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When pandemics impact economies and climate change: Exploring the impacts of COVID-19 on oil and electricity demand in China



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ABSTRACT

Despite all the scientific and technological developments in the past one hundred years, biologic issues such as pandemics are a constant threat to society. While one of the aspects of a pandemic is the loss of human life, the outbreak has multi-dimensional impacts across regional and global societies. In this paper, a comparative regressive and neural network model is developed to analyze the impacts of COVID-19 (coronavirus) on the electricity and petroleum demand in China. The environmental analysis shows that the epidemic severeness significantly affects the electricity and the petroleum demand, both directly and indirectly. The outputs of the model stated that the elasticity of petroleum and electricity demand toward the population of the infected people is -0.1% and -0.65% , respectively. The mentioned results show that pandemic status has a significant impact on energy demand, and also its impacts can be tracked into every corner of human society.

1. Introduction

The first and foremost aspect of a pandemic is human suffering and the loss of life, as evidenced by the coronavirus pandemic already having six million global confirmed cases of infection and closing on 400,000 confirm deaths (June 1, 2020) [1]. However, this type of epidemic can have significant multi-dimensional effects, including economic and environmental consequences [2,3]. While the link between the effects of the pandemic and the economy may vary, the severe rate of infection of COVID-19 has placed 30% of the global population in lockdown, with country-specific stay-at-home orders [4–6]. This has already shown severe economic impacts, with $\sim 80\%$ of the international workforce having their workplace closed, and an expected recession of 0.3% (the worst since the Great Depression) [7].

When looking at the literature, the economic impact of pandemics (and epidemics) has been analyzed by estimating the cost of deaths, such as with the severe global influenza (such as the 1918 epidemic) reaching 500 billion USD a year or about 0.6% of global GDP [8]. Noting, low-middle income countries tend to be strongly affected (1.6%), in comparison to high-income countries (0.3%). The World Health Organization (WHO) and World Bank joint report, on the other hand, estimated that the impact of such an epidemic is even more significant, with up to 2.2–4.8 percent of global GDP (the 3 trillion USD) [9]. While, another article from the IMF further adds that

vulnerable populations, especially the poor, are likely to suffer because they may have less access to health care and less protection in facing the financial disaster [10].

At the regional level, a World Bank report estimates that the Ebola epidemic in Guinea, Liberia, and Sierra Leone canceled many of the economic gains of these countries in the years prior to the epidemic, which had been categorized as their fastest-growing economic period [11]. Noting, a WHO report further explains that these types of outbreaks have a significant impact in the private sector, posing a threat to food security due to reduced agricultural production and cross-border trade with restrictions on movement, goods, and services.

China is an interesting case study, as it 1) was the first country suffering from COVID-19 resulting in the most longitudinal dataset available [12], 2) is the second-largest economy in the world, and finally 3) has the highest energy consumption in the world, and simultaneously the greatest growth in installation of wind and solar, respectively (measured in GW) [13]. This increase in energy consumption is a necessity, in order to support a growing domestic industrial market and a concurrently increasing export of goods, due to decades of globalization [14]. Despite a constant increase in production and export of especially crude steel [15], China is committed to reducing its CO₂ intensity by 40–45% in 2020 and 60–65% in 2030 compared to the 2005 levels [14]. However, the CO₂ emissions of China are experiencing continuous annual growth. Optimists might have hoped

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for China reaching the top of the Kuznet's curve as presented in a paper published in 2019 by Chen et al. [16], in a couple of years, where a turning point in pollution occurs in the transition between a nation's industrial and post-industrial economic stage. However, an emergent question is whether COVID-19 will push China, and potentially other countries, backward in its economic maturing, and thereby prolong the transition period towards reduced environmental pollution, or if COVID-19 might reduce the increasing foreign trade and immediately force China into the next stage.

Although the current pandemic is still ongoing, in the short term, the energy and electricity systems have been significantly affected by COVID-19 with changes not only in the total levels of consumption and production but, perhaps more importantly, on the usage patterns [17]. In the case of the oil industry, the effect has been in the reduced usage for transportation with global air traffic coming to a halt, as well as passenger and goods transport [18]. Such trends will undoubtedly inform about future energy policies, and not only in China but globally in the period post-COVID-19.

It is on this light of the coronavirus pandemic that this paper aims to do quantitative analysis, through an auto-regressive elasticity and neural network-based sensitivity analysis, to determine the importance and vulnerability of different economic sectors with a specific focus on the petroleum and electricity demand [7].

1.1 Energy demand and neural networks

With increasing energy demands and fluctuations, modeling, and forecasting of energy gain increasing importance. The mining and consumption of fossil fuels directly influence phenomena such as air pollution in metropolitan areas. In the meantime, the energy industry is a sophisticated yet essential part of the economic growth in every country. Therefore, providing an appropriate model that can predict changes in energy consumption in the economic sectors seems to be necessary. Different methods and tools are used to analyze energy demand and determine the effect of various factors. Most of the researches conducted was to estimate petroleum and electricity demand through linear function and econometric methods [8]. However, since the variables affecting energy carrier demand are volatile over the studied time series period, nonlinear methods can provide better estimates for energy consumption [9].

Completely nonlinear trends such as oil and electricity consumption are highly complex and are influenced by various factors, each of which exhibiting complicated behavior. For this reason, modeling through the analysis method is practically impossible for these phenomena. For modeling such phenomena, traditionally, statistical techniques and regression modeling, and recently, methods based on artificial intelligence, such as Artificial Neural Networks (ANNs) or nonlinear Regression and other hybrid models, are used. The advantage of using neural networks is in their ability to identify and determine the relationship between input and output variables without the need to acquire a comprehensive knowledge of phenomenal physics [10], and the advantage of the regression is its simplicity and more precise results which can be implemented in the structural relations.

