages with GA linear and quadratic models.

Year	Energy Consumption (MTOE)	Ga linear model forecasting	Ga quadratic model forecasting	GA linear model error percentage (%)	GA quadratic model error percentage (%)
1990	47,7	48,98	59,85	2,68	25,47
1991	48,7	49,64	60,76	1,93	24,76
1992	51,1	50,32	62,67	1,53	22,64
1993	55,4	50,06	65,55	9,64	18,32
1994	53,7	54,63	58,43	1,73	8,81
1995	60,1	56,03	64,29	6,77	6,97
1996	65,5	57,07	64,74	12,87	1,16
1997	68,6	59,38	66,14	13,44	3,59
1998	70,3	55,76	85,89	20,68	22,18
1999	68,6	56,42	84,43	17,76	23,08
2000	73,5	56,64	82,68	22,94	12,49
2001	66,9	63,15	75,24	5,61	12,47
2002	73,1	65,6	82,01	10,26	12,19
2003	77,4	71,53	95,79	7,58	23,76
2004	82,8	80,59	110,77	2,67	33,78
2005	84,9	84,65	126,14	0,29	48,57
2006	94,3	92,67	133,03	1,73	41,07
2007	100,4	104,91	155,42	4,49	54,80
2008	100,8	121,33	173,62	20,37	72,24
2009	102,2	101,7	162,64	0,49	59,14
2010	107,6	106,27	171,16	1,24	59,07
2011	115,1	121,82	166,80	5,84	44,92
2012	122,3	133,83	192,69	9,43	57,56
2013	121,5	130,15	197,58	7,12	62,62
2014	125,4	135,51	205,93	8,06	64,22
2015	137,2	127,34	202,00	7,19	47,23
2016	144,6	126,02	207,01	12,85	43,16
2017	152,7	139,31	198,52	8,77	30,01
2018	153,5	152,08	197,96	0,93	28,96
2019	155,2	155,2	207,28	0,00	33,56

MTOE= Million Tonnes of Oil Equivalent

In Table 6.4, the observed energy consumption between 1990-2019 and the forecasted values of GA generated models were compared. As can be seen from the table, the error percentage values of the linear model were lower than the quadratic model.

Table 6.5: GA energy consumption forecast results, according to Scenario 1 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	GA linear model forecasting	GA quadratic model forecasting
2020	780,39	83,51	216,89	180,11	161,17	211,62
2021	807,7	83,6	232,07	189,11	167,46	215,94
2022	835,97	83,68	248,32	198,57	174,09	220,24
2023	865,23	83,76	265,7	208,5	181,09	224,48
2024	895,52	83,85	284,3	218,92	188,47	228,64
2025	926,86	83,93	304,2	229,87	196,25	232,69
2026	959,3	84,02	325,49	241,36	204,45	236,58
2027	992,87	84,1	348,28	253,43	213,1	240,27
2028	1027,62	84,18	372,66	266,1	222,22	243,72
2029	1063,59	84,27	398,74	279,4	231,84	246,85
2030	1100,82	84,35	426,65	293,37	241,98	249,61
2031	1139,35	84,44	456,52	308,04	252,67	251,9
2032	1179,22	84,52	488,48	323,45	263,94	253,63
2033	1220,5	84,61	522,67	339,62	275,83	254,66
2034	1263,21	84,69	559,26	356,6	288,36	254,87
2035	1307,43	84,77	598,4	374,43	301,56	254,05
2036	1353,19	84,86	640,29	393,15	315,49	252
2037	1400,55	84,94	685,11	412,81	330,17	248,43
2038	1449,57	85,03	733,07	433,45	345,64	242,97
2039	1500,3	85,11	784,39	455,12	361,95	235,12
2040	1552,81	85,2	839,29	477,88	379,15	224,21

In Table 6.5, GA energy consumption was forecasted according to the first scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 379,15 MTOE, in quadratic model 224,21 MTOE has been achieved.

Table 6.6: GA energy consumption forecast results, according to Scenario 2 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	GA linear model forecasting	GA quadratic model forecasting
2020	806,78	83,53	209,79	175,82	156,24	216,76
2021	863,25	83,63	217,14	180,21	157,18	226,77
2022	923,68	83,73	224,74	184,72	158,03	237,34
2023	988,34	83,83	232,6	189,34	158,76	248,52
2024	1057,52	83,93	240,74	194,07	159,37	260,35
2025	1131,55	84,03	249,17	198,92	159,84	272,87
2026	1210,76	84,13	257,89	203,9	160,17	286,13
2027	1295,51	84,23	266,92	208,99	160,33	300,18
2028	1386,2	84,34	276,26	214,22	160,3	315,08
2029	1483,23	84,44	285,93	219,57	160,08	330,9
2030	1587,06	84,54	295,94	225,06	159,63	347,7
2031	1698,15	84,64	306,29	230,69	158,95	365,55
2032	1817,02	84,74	317,01	236,46	158,01	384,52
2033	1944,21	84,84	328,11	242,37	156,78	404,7
2034	2080,31	84,94	339,59	248,43	155,24	426,18
2035	2225,93	85,05	351,48	254,64	153,36	449,06
2036	2381,75	85,15	363,78	261	151,12	473,43
2037	2548,47	85,25	376,51	267,53	148,47	499,4
2038	2726,86	85,35	389,69	274,22	145,39	527,09
2039	2917,74	85,46	403,33	281,07	141,85	556,64
2040	3121,98	85,56	417,45	288,1	137,79	588,17

In Table 6.6, GA energy consumption was forecasted according to the second scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 137.79 MTOE, in quadratic model 588.17 MTOE has been achieved.

Table 6.7: GA energy consumption forecast results, according to Scenario 3 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	GA linear model forecasting	GA quadratic model forecasting
2020	791,7	84,1	209,79	178,39	159,11	216,01
2021	831,29	84,77	217,14	185,53	163,16	225,15
2022	872,85	85,45	224,74	192,95	167,34	234,72
2023	916,49	86,13	232,6	200,67	171,67	244,73
2024	962,32	86,82	240,74	208,69	176,14	255,22
2025	1010,43	87,52	249,17	217,04	180,76	266,19
2026	1060,95	88,22	257,89	225,72	185,55	277,69
2027	1114	88,92	266,92	234,75	190,49	289,72
2028	1169,7	89,63	276,26	244,14	195,6	302,32
2029	1228,19	90,35	285,93	253,91	200,88	315,51
2030	1289,6	91,07	295,94	264,06	206,34	329,33
2031	1354,08	91,8	306,29	274,63	211,98	343,8
2032	1421,78	92,54	317,01	285,61	217,82	358,95
2033	1492,87	93,28	328,11	297,03	223,84	374,82
2034	1567,51	94,02	339,59	308,92	230,07	391,44
2035	1645,89	94,77	351,48	321,27	236,5	408,85
2036	1728,18	95,53	363,78	334,12	243,15	427,08
2037	1814,59	96,3	376,51	347,49	250,02	446,18
2038	1905,32	97,07	389,69	361,39	257,11	466,19
2039	2000,59	97,84	403,33	375,84	264,44	487,15
2040	2100,62	98,63	417,45	390,88	272,01	509,11

In Table 6.7, GA energy consumption was forecasted according to the third scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 272,01 MTOE, in quadratic model 509,11 MTOE has been achieved.

