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While Covid-19 Outbreak Affects Economies and Societies; Exploring The Energy Demand in Turkey

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ABSTRACT

The fear and panic environment created by the Coronavirus infectious disease 2019 (COVID-19), which affects the whole world, deeply affects the market mechanisms and causes energy supply and demand shocks. The common point of the predictions is that 2021 will pass with negative growth and increasing unemployment problem all over the world, with the economic reflections of the epidemic being felt seriously. In this study, Turkey in particular; a neural network and comparative regression model has been developed to analyze the effects on electricity and oil demand as part of COVID-19 economic measures. The purpose of this article is to contribute to the determination of Turkey's demand for electricity and oil during the epidemic and future by collecting information about direct and indirect factors, the events in the internal and external environments, and their relationships of the pandemic. As a consequence, the elasticity of electricity and petroleum demand toward the population of the infected people is −0.323% and −0.397% respectively. The impact of COVID-19 on energy demand will be many times greater than the impact of the 2008 financial crisis on global energy demand. The mentioned findings show that the crisis deeply affected not only human health but also the global economy, clearly showed how the energy sector interacts with other factors of the economic structure.

1. INTRODUCTION

The Coronavirus infectious disease 2019 (COVID-19) has affected our societies, also it has impacted the energy sector worldwide [1]. Although the full impact of the energy sector is very difficult to predict precisely, because the market is fluctuating, decreased energy consumption and energy prices, as well as a sharp decline in oil prices, are already observed. Due to the supply chain and the logistical risks to companies across the different energy transition sub-sectors the current situation also represents the main uncertainty as to whether the pandemic will speed up or slow down the energy transition. Many researchers [2-4] and companies [5,6] discuss the implications of COVID-19 on the energy transition towards a sustainable future. The authors [7,8] share their research consequences faced by the renewable electricity generation sector and possible reactions of energy regulators. For many experts and researchers, it is difficult to assess the whole impact we are still only at the start; but some of the first effects can be seen at least the short-term effects [9, 10]. The first step and also what it meant for energy regulators was that is seen a lot of emergency decisions taken by governments across all Europe [11] and in Turkey [12]. It implied immediately some measures for the day-to-day work of National Regulatory Authorities, energy market actors and operators and etc.

Across the country as well as most of the operators are starting to say that weekdays now look like weekends. Because people are staying at home and using more electricity in the residential side versus the commercial side that had a change of energy demand, drop in demands [13]. This has resulted in a wide variety of effects on the grid such as decreased electricity prices. Besides that, it implied that regulators could not have the usual contracts. The operators quite rapidly applied emergency plans successfully; on the other hand, the security of supply stability of the grid provided, and what was most important of course was that they re-organized the staff and the workers in the control center [14].

Also, it is needed to reduce global CO2 emissions by 70% by 2050 perhaps even more to be in line with the Paris agreement and to reach an energy transformation [15]. The energy transformation needs to be based on renewables, needs to be based on energy efficiency, and it needs to be based on electrification of enthuses. These three strategies are really critical and it can be concluded that such a transition is technically and economically feasible. The investment needs significant between 110 and 130 trillion dollars, but it's not so much higher than a reference case it's around 95 trillion dollars between now and 2050 [15].

With the effect of the COVID-19 epidemic the energy demand is down; CO2 emissions are down 7% on an annual basis [16]. It is also seen that the impact on fossil fuels is much more significant than the impact on renewables in terms of consumption, generation and pricing [17]. The European electricity market and compare that the May 2020 numbers with the same numbers from the last year; it has been reported that electricity production and electricity demand decreased by about 10% [18]. But if you look at the generation side in more detail then you see a significant drop in call against based power generation 20 to 30 % drop. But renewables generation increased by about 8 % [18]. The reason is that because first of all last year it is added significant new renewable generation capacity that starts to produce this year. Secondly, the solar and wind have virtually zero operating costs. That makes the renewables generation share has increased very significantly; as of January 2021, 48% of all power generated in Europe was renewable. That is a very remarkable number thanks to the good work of the power plant and grid operators and regulators. As a result of this, fossil fuel prices have been significantly decreased. As the natural gas prices in Europe; so, the enterprises for imported gas and the gas prices in the Turkish system are about $2 per meter of €2 per division so that's a very low price not seen before [19]. But it's not completely attributable to the crisis because if you look at the import prices it has been declining already for some time.

There are also other things going on in the system; it's not only the demand effect but also important supply effects. The gas prices this year half, the oil prices have nearly half the coal price went down from $70 to $55 [20]. The change in prices has also affected the relative competitiveness of gas versus coal-based power generation. That access baits the impacts on coal-based generation and that's why it is seen that coal-based generation has dropped faster than a gas-based generation.

Another important cost component in the power market is the CO2 permit prices, and it has been fairly stable over this year; which is at around slightly above 20 euros per ton of CO2. It translates into an incremental cost of about 2 cents per kilowatt-hour of coal-based generation or a cent per kilowatt hour of gas-based generation [21]. That is also still a very important cost component that also affects the competitiveness of renewables versus oil, especially in coal.