Several studies have reported better efficiency and lower error of the neural networks in comparison with traditional methods [19–22]. In this study, a multi-layer feedforward perceptron neural network is used with a hidden layer to provide an oil and electricity consumption model in the economic sectors of China, such as industry, residential, agriculture, services (please refer to the methodology section for a complete breakdown of variables). Due to the increasing growth of infections in world and challenges in providing energy demand as well as the significant contribution of the oil and electricity sector in the economic status of countries, analysis of oil and electricity consumption in the economic sectors and evaluation of factors affecting it have caught the attention of many researchers. Many researchers estimated, forecasted, and investigated energy demand in economic sectors of

China using models with linear equations, quadratic and exponential equations, and based on conventional criteria.

Artificial neural networks are presented as one of the most used modeling and predictive tools of energy consumption and are compared with other modeling techniques [23,24]. A paper published in 2015 has predicted Thailand's energy demand in the transportation sector through artificial neural networks and nonlinear regression models for the next twenty years [25]. Another reference from 2003 has modeled the energy consumption of the transportation sector in Jordan and predicted it through the neuro-fuzzy neural network [26]. Energy demand is that South Korea has been modeled and predicted using artificial neural networks with a similar structure to the method presented in this study [25].

The ability of artificial neural networks to estimate the complex nonlinear functions has made them a useful tool for complex modeling phenomena. In recent years neural networks have been applied for various energy forecasting studies, ranging from forecasting the fluctuation of wind power in various timescales [27], energy consumption in buildings [28], to prices, and supply and demand in energy systems [29,30].

1.2 The present study

This paper aims to investigate the relationship between the macroeconomic parameters (especially the petroleum and electricity demand) in the time of a pandemic situation. The first global pandemic in the 21st century. It uses an auto-regressive elasticity and neural network-based sensitivity analysis to determine the structural correlative coefficients, which governs the relationship between the specified parameters. These correlative coefficients are being used to model the response of the economy to the pandemic situation. This model is the main contribution of this paper to the field of energy and economic decision-making body in the time of the pandemic outbreak.

Additionally, the novelty of this paper lies in the use of descriptive variables of the model that are extensively linked to the novel COVID-19 pandemic. Exploring the energy consumption sensitivity from variables such as GDP and Labour performance index is a novel aspect in literature [9,10]. The timeliness and data resolution of this study is also unique; as previous case studies on energy demand analysis in China, the data are measured on an annual basis, whereas the time interval in this paper is more detailed being analyzed monthly. This issue, besides the enlargement of the data, can lead to the improvement of the efficiency of the neural network and regression. The use of an energy consumption neural network model in China for sensitivity analysis is also a novel attribute of this paper, as it is implemented to estimate the impact of the novel coronavirus pandemic on the electricity and oil demand.

Overall, this paper contributes to decision-makers to better predict the responses of the demand and supply side of the markets, guiding the management of the impacts of economic stagnation during and after a pandemic. The suggested guidelines of this study also aim to support future studies in the field of energy policy, when developing adaptive econometric models for severe and multi-dimensional social problems.

2. Methodology

Investigating the structural relationships between core parameters of the economy and their direct or indirect impacts on petroleum and electricity demand is the main target of this paper. However, many classical methods are introduced by the literature for the analysis of the structural correlations [31–36], which make it difficult the choice depending on the period, problem, and field of study. This study investigates the current novel coronavirus outbreak, where there is a clear and distinct shift in global trends has occurred in early 2020. This trend shift makes most of the classical methods unsuitable for the analysis, considering the vulnerabilities of the classical methods. Therefore, this

study proposes two new hybrid methods for model construction: a) Auto-Regressive-time series hybrid and b) the artificial neural network sensitivity analysis hybrid to manage and overcome the obstacles of the problem modeling occurred because of the trend shift. After the method selection, the length of the investigation period is the most important problem that must be dealt with. As it was mentioned, trend shift phenomena caused by the pandemic makes all of the models developed using the historical trends useless and inaccurate. Thus, the long-term trend analysis decreases the inaccuracy of the model, and short time periods increase the uncertainty of the model because of the smaller data sets for model training and test process. Therefore, to overcome the trend-shift and lack of enough data problems, the authors trained the model with the daily data of Jan 2019 to Jan 2020 and tested the model using the data of the Feb and March 2020 for accounting for contextual factors such as seasonality.

2.1. Method selection

Accurate prediction of economic outcomes is integral to successful decision making. It can lead to better government policies and planning, although economic forecasts and foresight models might prove valuable, its a challenge for econometric researchers, who must develop the framework of an accurate model [8]. The accuracy of the econometric methods varies with different problems, and although these models are useful in illustrating the future of the different parameters and their trends, they can be biased and lead to systematic errors [9].

In this matter, the models can assist in processing a large number of parameters and filling the gap between risk factors and estimations. Different models have been developed in the field of machine learning and statistics that can be used for predicting economic and social complexities. Regressions were developed by the statistics community, whereas others such as decision trees were developed by the machine-learning community [10]. The regression, which is a statistical method, is widely used in the economic and social fields of study, and the methodology is mature and well-established, and coefficients can have intuitive economic and social interpretations. The decision tree method is a graphical method that contains the rules for predicting the target variables. Neural network and Bayesian networks are nature-based models consisting of nodes and interconnections [11]. Although they are similar in type, they are intrinsically different in the term of the process and mathematical model. The Bayesian model's interconnections (arcs) illustrate the conditional dependence relationships between the variables as defined with probability theory, and each node of the graph represents the variable of interest. In the neural network (ANN) arcs and nodes are not representing a predefined relationship, and the values are discovered during the training analysis, and the interpretations are made according to the model defined relationships [12]. The ANN is more complicated, with more nodes and a more comprehensive process and relationships. This complexity makes ANN able to process any large scale data of multivariable clusters and derive the most accurate model according to that data. Considering all the mentioned facts and reviewing the literature, the regression and ANN are the most suitable methods for the data processing of this paper because they enjoy the most widespread use, relatively easy to build, fast respond, and more accurate with the excellent predictive ability [13].