Table 6.8: GA energy consumption forecast results, according to Scenario 4 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	GA linear model forecasting	GA quadratic model forecasting
2020	991,51	83,16	262,06	179,19	151,31	226,07
2021	1023,49	84,16	271,14	185,59	155,25	232,44
2022	1055,47	85,15	280,23	191,99	159,19	238,81
2023	1087,45	86,15	289,31	198,39	163,13	245,18
2024	1119,42	87,14	298,39	204,8	167,06	251,55
2025	1151,4	88,14	307,47	211,2	171	257,93
2026	1183,38	89,13	316,55	217,6	174,94	264,3
2027	1215,36	90,13	325,64	224	178,88	270,68
2028	1247,33	91,12	334,72	230,41	182,81	277,06
2029	1279,31	92,11	343,8	236,81	186,75	283,44
2030	1311,29	93,11	352,88	243,21	190,69	289,81
2031	1343,27	94,1	361,97	249,61	194,62	296,19
2032	1375,24	95,1	371,05	256,02	198,56	302,57
2033	1407,22	96,09	380,13	262,42	202,5	308,95
2034	1439,2	97,09	389,21	268,82	206,44	315,33
2035	1471,17	98,08	398,29	275,22	210,37	321,71
2036	1503,15	99,08	407,38	281,63	214,31	328,09
2037	1535,13	100,07	416,46	288,03	218,25	334,48
2038	1567,11	101,07	425,54	294,43	222,19	340,86
2039	1599,08	102,06	434,62	300,83	226,12	347,24
2040	1631,06	103,06	443,7	307,24	230,06	353,62

In Table 6.8, GA energy consumption was forecasted according to the fourth scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 230,06 MTOE, in quadratic model 353,62 MTOE has been achieved.

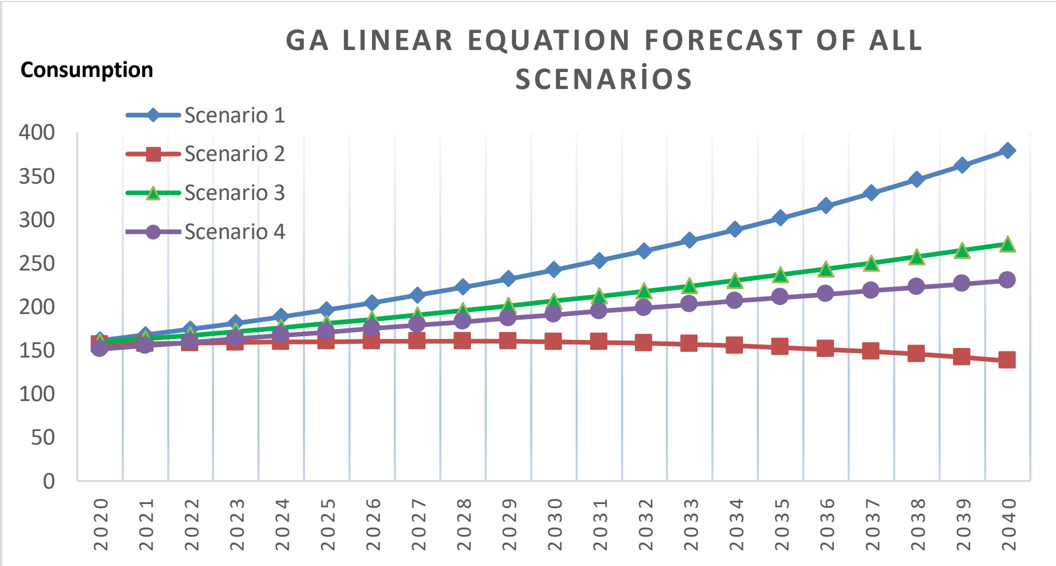

Figure 6.3: GA linear model energy consumption forecast, according to all scenarios.

According to Figure 6.3, scenario 1 is the only scenario that forecasted that energy consumption would decrease made as a result of GA linear modeling. According to all other scenarios, energy consumption in Turkey will increase.

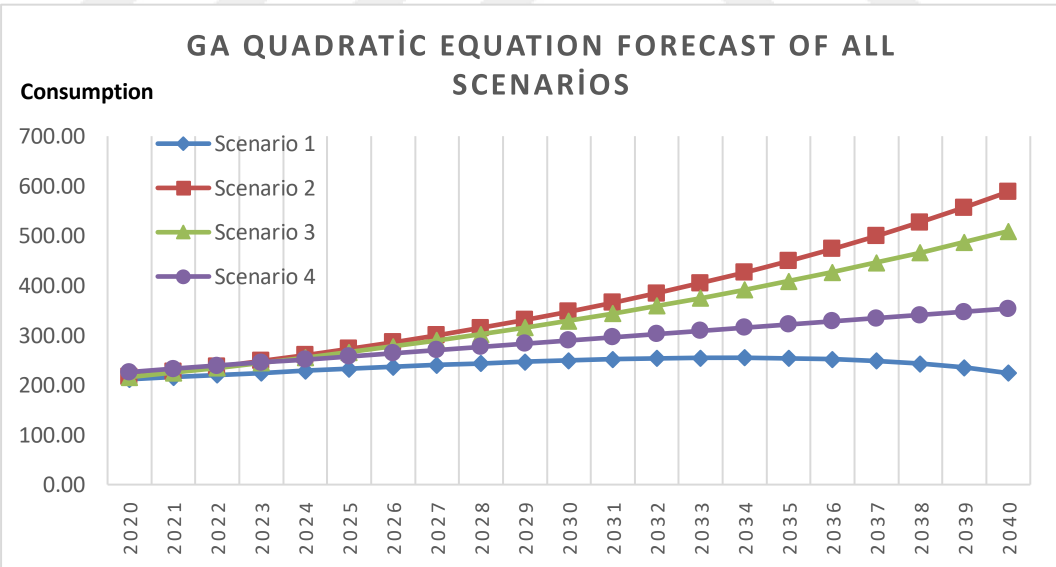

Figure 6.4: GA quadratic model energy consumption forecast, according to all scenarios.

According to Figure 6.4, it has been revealed that energy consumption in Ga quadratic models of all scenarios will be greater than today. The biggest increase is in scenario 4.

6.2 Turkey's Energy Consumption Forecast by Whale Optimization Algorithm

6.2.1 Linear Equation Modeling

The control parameters selected for linear forecasting using the whale algorithm are as follows:

- Number of Search Agents: 30
- Maximum Number of Iterations:10000

The control parameters given above are the objective function given in equation 6.3 and using the linear model given in equation 6.1, the following equations and values are obtained.

$$Y_{lineer} = 0.021949.X1 + 1.X2 - 0.25249.X3 + 0.671006.X4 - 9.0608$$

$$R^2_{lineer} = \%98$$

The modeling of the past 30 years for the linear model is shown in Figure 6.5 and Table 6.9.