Due to this epidemic that affected the world, the expected growth in electricity demand could not be achieved in Turkey due to the following reasons; (i) It is one of the main countries suffering from COVID-19 [22,23], (ii) it is the seventeenth largest economy in the world, (iii) It has the one of the highest energy consumption in Europe and the largest growth in wind, solar and hydro installation respectively [24].

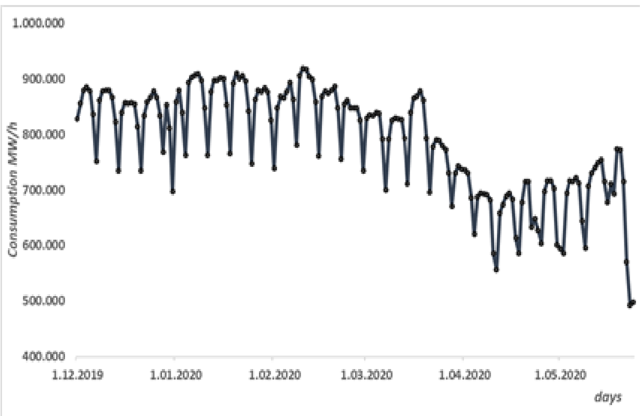

Figure 1. Daily electricity consumption in Turkey (December 1st 2019 – May 30th 2020)

As the daily electricity consumption seen in Figure 1, the developments in the months of January and February can be observed very easily. Demand increased by 2.45% in January and decreased by 4.02% in February [25]. However, from the first positive case on March 11, the measures taken by the companies in the process from the first positive case to the precautions, for example, from the first day the case was seen, people started to work directly at home; and it still continues that way.

The recovery in electricity demand in the short and medium-term will likewise depend on economic growth. For this reason, both domestic consumption and export dynamics of the country should be closely monitored. The correlation between Gross domestic product (GDP) growth rates and electricity demand growth rates between 2001 and 2020 is remarkable [25,26]. Figure 2 shows the relationship between the growth of Gross Domestic Product and electricity demand. As seen from Figure there was a sharp decline in Gross Domestic Product in 2009. Despite a nearly 5% decrease, electricity demand fell by 2.1%. On average, Turkey's economy grew by only 1.8% in 2020 due to the effects of COVID-19. With this shrinkage, according to estimates, it decreases between 2% and 4% compared to the previous year in different scenarios. In the IMF January 2021 report [27]; Turkey's economy shrinks by 5% in 2020, while next year it estimates will grow by 6%. In case of a single outbreak of the study looking at slightly different in the OECD predicted to fall by 4.8% of Turkey's economy. It estimates the growth as 4.3% in 2021. If there is a third wave of the epidemic; according to OECD analysis the things go wrong in Turkey and in the world, also predicts that there will be an 8.1% contraction in the economy and a growth of 2% next year.

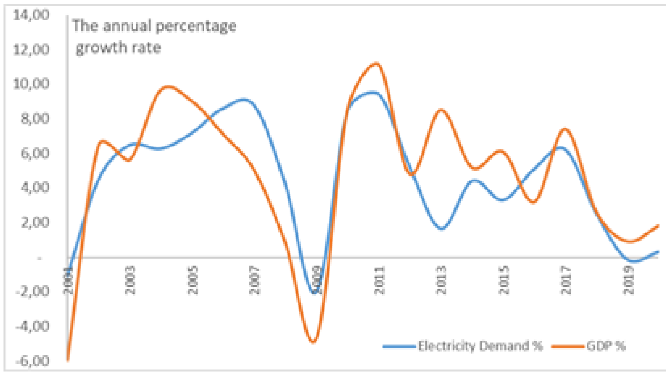

Figure 2. Comparison annual growth rate of GDP and electrical energy demand since 2001 up to 2020

As renewable energy for the first time in 2019, the total electricity production was increased from solar energy 3% and up to 7% in wind. The total production of other renewable resources was 4%. There was a wetland on the hydroelectric side, it broke the record for many years; there was a 34.1% share of hydroelectric production in 2019. The share of renewable energy in total has reached 44% [28]. In fact, for the first time since 1996, the capacity utilization rate of natural gas in electricity generation fell below 20%. On 24 May 2020, the total renewable energy reached 90% on the feast day and on a day of curfew [29].

It is very difficult to make predictions during the pandemic. One reason for the difficulty is that we are dealing with an ongoing crisis. However, how much the pandemic will shake the global economy, the change in consumption and production levels from COVID-19 in the energy and electricity systems, and perhaps more importantly, changes in usage patterns are not yet fully known. Travel bans imposed due to COVID-19 caused domestic and international flights to be disrupted to a great extent. When the measures are taken to prevent the spread of the epidemic slow down the economy and significantly reduce the demand for energy; Oil prices were the first to be affected by this lack of demand [1]. Then there were decreases in the prices of natural gas and other energy resources. The most important question for the global economy is whether the economies thousands of kilometers from where the virus originated will come to a standstill. Such approaches will clearly inform about energy policies in the post-COVID-19 era.