As it is shown in Fig. 1, the methodology of this paper uses the ANN and regression method to develop a structural model to interpret the pandemic impact on the economic status of China. The process begins with environmental scanning to determine the possible effective driving variables, then the main variables are being selected, and the data is gathered for them, and then the data is processed and analyzed through two different methods to provide us with an accurate comparative model [37].

2.2. Data

In recent years, the use of cointegration analysis to estimate energy demand patterns has grown widely [8,22]. Cointegration analysis is commonly used to test the long-term and short-term characteristics of energy demand [8]. One method of cointegration analysis that has been widely used in recent years is the autoregressive approach with distributed interruptions, which yields unbiased estimates of long-run coefficients. The variables used to model the coronavirus effect on economic status, and energy demand is summarized in Table 1 and 2 [37]:

2.3. Regressive model

In this paper, the conventional least squares, fully adjusted least squares, cointegration analysis, and ARDL approach was used to estimate China's energy and electricity demand pattern in the time of critical epidemic or pandemic conditions. Two tests of Engel-Granger and Johansson-Yuselius were used for the coagulation test [23]. The least-squares method has been used to estimate the simple energy demand pattern by Stoke and Watson [46]. Halisiagolu and Bakertasch's model also used the two-step Engel-Granger method to model the relationship between energy, economic activity, and price [47].

The model introduced by Shane and Boys also argues that time series must all be in the form of Eqs. (1) and (2) to use this approach effectively. The suggested pattern is shown below:

For Oil Demand

$$\begin{aligned} \text{LnDemand}_{oil} = & B_1 \text{GDP} + B_2 \text{LnDemand}_{electricity} + B_3 \text{LnEpidemic} \\ & * 10 + B_4 \text{LnPopulation}_{infected} + B_5 \text{LnPMI} + B_6 \\ & \text{LnExports} + B_7 \text{LnFDI} + B_8 \text{LnStocks} + B_9 \text{LnP}_{industry} + B_{10} \end{aligned} \quad (1)$$

For Electricity demand

$$\begin{aligned} \text{LnDemand}_{electricity} = & B_1 \text{LnDemand}_{oil} + B_2 \text{LnGDP} + B_3 \text{LnEpidemic} \\ & * 10 + B_4 \text{LnPopulation}_{infected} + B_5 \text{LnPMI} + B_6 \\ & \text{LnExports} + B_7 \text{LnFDI} + B_8 \text{LnStocks} + B_9 \\ & \text{LnP}_{industry} + B_{10} \end{aligned} \quad (2)$$

where B_i is the coefficient value, the dependent variable, and the interrupt operator, also, it is the vector of deterministic (non-random) variables such as source width, trend variable, virtual variables, or exogenous variables with fixed intervals. The number of interrupts used for the dependent variable is the number of interrupts used for the independent variables. The number of optimal interrupts for each of the explanatory variables can be determined using one of the Acaic, Schwartz-Bizin, and Hanan-Quinn criteria. Thus, the best selected ANN specifications for the ARDL model is given in Table 4 [48].

In recent years, the ARDL approach has been widely used in energy demand estimation. In this approach, energy consumption is explained by its interruption and the current and interrupting values of independent variables such as price and income. In the traditional ARDL approach, false regression may be obtained when the variables are invariant unless the variables are cumulative. Even if pattern variables are included, there is concern that standard methods of statistical inference are invalid [49]. Shane's research in 1999, showed that even when the model variables are unmanageable, the standard hypothesis test can be used by modifying the traditional ARDL approach [50–52]. In this approach, both long-run and short-run coefficients can be estimated following OLS, and valid statistical inferences can be made using asymptotic standard distribution theory [51]. The only point needed to validate these is the existence of a long-run relationship or a coexistence relationship between variables. Therefore, even if the variables are nameless, the ARDL approach can be valid, provided that there the