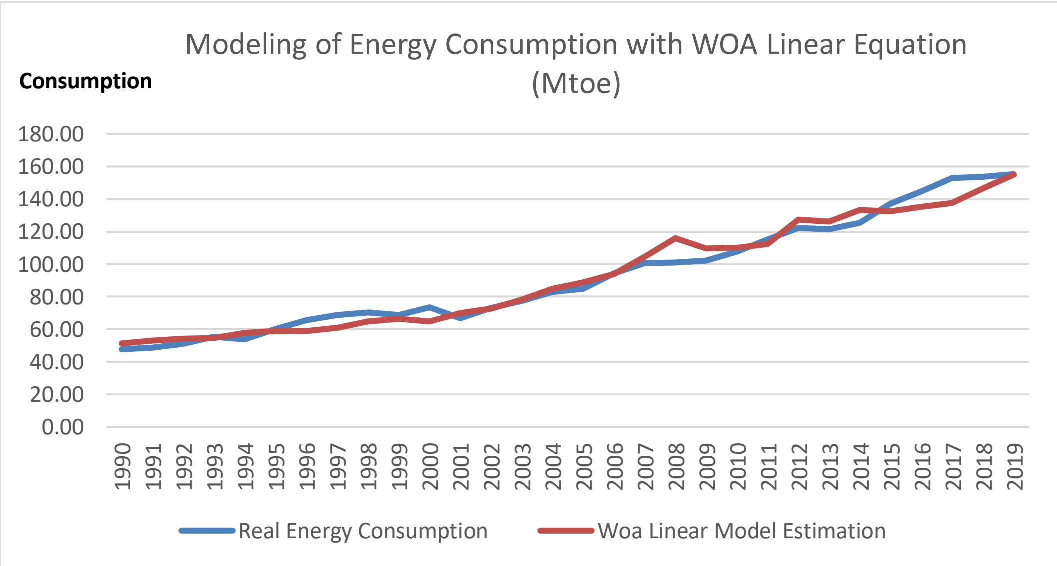

Figure 6.5: Energy consumption modeling with WOA linear model.

6.2.2 Quadratic Equation Modeling

The control parameters selected for quadratic forecasting using the whale algorithm are as follows:

- Number of Search Agents: 30
- Maximum Number of Iterations: 1000

The control parameters given above are the objective function given in equation 6.3 and using the quadratic model given in equation 6.2, the following equations and values are obtained.

$Y_{quadratic}$=$0.76016.X1 + 0.13064.X2 + 0.18282.X3 - 0.55514.X4 + 0.93674.X1.X2 + 0.43744.X1.X3 + 0.39033.X1.X4 - 0.05558.X2.X3 + 0.756247.X2.X4 + 0.410188.X3.X4 - 0.109415.X1^2 - 0.481397.X2^2 - 0.27506.X3^2 - 0.201182.X4^2 + 591.2372$

$R^2_{quadratic}$=%95

Modeling of the past 30 years for the WOA quadratic model is shown in Figure 6.6 and Table 6.9.

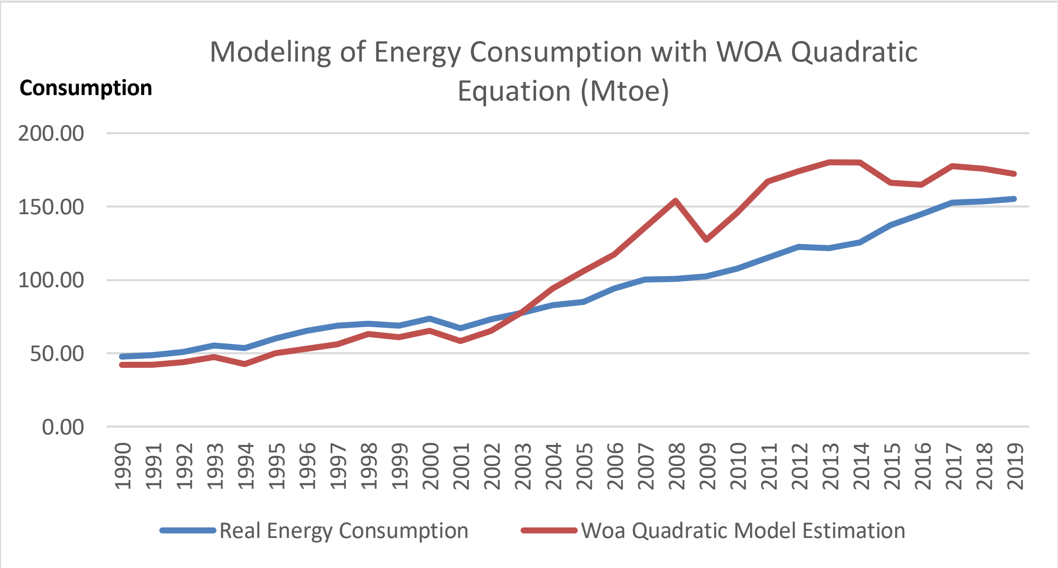

Figure 6.6: Energy consumption modeling with WOA quadratic model.

Table 6.9: Energy consumption forecasting and error percentages with WOA linear and quadratic models

Year	Energy Consumption (MTOE)	WOA linear model forecasting	WOA quadratic model forecasting	WOA linear model error percentage (%)	WOA quadratic model error percentage (%)
1990	47,7	51,3	42,1	7,55	11,74
1991	48,7	52,94	42,25	8,71	13,24
1992	51,1	54,32	43,95	6,30	13,99
1993	55,4	54,47	47,58	1,68	14,12
1994	53,7	57,71	42,47	7,47	20,91
1995	60,1	58,73	50,08	2,28	16,67
1996	65,5	58,99	53,26	9,94	18,69
1997	68,6	60,91	55,98	11,21	18,40
1998	70,3	64,89	62,93	7,70	10,48
1999	68,6	66,48	60,94	3,09	11,17
2000	73,5	64,74	65,3	11,92	11,16
2001	66,9	70,07	58,51	4,74	12,54
2002	73,1	72,54	65,44	0,77	10,48
2003	77,4	78,14	77,92	0,96	0,67
2004	82,8	84,66	94,1	2,25	13,65
2005	84,9	88,92	105,78	4,73	24,59
2006	94,3	94,03	117,32	0,29	24,41
2007	100,4	104,33	135,79	3,91	35,25
2008	100,8	115,79	153,8	14,87	52,58
2009	102,2	109,43	127,43	7,07	24,69
2010	107,6	109,83	145,58	2,07	35,30
2011	115,1	112,51	167,15	2,25	45,22
2012	122,3	127,41	173,84	4,18	42,14
2013	121,5	126,2	179,99	3,87	48,14
2014	125,4	133,34	180,02	6,33	43,56
2015	137,2	132,58	166,37	3,37	21,26
2016	144,6	135,27	164,78	6,45	13,96
2017	152,7	137,32	177,59	10,07	16,30
2018	153,5	146,73	175,75	4,41	14,50
2019	155,2	154,9	172,3	0,19	11,02

MTOE= Million Tonnes of Oil Equivalent

In Table 6.9, the observed energy consumption between 1990-2019 and the forecasted values of WOA generated models were compared. As can be seen from the table, the error percentage values of the linear model were lower than the quadratic model.