As the impact of the coronavirus pandemic continues to be explored, this article aims to conduct quantitative analysis through a neural network-based modeling and sensitivity analysis of energy inputs to determine the importance and fragility of different economic sectors, with a special focus on electricity and oil demand.

2. ENERGY DEMAND AND NEURAL NETWORKS

The increase in the world population and the developments in technology increase the energy demands and fluctuations. It is the main input of all kinds of sectors such as energy production, agriculture, transportation. Energy runs the economy so it has deep implications for the nature of work and economic growth in the coming years. Therefore, energy forecasting and modeling is becoming increasingly important. Many different estimation techniques and tools are used in the literature for energy demand forecasting. For example; time series [30-32], gray prediction [33], regression model [34], particle swarm optimization [35-37], genetic algorithm [38], fuzzy logic [39], artificial neural networks [40,41] and so on. Energy demands are estimated using forecasting techniques. To reach broader energy demand forecasting models, Suganthi and Samuel's [42] study can be examined.

One of the most frequently used estimation tools in the field of energy demand estimation is ANN. Dumitru and colleagues [43] Romania's wind power forecasting, Galvan et al [44] Oklahoma's daily solar energy, Jasinski [45] Slovakia's electricity consumption, Alanis [46] electric energy price prediction, Akarslan et al [47] Afyon Kocatepe University's total electricity demand, Gajowniczek and friends [48] detect Poland's peak load in the electricity system, Codur and colleagues [49] estimate the energy demand in the transportation sector and Tumbaz and Ipek [50] have used the ANN to estimate Turkey’s primary energy consumption. Oil and electricity consumption today is non-linear and variable, subject to a wide variety of exogenous variables such as weather conditions, calendar effect, demographic and economic variables, and general randomness in individual use. How to successfully integrate various factors and sources into the prediction model and obtain accurate load predicts are always a challenge toward the modern energy systems. For modeling such extraordinariness, the advantage of using neural networks is that when the functional structure of the data set cannot be determined exactly, it can successfully model the functional structure in many different forms based on the data. Artificial neural networks (ANN), also known as general function approximations, do not require any presumptions on the data set, unlike statistical methods.

There are many studies in the literature regarding the comparison of artificial neural networks and traditional methods [51-54]. Estimation accuracy has a significant impact on the planning of electrical energy generation, transmission and distribution systems investments, power system studies, and daily system operation. Overestimating the demand causes unnecessary use of spare reserves or the activation of too many power units. On the other hand, low demand forecasts may cause the electricity energy demand to be insufficient and the supply reserve to be insufficient and prevent the efficient operation of the system.

In recent times and after the COVID-19 outbreak started, ANN attracted the attention of many researchers. In this context neural networks have been carried out on many studies to forecast the prevalence of outbreak in Egypt [55] in Saudi Arabia [56], river flow forecasting [57], the wind power curve forecasting [58], the impact of the pandemic on GDP of major economies [59], liver cancer risk [60], water quality [61] fluid properties of kerosene [62], predict the number of COVID-19 cases [63]. In an article published in 2020, energy consumption for a residential building was estimated by 2050 through an ANN forecast model [64]. According to the results obtained by the author; ANN is better suited to estimating the energy consumption of residential buildings because other models perform better compared to traditional statistical methods, namely linear regression analysis. Another study [65] used a multiple nonlinear regression model for cooling systems in public buildings to accurately estimate short-term cooling loads.

Due to the variables affecting energy carrier demand variable over the time series period nonlinear stochastic methods are used to provide higher accuracy and lower run for energy consumption. In this study, to ensure Turkey's oil and electricity consumption patterns; forecasting models were created using time series analysis and feed-forward neural networks, and short-term estimation results were obtained using daily, weekly, and monthly data.

3. THE PRESENT STUDY AND METHODOLOGY

The purpose of this study is to analyze the impact of COVID -19, the first global epidemic in the 21st century, on electricity and oil consumption. The novelty of this article is that the IMF, world health organization, stock market, GDP indicators are used for variables in the analysis of the model that is comprehensively linked to the new COVID-19 pandemic. In order to compare the period before and after the COVID-19 outbreak, data from 2019, the year just before the beginning of the outbreak, is needed. However, in order to reduce the impact of possible shocks on the macroeconomic and public finance indicators of the country in 2019, the last three years, 2017, 2018 and 2019, were included in the analysis as the period before COVID-19. In this context, for the period before COVID-19, the daily and monthly values of the macroeconomic and public finance data of 2017, 2018 and 2019 were taken for three years. Since only the data for the years 2020 and 2021 for the post-COVID-19 period are included, the analysis is limited to the years 2017-2021. The main aim of this study contribute to decision-makers to have higher accuracy prediction the responses of the demand and supply side of the energy markets, the possible consequences of the impacts of economic stagnation during and post COVID-19.