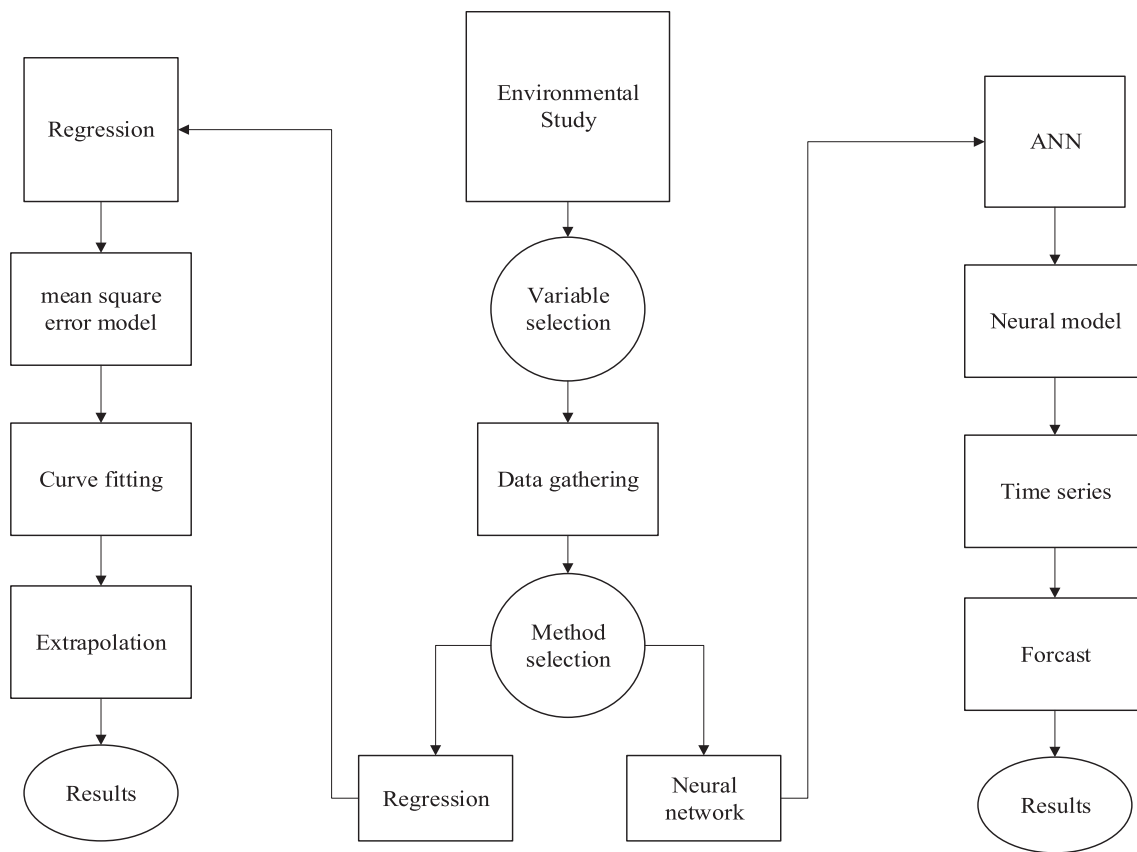


Fig. 1. The schematics of the methodology of this study.

Table 1

The summary of the variables used in the model.

Text sign	Variable	Sign	Unit	Reference	Description
X1	GDP Growth	GDP	[%]	World Bank [38]	The normalized daily economic growth rate in China.
X2	Oil Demand	Demand_oil	Million Barrel	IEA [39]	The daily oil demand for China
X3	Electricity Demand	Demand_electricity	TWh	IEA [39]	The daily oil electricity of China
X4	Epidemic status	Epidemic	–	Author (WHO) [40]	A control index showing severeness* of the epidemic
X5	Infected people	Population_infected	People	WHO [40]	The daily cumulative infected people in China.
X6	Manufacturing PMI	PMI	–	Trading economics [41]	The daily Caixin China General Manufacturing PMI showing the manufacturing productivity in China
X7	Export Income	Exports	USD HML	Trading economics [42]	The daily export income of China
X8	Foreign Direct Investment	FDI	B USD	Trading economics [43]	The cumulative daily foreign direct investment entered in China
X9	Industrial Productivity	P_industry	–	Trading economics [44]	Daily industrial productivity in China
X10	Stocks Value	Stocks	–	Shanghai Composite Stock Market [45]	The China Shanghai Composite Stock Market Index.

* Note: The severeness variable is an artificial parameter which shows the severeness of the situation, measured by the daily death cases and the worst WHO scenario of maximum daily death cases.

Table 2

The data description.

Parameter	Mean	Min	Max	Var.	Std. Dev.	Amount
X1	583.5630769	474.33	677.00	3324.853106	55.39941494	365
X2	10.32307692	7.9000	11.500	0.861923077	0.891976066	365
X3	1.223076923	–1.8000	1.6000	0.831923077	0.876315579	365
X4	0.142307692	0.0000	1.0000	0.088269231	0.285445774	365
X5	5316.153846	0.0000	60,000	276134225.6	15965.37289	365
X6	48.69230769	35.700	50.500	15.40243590	3.770627685	365
X7	2121.538462	1850.0	2390.0	25897.43590	154.6134711	365
X8	694.6815385	126.80	1367.0	170356.0294	396.5497692	365
X9	5.238461538	3.8000	8.6000	1.650897436	1.234465603	365
X10	2943.846154	2650.0	3300.0	33275.64103	175.2597396	365

Table 3
Choosing the number of hidden nodes.

Number of hidden neurons	Train set error (%)	Test set error (%)
9	15.1	18.1
10	14.9	19.5
11	11.0	13.4
12	8.7	9.1
13	5.5	6.4
Average Error Percent (APE)		

Table 4
The best selected ANN specifications.

Training rate	0.0075
The momentum coefficient	0.5
The number of hidden neurons	13
Activation Function	Hyperbolic Tangent

fully modified least squares method (FMOLS) is a semi-parametric approach that is used to estimate single cohesive relationships with a combination of variables in Eq. (1) [50]. This method was developed by Phillips and Hansen in 1990. Also, research done by Park and Phillips in 1988 and by Hansen and Phillips in 1990 has shown that this method has advantages that distinguish it from the conventional least-squares method [53]. These include the following:

- Supercomputing estimates
- Asymptotically, the estimates are not biased
- Having an asymptotic normal distribution

Providing a modified standard deviation that allows for statistical inferences, and thus, the *t*-test for long-run coefficients is valid [54]. Moreover, to reach higher accuracy in the modeling, a hybrid neural network method is also being used to the results being compared, and a more accurate model be developed [55].