Table 6.10: WOA energy consumption forecast results, according to Scenario 1 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	WOA linear model forecasting	WOA quadratic model forecasting
2020	780,39	83,51	216,89	180,11	157,73	178,9
2021	807,7	83,6	232,07	189,11	160,62	185,84
2022	835,97	83,68	248,32	198,57	163,57	193,14
2023	865,23	83,76	265,7	208,5	166,57	200,82
2024	895,52	83,85	284,3	218,92	169,62	208,88
2025	926,86	83,93	304,2	229,87	172,71	217,37
2026	959,3	84,02	325,49	241,36	175,84	226,28
2027	992,87	84,1	348,28	253,43	179,01	235,65
2028	1027,62	84,18	372,66	266,1	182,2	245,5
2029	1063,59	84,27	398,74	279,4	185,41	255,84
2030	1100,82	84,35	426,65	293,37	188,64	266,7
2031	1139,35	84,44	456,52	308,04	191,87	278,1
2032	1179,22	84,52	488,48	323,45	195,1	290,07
2033	1220,5	84,61	522,67	339,62	198,31	302,62
2034	1263,21	84,69	559,26	356,6	201,49	315,79
2035	1307,43	84,77	598,4	374,43	204,62	329,6
2036	1353,19	84,86	640,29	393,15	207,7	344,08
2037	1400,55	84,94	685,11	412,81	210,69	359,25
2038	1449,57	85,03	733,07	433,45	213,59	375,13
2039	1500,3	85,11	784,39	455,12	216,38	391,76
2040	1552,81	85,2	839,29	477,88	219,02	409,17

In Table 6.10, WOA energy consumption was forecasted according to the first scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 219,02 MTOE, in quadratic model 409,17 MTOE has been achieved.

Table 6.11: WOA energy consumption forecast results, according to Scenario 2 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	WOA linear model forecasting	WOA quadratic model forecasting
2020	806,78	83,53	209,79	175,82	157,24	177,52
2021	863,25	83,63	217,14	180,21	159,68	182,74
2022	923,68	83,73	224,74	184,72	162,21	187,95
2023	988,34	83,83	232,6	189,34	164,84	193,1
2024	1057,52	83,93	240,74	194,07	167,58	198,15
2025	1131,55	84,03	249,17	198,92	170,43	203,07
2026	1210,76	84,13	257,89	203,9	173,41	207,79
2027	1295,51	84,23	266,92	208,99	176,51	212,25
2028	1386,2	84,34	276,26	214,22	179,75	216,38
2029	1483,23	84,44	285,93	219,57	183,13	220,07
2030	1587,06	84,54	295,94	225,06	186,67	223,22
2031	1698,15	84,64	306,29	230,69	190,37	225,68
2032	1817,02	84,74	317,01	236,46	194,24	227,3
2033	1944,21	84,84	328,11	242,37	198,3	227,85
2034	2080,31	84,94	339,59	248,43	202,56	227,07
2035	2225,93	85,05	351,48	254,64	207,02	224,63
2036	2381,75	85,15	363,78	261	211,71	220,08
2037	2548,47	85,25	376,51	267,53	216,63	212,79
2038	2726,86	85,35	389,69	274,22	221,81	201,89
2039	2917,74	85,46	403,33	281,07	227,26	185,97
2040	3121,98	85,56	417,45	288,1	233	162,55

In Table 6.11, WOA energy consumption was forecasted according to the second scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 233 MTOE, in quadratic model 162,55 MTOE has been achieved.

Table 6.12: WOA energy consumption forecast results, according to Scenario 3 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	WOA linear model forecasting	WOA quadratic model forecasting
2020	791,7	84,1	209,79	178,39	159,2	177,85
2021	831,29	84,77	217,14	185,53	163,68	183,56
2022	872,85	85,45	224,74	192,95	168,33	189,44
2023	916,49	86,13	232,6	200,67	173,17	195,49
2024	962,32	86,82	240,74	208,69	178,19	201,72
2025	1010,43	87,52	249,17	217,04	183,41	208,12
2026	1060,95	88,22	257,89	225,72	188,85	214,71
2027	1114	88,92	266,92	234,75	194,5	221,48
2028	1169,7	89,63	276,26	244,14	200,37	228,44
2029	1228,19	90,35	285,93	253,91	206,48	235,58
2030	1289,6	91,07	295,94	264,06	212,84	242,92
2031	1354,08	91,8	306,29	274,63	219,46	250,46
2032	1421,78	92,54	317,01	285,61	226,34	258,19
2033	1492,87	93,28	328,11	297,03	233,51	266,11
2034	1567,51	94,02	339,59	308,92	240,97	274,24
2035	1645,89	94,77	351,48	321,27	248,73	282,56
2036	1728,18	95,53	363,78	334,12	256,81	291,07
2037	1814,59	96,3	376,51	347,49	265,22	299,78
2038	1905,32	97,07	389,69	361,39	273,99	308,69
2039	2000,59	97,84	403,33	375,84	283,11	317,78
2040	2100,62	98,63	417,45	390,88	292,61	327,06

In Table 6.12, WOA energy consumption was forecasted according to the third scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 292,61 MTOE, in quadratic model 327,06 MTOE has been achieved.

Table 6.13: WOA energy consumption forecast results, according to Scenario 4 (Mtoe).

Year	**GDP ($ 10^9)**	**Population (10^6)**	**Import ($$10^9$)**	**Export ($$10^9$)**	**WOA linear model forecasting**	**WOA quadratic model forecasting**
2020	991,51	83,16	262,06	179,19	149,99	196,62
2021	1023,49	84,16	271,14	185,59	153,69	202,22
2022	1055,47	85,15	280,23	191,99	157,39	207,81
2023	1087,45	86,15	289,31	198,39	161,09	213,39
2024	1119,42	87,14	298,39	204,8	164,79	218,98
2025	1151,4	88,14	307,47	211,2	168,49	224,56
2026	1183,38	89,13	316,55	217,6	172,19	230,13
2027	1215,36	90,13	325,64	224	175,89	235,71
2028	1247,33	91,12	334,72	230,41	179,59	241,28
2029	1279,31	92,11	343,8	236,81	183,29	246,85
2030	1311,29	93,11	352,88	243,21	186,99	252,41
2031	1343,27	94,1	361,97	249,61	190,69	257,98
2032	1375,24	95,1	371,05	256,02	194,38	263,54
2033	1407,22	96,09	380,13	262,42	198,08	269,1
2034	1439,2	97,09	389,21	268,82	201,78	274,66
2035	1471,17	98,08	398,29	275,22	205,48	280,21
2036	1503,15	99,08	407,38	281,63	209,18	285,77
2037	1535,13	100,07	416,46	288,03	212,88	291,32
2038	1567,11	101,07	425,54	294,43	216,58	296,87
2039	1599,08	102,06	434,62	300,83	220,28	302,42
2040	1631,06	103,06	443,7	307,24	223,98	307,97

In Table 6.13, WOA energy consumption was forecasted according to the fourth scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 223,98 MTOE, in quadratic model 307,97 MTOE has been achieved.