The subject of this study is to investigate the relationship between the consumption of petroleum and electrical energy and the basic parameters of the economy in the epidemic period. The experimental results obtained by the author also revealed that the Regression model generally performed better in predicting linear time series, while ANN performed better in predicting nonlinear time series [66]. This study proposes a nonlinear ANN method to investigate the current novel coronavirus epidemic that occurred in early 2020, instead of the classical method available in the literature [67, 26].

The most important problem to be addressed after the method selection is the research period. The economic and social changes caused by the outbreak make the existing models developed using the historical data worthless and incorrect. The model was trained with daily and monthly data between January 2019 and January 2020, as long-term analysis would reduce the model's inaccuracy and overcome the lack of data problem. The methodology of this paper is shown in Figure 3 which uses the regression and ANN method to develop a stable framework to interpret the impact of the COVID-19 epidemic on the Turkish economy.

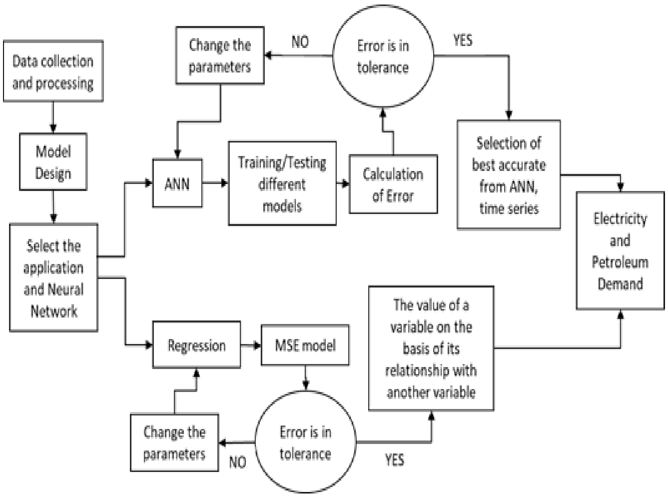

Figure 3. The schematics diagram of the methodology to understand the impact of COVID-19 epidemic on the Turkish economy

The variables used to model the impact of COVID-19 on the economic situation and energy demand are summarized in Table 1. Table 2 presents the descriptive statistics for each data.

TABLE I
DEFINITIONS AND SUMMARY OF INDEPENDENT VARIABLES USED IN THE MODEL

Variable	Unit	Reference		Definition
GDP Growth	%	tradingeconomics	[68]	The Turkish gross domestic product (GDP) growth
Oil Demand	Ton Barrel	EPDK	[25]	The monthly oil demand for Turkey
Electricity Demand	MWh	teias	[22]	The daily electricity demand for Turkey
Epidemic status	-	WHO	[23]	The daily death cases
Infected people	People	ourworldindata	[69]	The number of infected people in Turkey.
Manufacturing PMI	-	tradingeconomics	[70]	The manufacturing productivity in Turkey.
Export Income	USD Million	tradingeconomics	[71]	The monthly export income of Turkey.
Foreign Direct Investment	USD Million	tradingeconomics	[72]	The monthly foreign direct investments into Turkey
Industrial Productivity	-	tradingeconomics	[73]	Turkey's monthly industrial production
Stocks Value	-	investing.com	[74]	The Turkey Istanbul Stock Market Index.

TABLE II
THE SUMMARY STATISTICS OF THE VARIABLES

	Min	Max	Skew	Mean	Median	Std. D.	Var.
Petroleum demand	730,00	1338,00	0,25	1038,64	1014,50	171,08	29269,96
EI	0,00	0,98	1,43	0,20	0,00	0,35	0,12
IP	0,00	320070,0	1,47	60344,68	0,00	102853,37	10578815137,94
IP	-31,30	10,60	-1,68	-0,43	-0,35	9,67	93,51
Diesel	775200,0	1423000	0,43	1032993,18	1016620,0	198177,69	39274398594,42
Gasoline	389500,0	470000,0	-0,21	430970,45	432100,00	22952,36	526810831,61
Stocks	888,65	1192,43	0,05	1031,18	1031,02	85,79	7359,26
PMI	33,00	56,00	-1,27	48,48	48,50	4,94	24,43
FDI	170,00	1223,00	1,19	474,64	395,50	259,76	67472,96
Exports	8971,15	17308,72	-1,11	14037,39	14526,22	1947,59	3793089,95
Electricity	670193,0	986254,0	0,18	817757,64	830542,50	98919,17	9785002694,78
GDP growth	-9,72	5,99	-1,12	0,17	0,17	3,86	14,94