2.4. Hybrid regressive model

The structure of neural networks is generally composed of a certain number of neurons in layers with different configurations, and strings of communication, which are called synapses in the nervous system literature, that provide the contact between neurons [56]. Each synapse has value as the weight of the synapse, which, according to its weight, transmits the output of a neuron to the input of another neuron [57].

ANNs have been developed for a wide range of applications and issues. The most common form of the artificial neural networks to approximate complicated functions and modeling phenomena with such behavior is a type of feedforward neural network that is called a multi-layered perceptron with a nonlinear activation function [58]. This type of neural network provided the number of the neurons of the middle layer, is capable of approximating any continuous function with arbitrary precision [53]. The structure of this network is composed of an input layer, an output layer, and some hidden layers. Each of the neurons of each layer is connected to all the neurons of the next layer, such that the output of each neuron is multiplied by the weight of each output synapse connected to it and is transferred to the next layer. Also, at the entrance of neurons, signals received are first added up together. Then they enter the activation function of the neuron and specify its output [52]. In this type of network, nonlinear continuous function and bounded from above and bounded from below is used as the activation function. Considering that the number of layers has no effect on this ability of the network, and only the middle layer is sufficient, the perceptron neural network with one hidden layer is used in this model [59].

After selecting the appropriate network type for the desired model,

the preparation of the neural networks often needs the determination of the values of its synapse weights according to the studied data. The search process to find optimal weights for the network is called the “training phase.” Typically, a portion of the available data is used for network training, and the other is used for testing the efficiency of the neural network. One of the most widely used methods of training feedforward networks is the “error backpropagation algorithm” [58,60].

The initial values of the synaptic weights are randomly selected between -1 and 1 . Hyperbolic tangent has been selected for the activation function of the network. In training the neural network, an appropriate selection of the training coefficient is critical for achieving optimal response. In training MLP neural networks, the training coefficient of the different layers can be defined differently. The learning coefficient of the output layer is usually selected lower than the other layers to avoid fluctuations in the network around the optimal response. Such an approach is also adopted in this model, and the training coefficient for the last layer is selected equal to the half the coefficient of the hidden layer. Parameters of the artificial neural network are generally set in a trial and error way [56]. The number of the hidden layer neurons was selected considering the complexity of the data and by experts in a practical way, and the number of neurons was increased according to the response of the network, as shown in Table 3. The final values chosen for various parameters of the network are shown in Table 4. The structure of the selected ANN is illustrated in Fig. 2.

Table A1 (see Appendix) provides instructions for the analysis process and the meaning of each estimated model parameter for both ANN and regressive models.

3. Results

Considering the economy and energy demand have a complex relationship, a single linear model cannot model such dynamic, especially in the trend shift periods. Therefore, a correlative regressive model is needed to investigate all of the direct and indirect relationships between dozens of the main parameters deriving the system. Correlations between the parameters are described using the Pearson coefficient, and this amount is in the range of $[-1, +1]$. While $-1 \leq p \leq 0$ means an inverse relation, and $0 \leq p \leq +1$ means a direct relationship. Table 5 below shows the results of the effect of each parameter and the significance of this effect, noting the importance of the Epidemic status in the world's economic well-being. The information provided in this table is the output of the correlation analysis between the variables of the model.

The pandemic outbreak affected economic parameters through deactivating many industrial and economic units, which in turn affected energy demand across many countries, including China; nothing is such demand is significantly dependent on economic parameters. Nonetheless, the impacts between demand and each parameter are not homogeneous. Table 5 presents the elasticity of each economic parameter toward the pandemic, showing that PMI and GDP growth are damaged more significantly by the COVID-19. Whereas all of the other parameters, such as export income, foreign direct investment, and industrial productivity, are also affected but less significantly by the pandemic outbreak. These, in turn, are directly or indirectly affecting the energy demand and supply side. While the stock index is not directly affected by the COVID-19's outbreak, it is significantly affected by the decrease in the PMI and industrial productivity, thereby being indirectly affected by the COVID-19.

According to the model outputs, the elasticity of each target parameter to the coronavirus is being calculated and reported in Table 6. This shows that the novel coronavirus has an essential impact on the economic and energy demand status of China, and likely other regions of the world (if the region is has confirmed cases of infection).

The results here show that Industrial Productivity is being reduced because of the disease, but the more significant impact is through