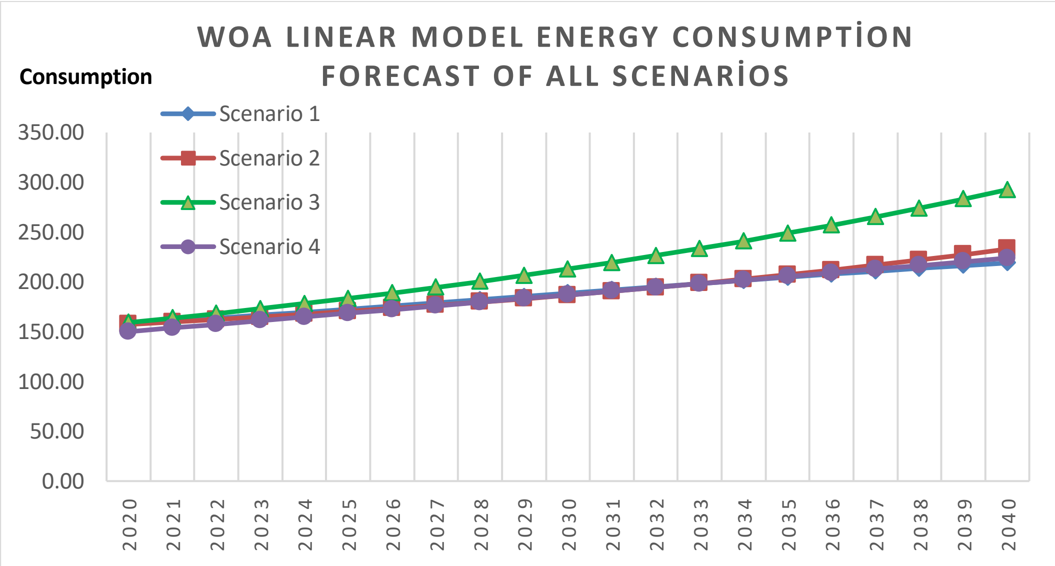

Figure 6.7: WOA linear model energy consumption forecast, according to all scenarios.

According to Figure 6.7, all scenarios in the WOA linear model energy consumption forecast show rising acceleration. But scenario 3 shows that there will be more energy consumption than any other scenarios.

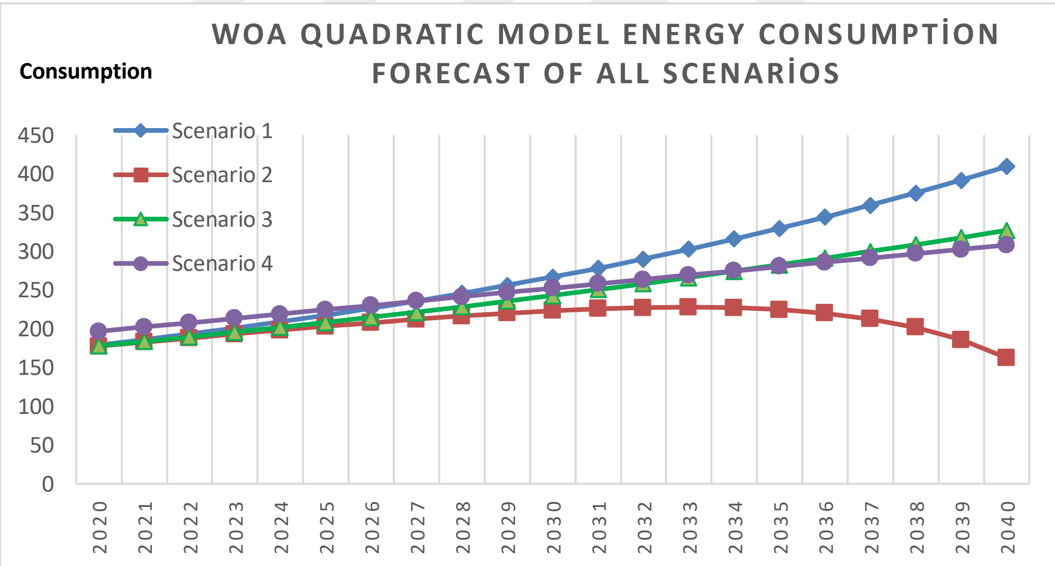

Figure 6.8: WOA quadratic model energy consumption forecast, according to all scenarios.

According to Figure 6.8, the scenarios other than scenario 2 show an increasing acceleration in the WOA quadratic model energy consumption forecast value. In Scenario 2, it is forecasted that energy consumption will decrease especially after 2033.

6.3 Turkey's Energy Consumption Forecast by Artificial Bee Colony Algorithm

6.3.1 Linear Equation Modeling

The control parameters selected for linear forecasting with ABC algorithm are as follows:

- Population Size: 100
- Maximum Number of Iterations: 500

The control parameters given above are the objective function given in equation 6.3 and using the linear model given in equation 6.1, the following equations and values are obtained.

$$Y_{lineer} = -0.00643.X1 + 1.9113.X2 - 0.1524.X3 + 0.5177.X4 - 58.3585$$

$$R^2_{lineer} = \%99$$

The modeling of the past 30 years for the ABC linear model is shown in Figure 6.9 and Table 6.14.

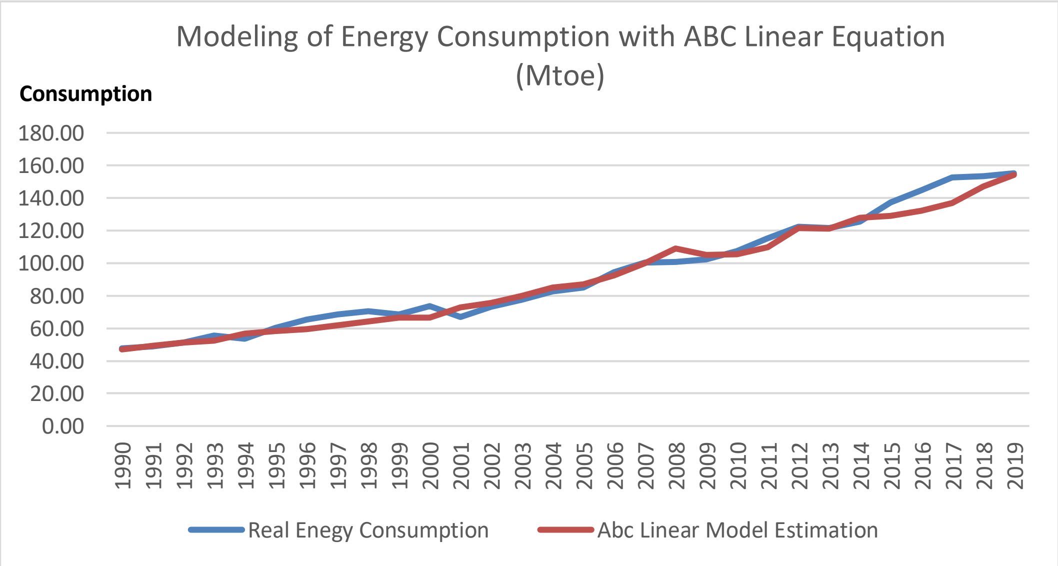

Figure 6.9: Energy consumption modeling with ABC linear model.