3.1. Regressive model and ANN

In the present paper, the NARX neural network model and cointegration analysis were used to estimate Turkey's electricity and energy demand pattern at the time of COVID-19 or actual epidemic situations. The Autoregressive Distributed Lag Model (ARDL) procedure employs a single equation to estimate the long-term relationships between the variables. So, the ARDL model consists of time series for the functional specification of long-run relationship between energy and COVID-19. In the next step, if there is an evidence of long-run cointegration between variables, the form of Equations (1) and (2) to use this approach efficiently, are estimated using the following selected ARDL models:

$$LnDemand_{electricity} = B_1 GDP + B_2 LnDemand_{oil} + B_3 LnEpidemic + B_4 LnPopulation_{infected} + B_5 LnPMI + B_6 LnExports + B_7 LnFDI + B_8 LnStocks + B_9 LnP_{industry} \tag{1}$$

$$LnDemand_{oil} = B_1 GDP + B_2 LnDemand_{electricity} + B_3 LnEpidemic + B_4 LnPopulation_{infected} + B_5 LnPMI + B_6 LnExports + B_7 LnFDI + B_8 LnStocks + B_9 LnP_{industry} \tag{2}$$

In the study, an estimation equation given in Equation (1, 2) is created. Calculations are made by taking the natural logarithms of the variables in the estimation equation. After determining the existence of a long-term equilibrium relationship between the variables, the parameters reflecting the long-term relationship should be estimated. The specifications of the selected ANN for the ARDL model are 10 neurons and 0.5 momentum coefficient.

The ARDL test developed by Pesaran, Shin, and Smith, which can be used in samples with a limited number of observations and allows variables to be analyzed without the need for integration as in the Johansen-Juselius and Engle-Granger cointegration tests, is an effective method to predict short- and long-term relationships. In other words, with this method, a variable at the level of variables, the first aware or a variable level can be included in the analysis as the first awareness constant [75].

ANN is the system that learn the relationship between the given events and make decisions based on the information they learned about the situations they have never seen. There are a wide variety of network structures and models in artificial neural networks. An ANN consists of a series of neural cells connected by forward-driven and feedback-linking forms. Today, many neural network models suitable for specific purposes and use in different fields have been developed. Among these network structures, multi-layer feed-forward neural networks are the most widely used and used in our study. The feed-forward network consists of an input layer, an output layer, multiple hidden layers, and several successive neuron layers. Neurons are linked together using weight vectors.

Theoretically, the main purpose of an ANN is to learn the structure in the sample data set and make generalizations to fulfill the expected task [76]. In order to do this, the network is trained with the examples of the relevant event and gained the ability to make generalizations. The learning of ANN is done by changing the weights of the process elements with the selected training algorithms. Multi-Layer Perceptron is a learning algorithm based on error. It performs the two basic functions of learning and decision-making through weighting, activation function and bias. Weight is the coefficient by which each input is multiplied before going to the next stage. All entries are added up by multiplying them by their respective weights. Then, the response resulting from sending this value to the activation function becomes the decision of the system. Bias, on the other hand, is a parameter added by the user, which can vary from user to user, the way the mechanism works or its purpose. In order to be used in the time series estimation of MLP networks, the structure of the network must be determined. When determining the ANN structure, it is necessary to determine the values such as how many layers the network will consist of, how many operations these layers will perform, how many different layers and how much weight it will be attached to. The number of output neurons is determined depending on how many periods the estimation will be made. Determining the number of neurons to be used in input is not as easy as determining the number of output neurons, because determining how many observations values the series' value at time t is affected by is a critical question and the answer to this question shows how many input processing elements will be.

In artificial neural networks, there is no certain rule of numbers such as how many hidden layers the structure will consist of or how many neurons it will combine with. These numbers are determined by the trial-and-error way. The number of the hidden layer neurons was adjusted considering the complexity of the data and in a practical way, and the number of neurons was optimized (increases or decreases in numbers) according to the feedback of the network environment. The number of nodes in the input layer is 9 and the hidden layers/neurons are 10; as the structure of the selected ANN is illustrated in Figure 4.

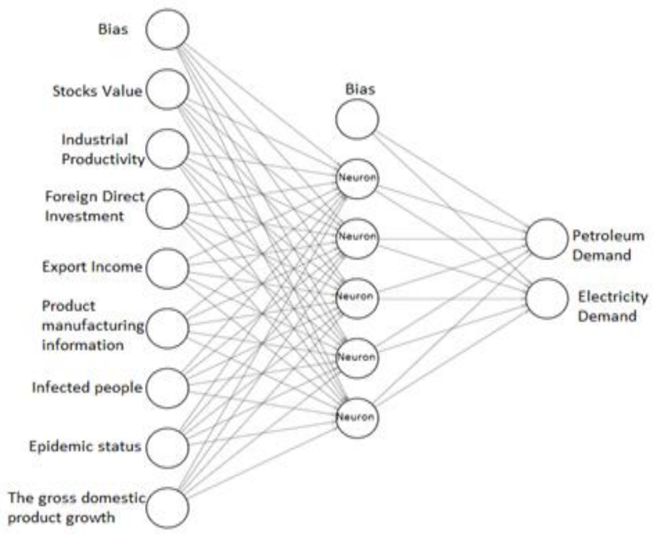

Figure 4. The selected neural network structure

4. RESULTS

Considering that energy consumption and economy have a complicated relationship, after determining the cointegration relationship between the series and there was a relationship between the variables in the short and long term. Since a single linear approach cannot model by that much data, especially during periods of trend change, a correlated regression model is used to investigate all of the direct and indirect relationships between the main parameters that derive the system.