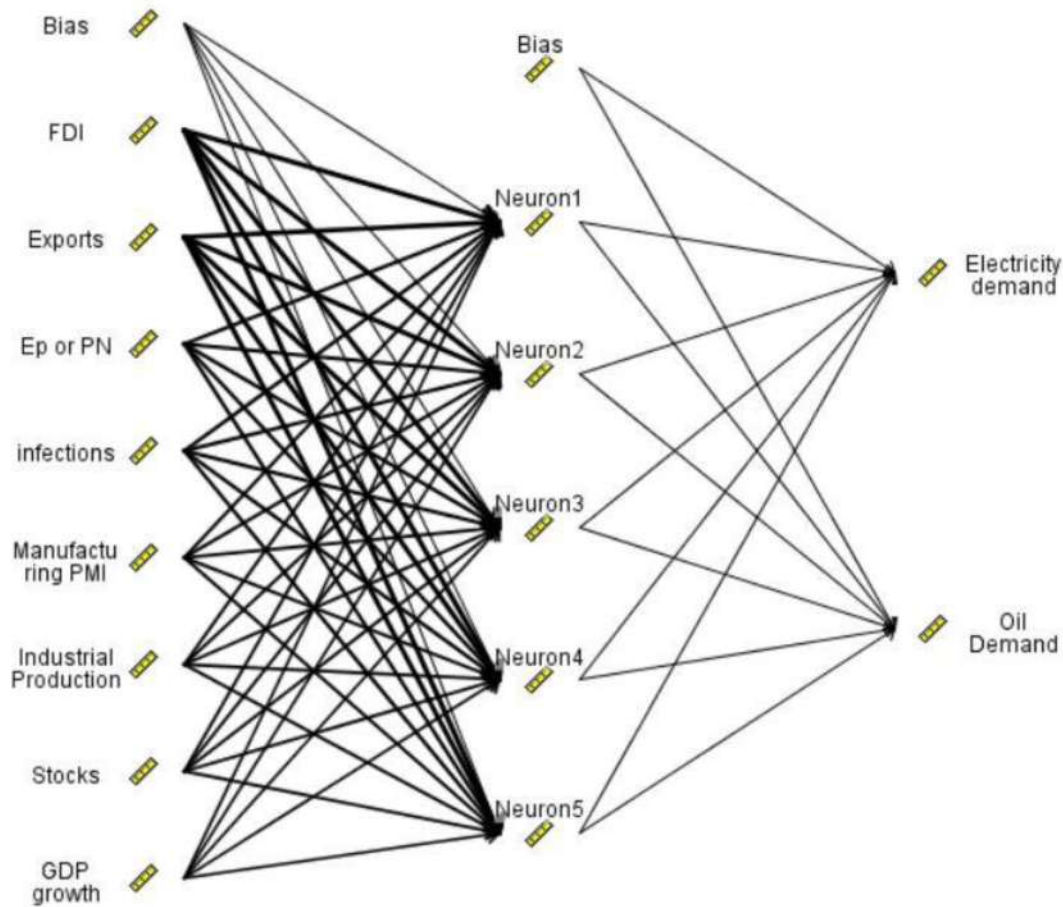


Fig. 2. The structure of selected ANN.

severeness, as a 1% increase in the severeness index causes a 10.57% decrease in the productivity index. For the stocks index, also the severeness index is the most important factor causing a 0.67% decrease in the stock's value index. GDP growth is also being hit by the population of the infected people, which a 1% increase causes a 1.12% decrease in the GDP growth rate. The electricity demand is also decreasing by 0.65% when the population increase by 1%. However, the oil demand is the second most sensitive to the severity index, which experiences a 0.9% decrease due to a 1% increase in the severeness index. Table A2 (see Appendix) shows the indirect impact of the coronavirus on the other economic parameters by affecting the more critical parameters that the main affected parameters have a significant effect on them. Table A2 is only a graphical schematic of the driving variables in other important variables, which are presented in this section to show that there is an indirect relationship between the parameters and the pandemics. Table 6 presents the results of different correlative models developed to investigate the structural model of Fig. 3. Diagrams are

shown in Table A2 clearly illustrate the indirect impacts of the different parameters which don't have direct relationships with each other. Thus, a more detailed schematics of the relationships (Fig. 3) is needed to illustrate the structural model of the problem in this paper.

Fig. 3 shows the impact of each parameter of the model on the other parameters. The coefficient shows the elasticity of each parameter to the other parameters, and this figure clearly shows the direct and indirect impact of the coronavirus on the energy demand, especially oil and electricity consumption in China.

Using the model, first, through conducting sensitivity analysis on different variables, the amount of the influence and the way they affect the change in the output of the model are investigated. Then, using different scenarios, the amount of oil and electricity demand in the industry and residential sectors of China will be predicted for the coming months.

Changes in the output variable would be observable by modifying the desired input and keeping other input variables constant to

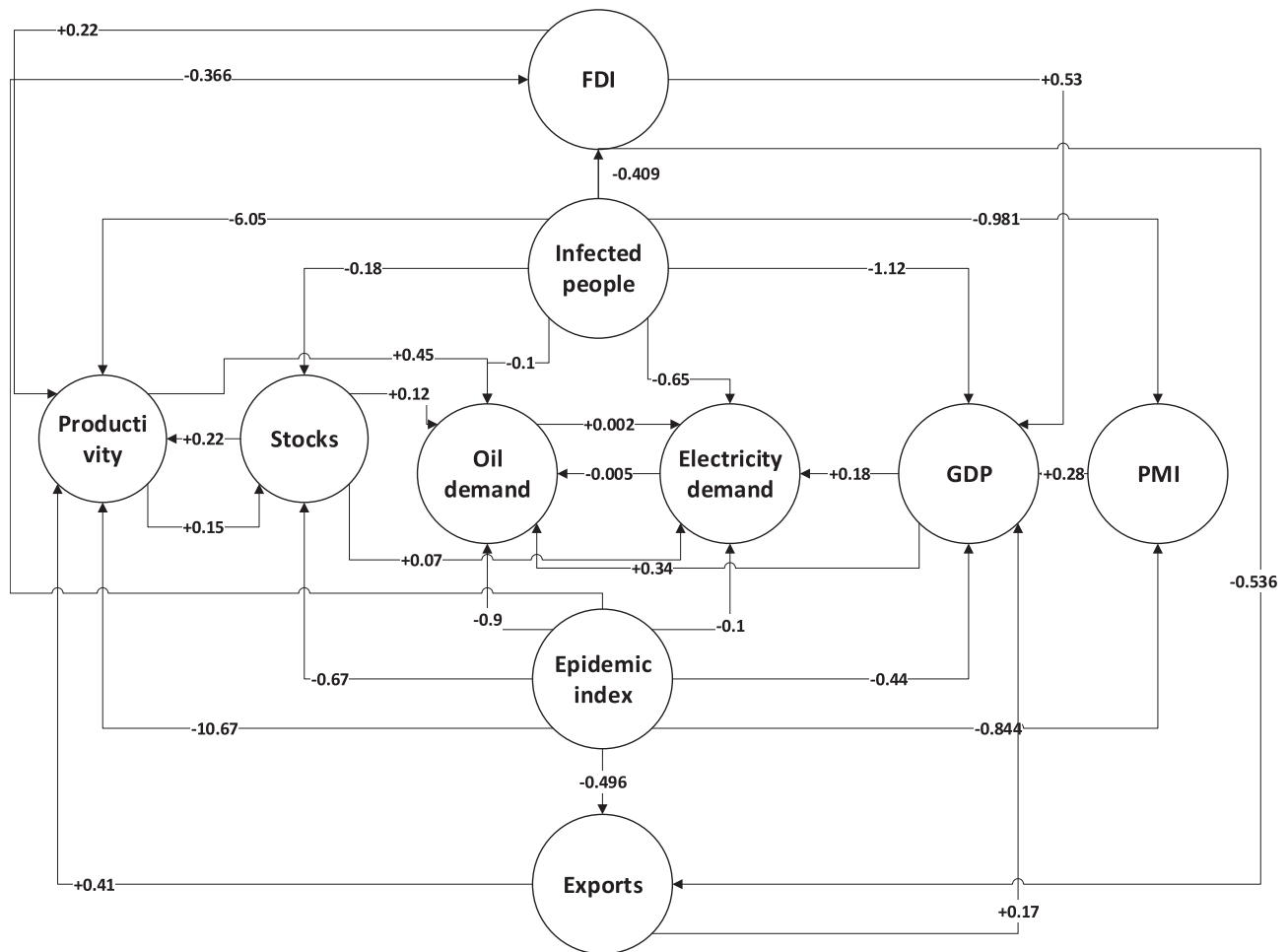
Table 5
Pearson Correlation of the parameters.