6.3.2 Quadratic Equation Modeling

The control parameters selected for quadratic forecasting with artificial bee colony algorithm are as follows:

- Population Size: 100
- Maximum Number of Iterations: 1000

The control parameters given above are the objective function given in equation 6.3 and using the quadratic model given in equation 6.2, the following equations and values are obtained.

$$Y_{quadratic} = -2.259.X1 - 1.222.X2 - 3.8975.X3 + 2.78139.X4 - 1.329.X1.X2 + 0.50199.X1.X3 + 0.058496.X1.X4 + 2.291508.X2.X3 + 2.833157.X2.X4 - 2.12723.X3.X4 - 0.05116.X1^2 - 1.895.X2^2 - 1.38464.X3^2 - 2.603717.X4^2 + 225,45$$

$$R^2_{quadratic} = \%95,33$$

Modeling for the ABC quadratic model for the past 30 years is shown in Figure 6.10 and Table 6.13.

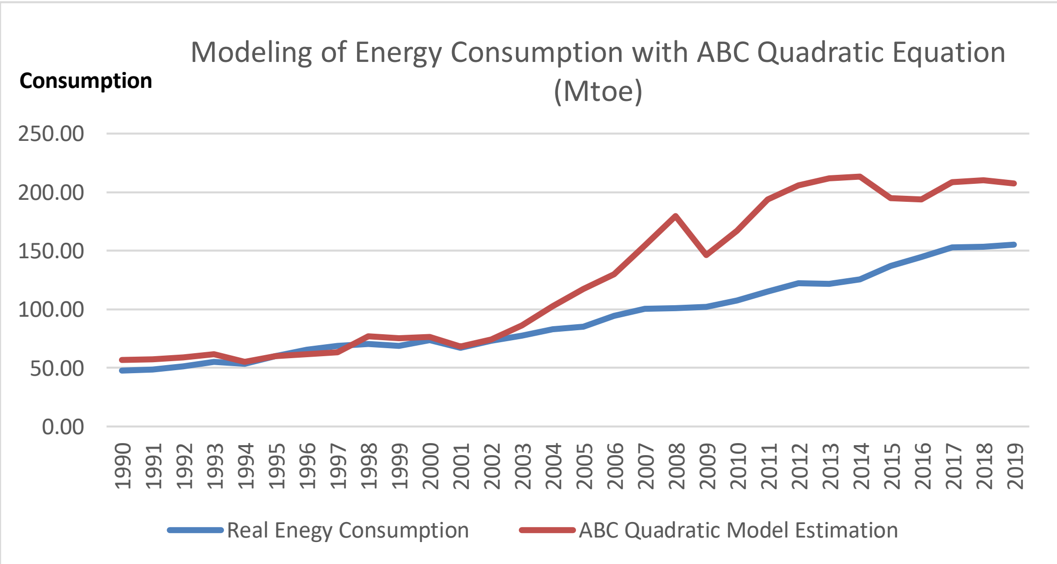

Figure 6.10: Energy consumption modeling with ABC quadratic model.

Table 6.14: Energy consumption forecast and error percentages with ABC linear and quadratic models

Year	Energy Consumption (MTOE)	ABC linear model forecasting	ABC quadratic model forecasting	ABC linear model error percentage (%)	ABC quadratic model error percentage (%)
1990	47,7	47,04	56,88	1,38	19,25
1991	48,7	49,33	57,57	1,29	18,21
1992	51,1	51,32	59,03	0,43	15,52
1993	55,4	52,23	61,83	5,72	11,61
1994	53,7	56,65	55,17	5,49	2,74
1995	60,1	58,11	60,19	3,31	0,15
1996	65,5	59,42	61,74	9,28	5,74
1997	68,6	62,02	63,34	9,59	7,67
1998	70,3	64,04	76,85	8,90	9,32
1999	68,6	66,62	75,4	2,89	9,91
2000	73,5	66,55	76,62	9,46	4,24
2001	66,9	72,9	68,34	8,97	2,15
2002	73,1	75,43	74,27	3,19	1,60
2003	77,4	79,86	86,24	3,18	11,42
2004	82,8	84,96	102,89	2,61	24,26
2005	84,9	86,92	117,34	2,38	38,21
2006	94,3	92,54	130,17	1,87	38,04
2007	100,4	99,85	154,59	0,55	53,97
2008	100,8	108,91	179,67	8,05	78,24
2009	102,2	105,22	146,48	2,95	43,33
2010	107,6	105,6	167,28	1,86	55,46
2011	115,1	109,85	193,79	4,56	68,37
2012	122,3	121,6	205,66	0,57	68,16
2013	121,5	121,06	212	0,36	74,49
2014	125,4	127,95	213,27	2,03	70,07
2015	137,2	129,09	195,14	5,91	42,23
2016	144,6	132,18	193,66	8,59	33,93
2017	152,7	136,94	208,67	10,32	36,65
2018	153,5	147,08	210,18	4,18	36,93
2019	155,2	154,18	207,19	0,66	33,50

MTOE= Million Tonnes of Oil Equivalent

In Table 6.14, the observed energy consumption between 1990 and 2019 is compared with the forecasted values of the models created with ABC. As seen, the error percentage values of the linear model are lower than the quadratic model.

Table 6.15: ABC energy consumption forecast results, according to Scenario 1 (Mtoe).

Year	GDP ($\$ 10^9$)	Population (10^6)	Import ($\$10^9$)	Export ($\$10^9$)	ABC linear model forecasting	ABC quadratic model forecasting
2020	780,39	83,51	216,89	180,11	156,45	217,04
2021	807,7	83,6	232,07	189,11	158,78	227,64
2022	835,97	83,68	248,32	198,57	161,18	239,04
2023	865,23	83,76	265,7	208,5	163,65	251,31
2024	895,52	83,85	284,3	218,92	166,17	264,49
2025	926,86	83,93	304,2	229,87	168,77	278,64
2026	959,3	84,02	325,49	241,36	171,43	293,85
2027	992,87	84,1	348,28	253,43	174,15	310,16
2028	1027,62	84,18	372,66	266,1	176,93	327,66
2029	1063,59	84,27	398,74	279,4	179,77	346,42
2030	1100,82	84,35	426,65	293,37	182,68	366,53
2031	1139,35	84,44	456,52	308,04	185,63	388,07
2032	1179,22	84,52	488,48	323,45	188,64	411,14
2033	1220,5	84,61	522,67	339,62	191,7	435,83
2034	1263,21	84,69	559,26	356,6	194,81	462,26
2035	1307,43	84,77	598,4	374,43	197,95	490,54
2036	1353,19	84,86	640,29	393,15	201,13	520,79
2037	1400,55	84,94	685,11	412,81	204,34	553,14
2038	1449,57	85,03	733,07	433,45	207,56	587,73
2039	1500,3	85,11	784,39	455,12	210,8	624,7
2040	1552,81	85,2	839,29	477,88	214,04	664,21

In Table 6.15, ABC energy consumption was forecasted according to the first scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 214,04 MTOE, in quadratic model 664,21 MTOE has been achieved.