Correlation analysis is a statistical method that reveals the direction, rate, and importance of the relationship between variables [77]. By using the Pearson coefficient, the coefficient indicates the direction and rate of the relationship is called the correlation coefficient, denoted by r. The correlation coefficient takes values ranging from -1 to +1 ($-1 \leq r \leq +1$), and the sign of the correlation coefficient determines the direction of the relationship. If the value of r takes values close to -1, it is determined that there is a negative relationship between the variables, and a positive relationship if it takes values close to +1. If the value of r takes values close to zero, it is concluded that there is no relationship between the two variables.

The epidemic resulting in disease and death deeply affected the supply and demand leg of the economy. This process includes the real aspect of the economy, the goods, wage and factor markets; in its financial aspect, the monetary policy authority has transformed the economic relations network in another direction by influencing the preferences and precautionary policies of institutions such as banking, especially the Central Banks. As in the whole world in Turkey as well the physical and social isolation and non-contact life have resulted in the contraction of the supply of agriculture, industry and especially the service sector by affecting the labor supply through the production pillar.

Table 3 presents the flexibility of each economic parameter against the pandemic and shows that PMI, stock market and GDP growth are more severely damaged by COVID-19. Although all other parameters such as production efficiency, and foreign direct investment are also affected by the epidemic, they are less important. These in turn affect the energy demand and supply side directly or indirectly. The Foreign Direct Investment is not directly affected by the COVID-19's outbreak, it is considerably affected by the decrease in petroleum demand and export income, therefore being indirectly affected by COVID-19.

TABLE III
CORRELATION MATRIX OF VARIOUS PARAMETERS

	GDP growth	Infected People	Petroleum demand	FDI	Stocks	Exports	PMI	Industrial Productivity	Epidemic
GDP growth	1	.410	-.025	.034	.169	.232	.282	-.617	-.390
Infected People	.410	1	.042	.014	-.068	.099	.377	-.360	-.986
Petroleum demand	-.025	.042	1	-.386	.377	-.514	-.375	.289	-.021
FDI	.034	.014	-.386	1	-.334	.508	.360	-.399	.012
Stocks	.169	-.068	.377	-.334	1	-.183	-.328	.020	.051
Exports	.232	.099	-.514	.508	-.183	1	.565	-.736	-.124
PMI	.282	.377	-.375	.360	-.328	.565	1	-.828	-.446
Industrial Productivity	-.617	-.360	.289	-.399	.020	-.736	-.828	1	.396
Epidemic	-.390	-.986	-.021	.012	.051	-.124	-.446	.396	1

According to the results obtained, the flexibility of each target parameter to coronavirus is calculated and shown in Table 4. This demonstrates that the COVID-19 has a significant influence on the financial system and electricity/petroleum demand status of Turkey.

TABLE IV
FLEXIBILITY OF EACH PARAMETER TO THE SEVERITY OF THE CORONAVIRUS OUTBREAK AND THE INFECTED POPULATION.

		Elasticity Value	t-parameter	Sigma
Petroleum Analysis	Industrial Productivity	-0.257	-4.152	0.0082
Electricity Analysis		-0.089	2.047	0.00963
Petroleum Analysis	Stocks	-0.407	-2.281	0.0224
Electricity Analysis		-0.018	-2.049	0.00962
Petroleum Analysis	GDP growth	0.028	5.062	0.00952
Electricity Analysis		0.025	5.051	0.00960
Electricity demand		-0.323	2.328	0.0209
Petroleum demand		-0.397	4.328	0.00209

The findings indicate that Industrial Productivity has decreased due to pandemic, but the more important effect is due to the severity, as a 1% increase in the severity index causes a 1.465% decrease in the petroleum demand index. Also, for export income and Manufacturing PMI decreasing by 0.62% and 0.743% respectively when the electricity demand decreases by 1%. GDP growth is also being hit by the population of the infected people, which a 1% increase experiences a 0.394% decrease in the GDP growth rate. At the same time, the electricity demand is one of the most sensitive to the severity index, when a 1% increase in the severeness index causes a 0.89% decrease in demand. Foreign direct investments are less affected than other parameters by the epidemic, as the imposition of restrictions on economic activities to prevent the spread of the epidemic slows down existing investment projects. When the activities of some workplaces are stopped, the production of the sectors that provide raw materials to these workplaces will naturally decrease [78]. For this reason, there will be shrinkage and loss of employment not only in the sectors that are suspended, but also in the sectors that provide input. In addition, unpaid leave and dismissal practices will be experienced in shrinking sectors, and the income of employees in these sectors will decrease. As a result, consumption demand will decrease and the production of consumer goods sectors will decrease. All these effects result from the direct or indirect effects of crisis on energy demand and supply side. Some parameters are directly affected by the COVID-19 outbreak, while others are indirectly affected.