	Epidemic	Infections	Manufacturing PMI	Exports	FDI	Industrial Productivity	Stocks	GDP growth
Epidemic	1	0.923	−0.844	−0.496	−0.366	−0.43	0.068	−0.873
Infections	0.923	1	−0.981	−0.563	−0.409	−0.377	−0.1	−0.988
Manufacturing PMI	−0.844	−0.981	1	0.506	0.353	0.354	0.219	0.987
Exports	−0.496	−0.563	0.506	1	0.917	0.36	0.025	0.519
FDI	−0.366	−0.409	0.353	0.917	1	0.15	−0.112	0.353
Industrial Productivity	−0.43	−0.377	0.354	0.36	0.15	1	0.484	0.336
Stocks	0.068	−0.1	0.219	0.025	−0.112	0.484	1	0.161
GDP growth	−0.873	−0.988	0.987	0.519	0.353	0.336	0.161	1

Table 6

The elasticity of each parameter to the coronavirus epidemic severeness and the population of infected.

	Population_infection Elasticity	Severeness Elasticity	t-parameter	Sig.
Industrial Productivity	−6.05	−10.67	−9.87	0.000
Stocks	−0.18	−0.67	−0.001	0.000
GDP growth	−1.12	−0.44	−21.546	0.000
Electricity Demand	−0.65	−0.1	−2.232	0.04
Petroleum Demand	−0.1	−0.9	−6.770	0.000

**Fig. 3.** the co-integrated relation between the model parameters and the elasticity of each parameter on the others (Pro. > 95%).

determine the output sensitivity toward different input variables. The average ratio of the output changes to the changes in each input has been mentioned.

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

The changes of the output variable have been observed to determine the output sensitivity to different input variables, by applying changes to the desired input and keeping other input variables constant, according to the Eq. (3). The more significant changes of the output variable concerning the changes of the input variable, and the more consistent it is indifferent samples, the more effective the desired variable on the output. Table 7 includes the ratio of the output changes to the changes in different variables.

According to the main aims of this paper, investigating the trends of oil and electricity demand are the main objectives of this research. The driving parameters of a system must be analyzed to understand the responses of the system to a phenomenon. Similarly, the oil and gas

Table 7

The ratio of the output changes to the changes of each variable.

Variable	Description	The Ratio of the Changes (S_{ω}^F) petroleum	The Ratio of the Changes (S_{ω}^F) electricity
GDP	GDP Growth	0.3168	0.34848
Demand_oil	Oil Demand	−	−0.9372
Demand_electricity	Electricity Demand	−0.852	−
Epidemic	Epidemic status	−0.5544	−0.60984
Population_infected	Infected people	−0.5346	−0.58806
PMI	Manufacturing PMI	0.4356	0.47916
Exports	Export Income	0.8118	0.89298
FDI	Foreign Direct Investment	−0.9504	−1.04544
P_industry	Industrial Productivity	0.3762	0.41382
Stocks	Stocks Value	−0.3564	−0.39204

demand responses to the pandemic outbreak, the driving factors must be investigated to model and predict the future of the target variables (Oil and electricity demand). In this paper, ten driving factors (X_1 – X_{10}) are determined as the main thrusts of the objective parameters, and the impacts of these parameters on the oil and electricity demand illustrate the correlation between the parameters of the structural model. These impacts (as it was mentioned in the methodology) are being estimated using two methods of neural network and auto-regressive. In the auto-regressive model, elasticity and Pearson relationships can be used for the estimation, and in the artificial neural network, the sensitivity analysis was put to this task. As it is formulated in the Eq. (3), the ratio of change (S_{ij}^p) or the impact of each variable on the electricity and petroleum demand is calculated. Briefly, the sensitivity index shows the sensitivity or the dependence amount of the dependent variable toward the independent parameters for example if the dependent variable's sensitivity toward the parameter "A" be estimated 0.6% it means that the 1% increase in the parameter A causes a 0.6% increase in the amount of the dependent variable (Table 7).