Table 6.16: ABC energy consumption forecast results, according to Scenario 2 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($\$10^9$)	Export ($\$10^9$)	ABC linear model forecasting	ABC quadratic model forecasting
2020	806,78	83,53	209,79	175,82	155,17	213,92
2021	863,25	83,63	217,14	180,21	156,16	220,88
2022	923,68	83,73	224,74	184,72	157,14	228,08
2023	988,34	83,83	232,6	189,34	158,11	235,54
2024	1057,52	83,93	240,74	194,07	159,06	243,27
2025	1131,55	84,03	249,17	198,92	160,01	251,3
2026	1210,76	84,13	257,89	203,9	160,94	259,63
2027	1295,51	84,23	266,92	208,99	161,85	268,3
2028	1386,2	84,34	276,26	214,22	162,74	277,32
2029	1483,23	84,44	285,93	219,57	163,61	286,73
2030	1587,06	84,54	295,94	225,06	164,46	296,55
2031	1698,15	84,64	306,29	230,69	165,27	306,83
2032	1817,02	84,74	317,01	236,46	166,05	317,59
2033	1944,21	84,84	328,11	242,37	166,8	328,87
2034	2080,31	84,94	339,59	248,43	167,51	340,74
2035	2225,93	85,05	351,48	254,64	168,17	353,23
2036	2381,75	85,15	363,78	261	168,79	366,4
2037	2548,47	85,25	376,51	267,53	169,35	380,32
2038	2726,86	85,35	389,69	274,22	169,85	395,05
2039	2917,74	85,46	403,33	281,07	170,29	410,68
2040	3121,98	85,56	417,45	288,1	170,66	427,28

In Table 6.16, ABC energy consumption was forecasted according to the second scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 170,66 MTOE, in quadratic model 427,28 MTOE has been achieved.

Table 6.17: ABC energy consumption forecast results, according to Scenario 3 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($$10^9$)	Export ($$10^9$)	ABC linear model forecasting	ABC quadratic model forecasting
2020	791,7	84,1	209,79	178,39	157,69	214,97
2021	831,29	84,77	217,14	185,53	161,29	223,05
2022	872,85	85,45	224,74	192,95	165,01	231,45
2023	916,49	86,13	232,6	200,67	168,83	240,17
2024	962,32	86,82	240,74	208,69	172,77	249,22
2025	1010,43	87,52	249,17	217,04	176,82	258,63
2026	1060,95	88,22	257,89	225,72	181	268,4
2027	1114	88,92	266,92	234,75	185,31	278,54
2028	1169,7	89,63	276,26	244,14	189,75	289,08
2029	1228,19	90,35	285,93	253,91	194,33	300,03
2030	1289,6	91,07	295,94	264,06	199,05	311,4
2031	1354,08	91,8	306,29	274,63	203,92	323,22
2032	1421,78	92,54	317,01	285,61	208,94	335,49
2033	1492,87	93,28	328,11	297,03	214,12	348,24
2034	1567,51	94,02	339,59	308,92	219,47	361,49
2035	1645,89	94,77	351,48	321,27	224,99	375,25
2036	1728,18	95,53	363,78	334,12	230,69	389,55
2037	1814,59	96,3	376,51	347,49	236,58	404,41
2038	1905,32	97,07	389,69	361,39	242,65	419,85
2039	2000,59	97,84	403,33	375,84	248,93	435,9
2040	2100,62	98,63	417,45	390,88	255,42	452,58

In Table 6.17, ABC energy consumption was forecasted according to the third scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 255,42 MTOE, in quadratic model 452,58 MTOE has been achieved.

Table 6.18: ABC energy consumption forecast results, according to Scenario 4 (Mtoe).

Year	GDP ($ 10^9)	Population (10^6)	Import ($\$10^9$)	Export ($\$10^9$)	ABC linear model forecasting	ABC quadratic model forecasting
2020	991,51	83,16	262,06	179,19	147,06	235,22
2021	1023,49	84,16	271,14	185,59	150,69	242,83
2022	1055,47	85,15	280,23	191,99	154,32	250,46
2023	1087,45	86,15	289,31	198,39	157,94	258,1
2024	1119,42	87,14	298,39	204,8	161,57	265,75
2025	1151,4	88,14	307,47	211,2	165,2	273,41
2026	1183,38	89,13	316,55	217,6	168,82	281,08
2027	1215,36	90,13	325,64	224	172,45	288,76
2028	1247,33	91,12	334,72	230,41	176,08	296,44
2029	1279,31	92,11	343,8	236,81	179,7	304,13
2030	1311,29	93,11	352,88	243,21	183,33	311,83
2031	1343,27	94,1	361,97	249,61	186,96	319,53
2032	1375,24	95,1	371,05	256,02	190,58	327,24
2033	1407,22	96,09	380,13	262,42	194,21	334,96
2034	1439,2	97,09	389,21	268,82	197,84	342,68
2035	1471,17	98,08	398,29	275,22	201,46	350,4
2036	1503,15	99,08	407,38	281,63	205,09	358,13
2037	1535,13	100,07	416,46	288,03	208,72	365,86
2038	1567,11	101,07	425,54	294,43	212,34	373,6
2039	1599,08	102,06	434,62	300,83	215,97	381,33
2040	1631,06	103,06	443,7	307,24	219,6	389,08

In Table 6.18, ABC energy consumption was forecasted according to the third scenario. The linear and quadratic models that we created as a result of the coefficients that the algorithm gave us gave us the above energy consumption values. According to these values Turkey's energy consumption in 2040 would be in linear model 219,6 MTOE, in quadratic model 389,08 MTOE has been achieved.

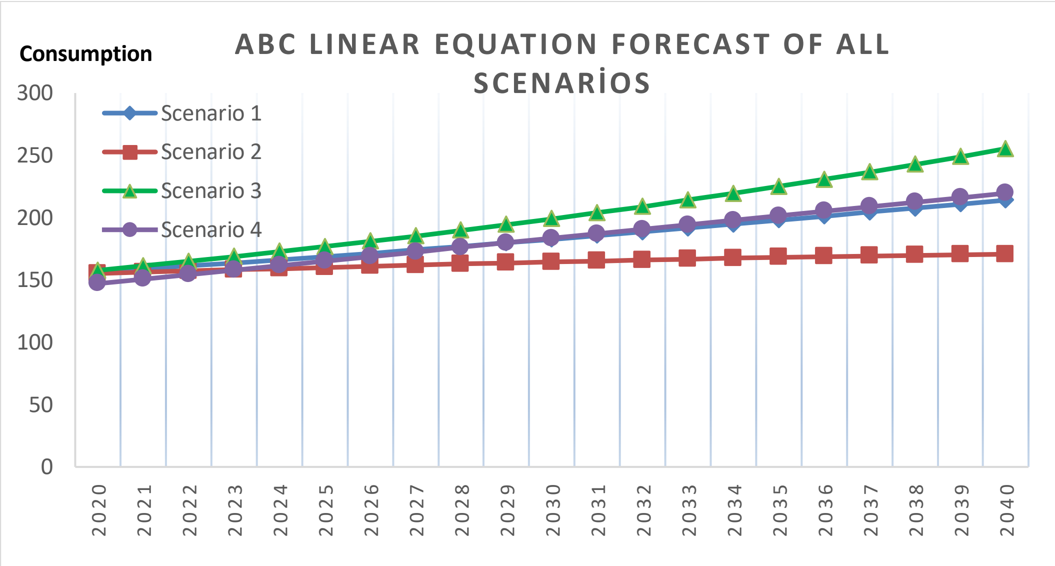

Figure 6.11: ABC linear model energy consumption forecast, according to all scenarios.