Equation 3 is used to determine how different values of an independent variable affect a particular dependent variable under a given set of assumptions. The F is the Dickey-Fuller Statista which shows the correctness of regression the hypothesis and the sigma (ω) is the probabilistic dual of F. The test is used to determine whether the unit root exists (the series is not stationary) in the observed series. Efficiency is stated by calculating the ratio of output changes to each input. The main factor affecting the accuracy of the research is the inability to choose well the independent variables that may affect the dependent variable to be examined. [77]

$$S_{\omega}^{F} = \frac{\partial F / F}{\partial \omega / \omega} \qquad (3)$$

Table 5 shows the elasticity of each parameter to the coronavirus outbreak index and the infected individuals to investigate the structural model of Figure 5-6 which shows the effect value of each parameter of different behavioral attitudes on the other parameters. The coefficients represent the elasticity of each parameter to the other parameters, and Figures 5a and 5b clearly show the impact of the COVID-19 pandemic on petroleum and electricity consumption respectively in Turkey. Initially, through performing sensitivity analysis on different variables, the amount of the impact and how it affects the change in the output of the model are investigated. Secondly, the amount of electricity and oil demand of Turkey will be predicted for the coming days and months.

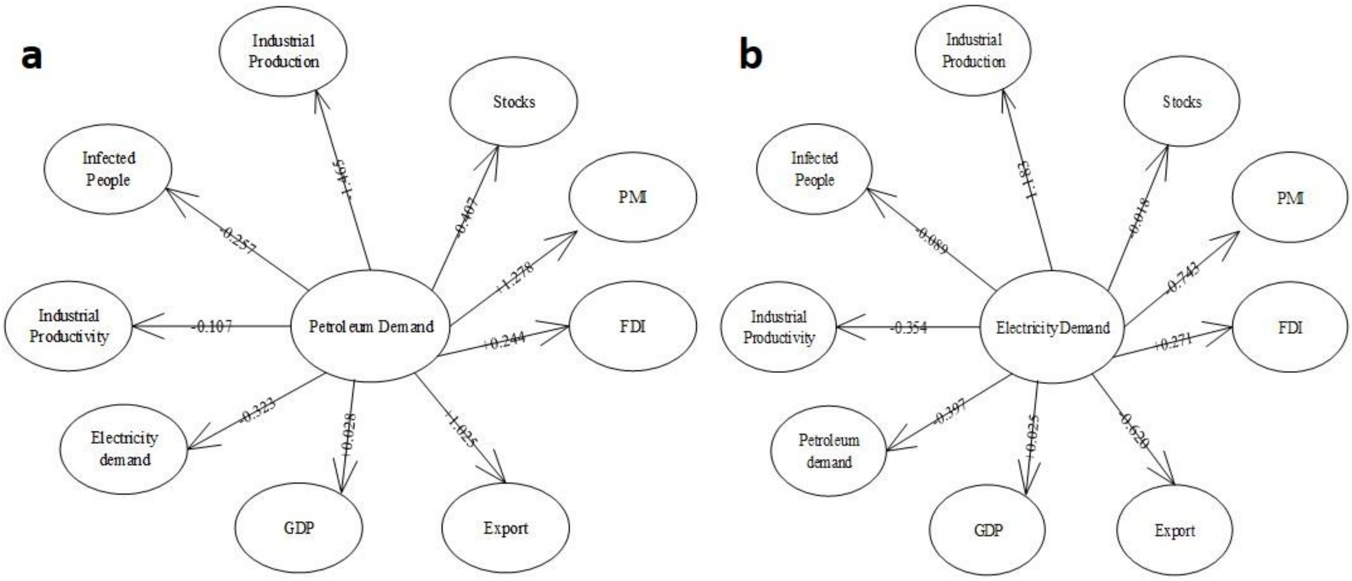

Figure 5. (a) The relation of each parameter of the petroleum model on the other parameters, (b) The relation of each parameter of the electricity model on the other parameters.

TABLE IV
THE RATIO OF ELASTICITY VALUES

Variable	The ratio of the output changes	
	For petroleum	For electricity
Infected People	-1,465	1,183
GDP growth	0,028	0,025
Petroleum demand	-	-0,397
Electricity demand	-0,323	-
Foreign Direct Investment	0,244	0,271
Stocks Value	-0,407	-0,018
Export Income	1,025	-0,62
Manufacturing PMI	1,278	-0,743
Industrial Productivity	-0,257	-0,089
Epidemic status	-0,107	-0,354

Different models were created in ANN models and the effective parameters on prediction were examined. The number of neurons is found by trial and error. The number of neurons has an effect on the prediction. The number of hidden layers; It is effective on estimates and is also related to the number of neurons to be selected. Excessive training data increases forecast performance.

While creating the analysis prediction model, the data with low correlation and high correlation relationship were used together and the data with low correlation values were removed from giving accurate results. The results have shown that the established ANN model and forecasting process was performed very successfully. High regression and low error values in the training, testing, and verification stages also supported results. This confirms that artificial neural networks give positive results especially in solving nonlinear problems.

Figure 6 shows the graphical representation of the estimation made with ANN and the values realized with 3-year data. As can be seen from the graph, the actual values tested and the predicted values were very close to each other. Figure 7 shows the prediction error by percentage.

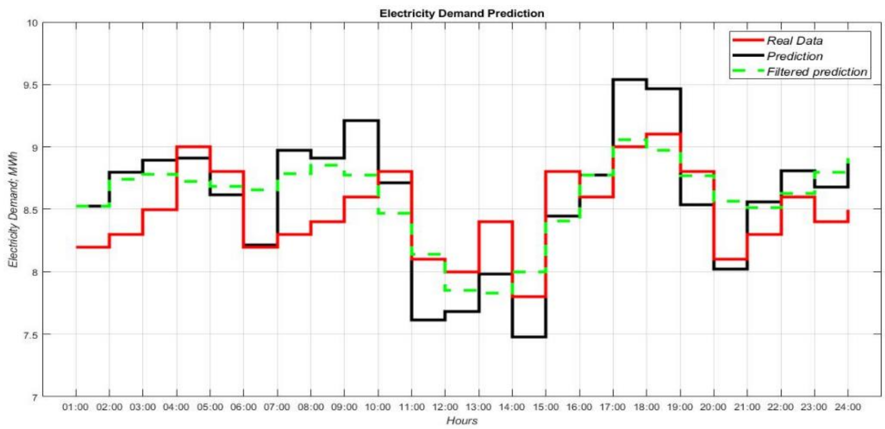

Figure 6. Electricity demand prediction.

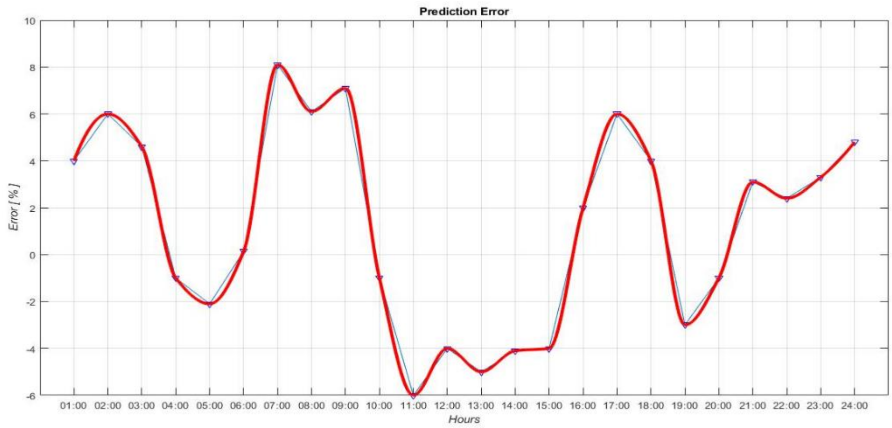

Figure 7. Electricity demand prediction error.

5. CONCLUSION

With the COVID-19 pandemic, all countries of the world have faced a very serious challenge that they have not experienced before. The world economy has witnessed some major economic crises that have had a global impact since the twentieth century. After the Ebola epidemic in Guinea, Liberia and Sierra Leone, the 2008 financial crisis caused by the USA changed the economic balances. While faced with an economic picture shaped by low growth rates after the last crisis, the COVID-19 epidemic, which emerged in China in December 2019 and spread to the world, leaves social, social and economic effects that are still ongoing and likely to continue. The rapid spread of the COVID-19 virus has caused countries to implement protective measures. However, the measures taken by countries against this epidemic bring unprecedented collapse to the economy.

Among the energy types, electricity and petroleum were the most affected during the COVID-19 outbreak. Because the first and most effective measure taken against the epidemic was to stop international/domestic flights and restrict travel to work or elsewhere, this hit air, land, and sea transportation the most. Due to the measures taken, electricity has seen significant declines in consumption in Turkey; As a result, decreases in peak loads are observed. The decrease in peak load means that this is to the advantage of the renewable energy sector. Because renewable energy sources with zero fuel cost in price competition after demand decrease while supply is constant will be able to dominate the market compared to fossil fuels.

When we look at Turkey's daily petroleum and electricity consumption in 2020 shows that major changes occurred prior to and after COVID-19 measures. Turkey, a country largely dependent on foreign energy sources; it is very important to correctly predict the demand for electricity and petroleum. In current predictions, it is essential to take into account epidemic status and infected people for the near future. As a consequence, the elasticity of electricity and petroleum demand toward the population of the infected people is -0.323% and -0.397% respectively. The actual values tested and the predicted values were very close to each other.

Currently, the new Coronavirus outbreak is still ongoing, preventing a thorough investigation of its full effect. As a future work; the impact of the energy demand and economic consequences of the epidemic on emissions and production should be investigated.

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