According to Figure 6.11, the third scenario forecasts the highest energy consumption values in the ABC linear model forecast value. Unlike the others, scenario 2 takes a more linear path.

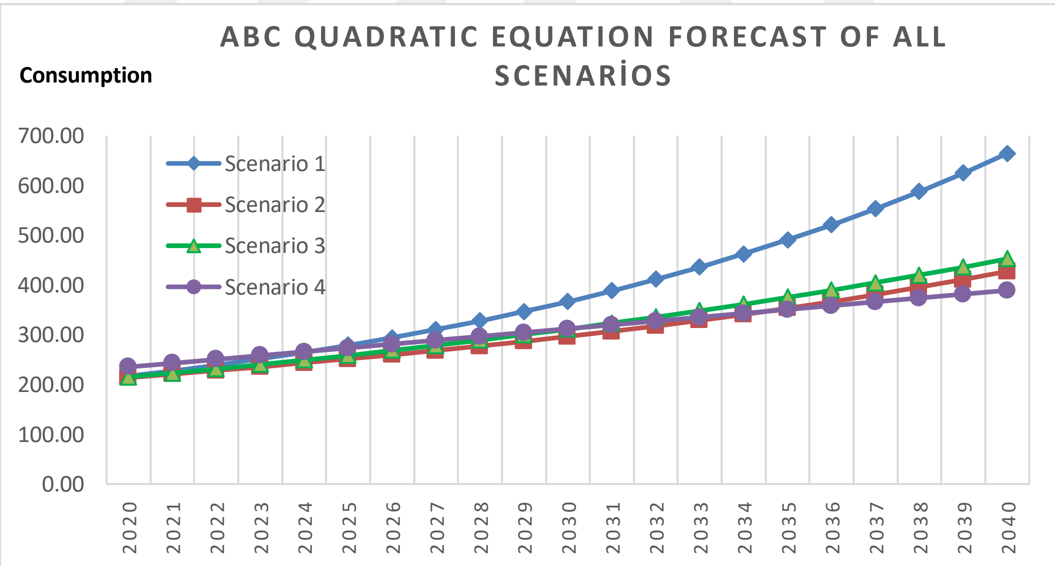

Figure 6.12: ABC quadratic model energy consumption forecast, according to all scenarios.

According to Figure 6.12, all scenarios in the ABC quadratic model forecasted values predict that energy consumption will increase. However, scenario 1 makes the highest forecasting.

Finding Accuracy Value Criteria of Results

The values of the stability coefficient (R^2), mean absolute deviation (MAD) and average absolute percentage error (MAPE) criteria used in comparison of GA, WOA and ABC models for the years 1990-2019 are shown in Table 6.19.

Table 6.19: Accuracy criterion values of GA, WOA and ABC.

ALGORITHM	MODEL	R^2	MAD	MAPE
GA	Linear Model	0,97	6,76	%7,56
	Quadratic Model	0,96	31,3	%28,5
WOA	Linear Model	0,98	4,79	%5,35
	Quadratic Model	0,95	21,66	%21,7
ABC	Linear Model	0,99	4,01	%4,35
	Quadratic Model	0,95	33,61	%30,5

Lewis (2002) grouped models with MAPE values below 10% as “very good”, models between 10% and 20% as “good”, models between 20% and 50% as “acceptable”, and models above 50% as “incorrect” (Yakut et al., 2014).

Based on this, the MAPE values of linear models of all algorithms have worked very well according to Lewis and can be used in energy consumption forecasting problems. But it was observed that the linear model of the ABC algorithm gives the best result with a 99% R^2 and a 4.35% MAPE value. The results of the quadratic model were found to be acceptable with values of 28.5%, 21.7% and 30.5%.

CONCLUSIONS

In a World where the age of technology is alive, dependence on energy is increasing every day. Especially the machines that technology produces in industrial areas, the systems developed for factories and then electronic devices produced to bring prosperity to living spaces, natural gas systems and water systems cause more energy depletion.

The effects of energy sources and energy use on natural life are the most talked about and worrying issue worldwide in recent years. The main reason for this concern is the increase in situations such as natural disasters and global warming. In particular, the depletion, irregular use of fossil fuels and subsequent environmental pollution should lead countries to invest more in renewable energy sources within themselves and provide incentives.

In view of the rising energy need, it can be seen that this requires very serious planning and responsibility. For this purpose, in our country, the values of energy consumption over the past 30 years were modeled and the next 20-years consumption was forecasted.

In order to realize the energy consumption forecasting before; YSA, ANFIS, ARIMA, genetic algorithm, particle swarm optimization, ant colony optimization, artificial bee colony optimization, grasshopper optimization etc. algorithms have been used.

Specific to this thesis, the WOA was used in linear and quadratic form to model Turkey's energy consumption and to forecast the future. In addition, a forecast study was conducted with GA and ABC, and the results were compared with WOA.

In order to be able to forecast energy consumption, GDP, population, import and export data were selected as the most commonly used independent variables in the literature. These variables are processed in GA, WOA and ABC algorithms with the objective function and linear and quadratic models with coefficients that give the most optimal result have been tried to create the most appropriate design. It has been tried to obtain 5 coefficients in the linear model and 15 in the quadratic model. The optimal formulas found in the aftermath were adapted to the future and the result was obtained.

Considering the historical data of variables affecting energy consumption in modeling analyses, applying different mathematical consumption functions to objective functions, and using various stability scales in performance benchmarking have yielded effective results based on annual energy consumption modeling.

According to these results;

- The ABC algorithm, which gives the lowest error compared to the modeling of past years, was obtained by the linear model. Therefore, the ABC algorithm using the linear model stands out for its successful performance in modeling the future energy consumption forecast. It has been observed that the ABC algorithm linear model models the energy consumption of past years with the closest similarity (99%). The second-best modeling was the WOA linear model with a ratio of 98%. In the square model, the best result was GA with a ratio of 96% R^2.
- In order to forecast energy consumption, scenarios are needed that can forecast the data of future independent variables. For this purpose, 4 different scenarios were studied in the study.
- According to a total of 24 separate modeling results obtained from these 4 scenarios, only 1 model in 2040 forecast that consumption will decrease, and all 23 other models that we will need more energy than today.
- If we look at the error percentages, it has been observed that in general, all linear models work better than quadratic models.
- ABC algorithm based on linear models which is given most optimum result that energy consumption in Turkey in 2040; It is forecasted that there will be 214.04 MTOE according to 1st scenario, 170,66 MTOE according to 2nd scenario, 255,42 MTOE according to 3rd scenario and 219,6 MTOE according to 4th scenario.
- Percentage accuracy criteria values according to MAPE (average absolute percentage error) results, it was determined that the ABC algorithm received a lower value than GA and WOA with a value of 4.35%. These results have been evidence that the ABC algorithm makes better forecast.
- In general, models with a linear model within the objective function provide high performance, while models with a quadratic model within the objective function show lower performance. We can also make this inference from calculated error percentages.
- This argument selected in operation and high performance of the generated model, making planning for the future of energy in Turkey and in the World and is expected to provide benefits in determining new strategies.

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