4. Discussion

In this section, the economic situation of China and the economic impacts of the COVID-19 is discussed to then elaborate with two scenarios to provide a broader view of the pandemic control strategies' impacts on the economy and energy demand. In the end, the different aspects of the energy demand side, as well as suitable policies to be implemented to control the damages of the pandemic crisis, are presented, supported by other studies in the literature.

The COVID-19 outbreak is also expected to cause deeper impacts than those during the SARS epidemic [22]. However, the damage is not be limited to China [23]. Indeed, given that Wuhan – the center of the crisis – is also one of the largest transport hubs in the country, the impact has extended to national and international airlines, severely affecting the tourist industry. Countries whose economies are dependent on tourism (e.g., Greece, France, or Italy) are currently adjusting their forecasts [24]. Many international technology companies or component providers for such companies (e.g., Apple or Samsung) have plants in damaged Chinese provinces, and the virus, along with preventive measures, damages international supply chains [25]. According to S&P rating agency assumptions and estimates, COVID-19 could reduce the GDP growth rate of Wuhan by 20%, for the world by 0.3% (ppt), for China with a total rate of 0.7 percent, for the Asia and the Pacific 0.5 percent; and for the United States and Europe with 0.1–0.2 percent [26]. Internationally, the effects risk other industries supply and value chains, as in the case of several car manufacturers, including Fiat, Renault, or BMW [27].

Considering the locations with the biggest to-date outbreaks, such as China, the United States, the UK, and mainland Europe it can be noticed that the industrial and technological hubs are in more danger than other places because of the vast trade communications and international commodity transfer system [60]. These locations are also the main demand sections of the energy (especially oil and electricity). In the case of China, the outbreak in Wuhan, which is one of the leading international terminals of the country and a hub of its economy, caused a significant impact not only nationally but also on the global energy market [61]. First, because of its direct impact on the energy demand and decrease in the productivity of the industries, which causes large-scale shutdowns. Second, its significant impact has indirect effects through panic in the stocks and gold market, which forces the petroleum price to further fall because of the lack of a global program to control the energy market (which is not the priority of most governments in the time of crisis) [62]. In recent years, China has grown to account for about 50% of the world's oil demand, so when demand in the country declined by 20–25% due to quarantine measures [63], oil prices were damaged significantly.

Moreover, the infections across Middle East countries can damage

oil supply significantly due to the lesser productivity [64–68]. Not only the shutdown industries but also the service and commercial sectors are affected. This energy demand reduction in the service and commercial sectors can be detected from the air pollution indexes, which is directly dependent on the energy demand in the cities and businesses [69].

More specifically, when analyzing the impacts of the coronavirus in relation to energy and electricity, this paper shows (see Table 7 above) through the output of its model, that petroleum has a high sensitivity toward electricity demand, export income, and foreign investment variables. The sensitivity of the petroleum demand model towards the population of the infected people, contrary to what is expected, is not high when compared to the electricity demand. This issue, which is consistent with the previous findings by Suganthi and Samuel and Shariatzadeh, indicates the relatively low impact of the pandemic status on residential electricity consumption since energy is an essential and inelastic good [61]. Still, it can be much more significant in the industrial sector. The changes in the manufacturing index show that it has a moderate impact on oil and electricity demand. Finally, the variables of the severeness index and infected people population, which was considered as the index of epidemic intensity, showed a moderate to a significant impact on the oil and electricity demand [62]. This shows that their direct impact is not as crucial as their indirect impacts shown in the Fig. 3.

Furthermore, considering the timeliness of change between current and future impact, the model forecasts two different scenarios for petroleum and electricity demand in the coming months in China [63,64]. The first scenario is formulated based on the disease being controlled, whereas, in the second scenario, the assumption is that the infection cannot be controlled. Below, we elaborate on other assumptions of each scenario as well as showing the results of both no Figs. 4 and 5.

Assumptions of the First Scenario

- The infected population growth is considered to be equal to 0.005%/week
- The FDI grows 2.5%/week.
- The Stocks return to the stability of the Pre-epidemic era
- Exports grow 4%/week

Assumptions of the Second Scenario:

- The infected population growth is considered to be equal to 2%/week
- The FDI decreases by 1.2%/week.
- The Stocks stays instable
- Exports reduce 1%/week

To elaborate on the comparison between the method for each model, Figs. 6 and 7 below shows the results of the regression model compared to the ANN developed model. The error figures show that the ANN model is lesser accurate comparing to the Regressive model. The broader range of error in the ANN model shows that to predict the short-time trend of petroleum and electricity demand in the term of sudden issues and crisis such as current global pandemic of COVID-19.

Furthermore, the impacts on the sector can be evidenced in the reduction of demand in the country, which is equivalent to the energy of about 30 million tonnes of thermal coal or about nine million tonnes of liquefied natural gas (LNG). China has sought to prevent the spread of the viral epidemic that has killed more than 1400 and more than 60,000 people by extending the New Year's holidays for another week (October 26, 2019, to January 7, 2020) and encouraging people to work from home. Last year, industrial users consumed 4.85 trillion kWh, accounting for 67% of the country's productivity [40]. Shizhou Zhou, global head of energy and renewables at IHS, said if the epidemic persists beyond March 2020, China's economic growth rate could drop to 4.2% by 2020, from the company's initial forecast of 5.8% [64] (See Fig. 8).

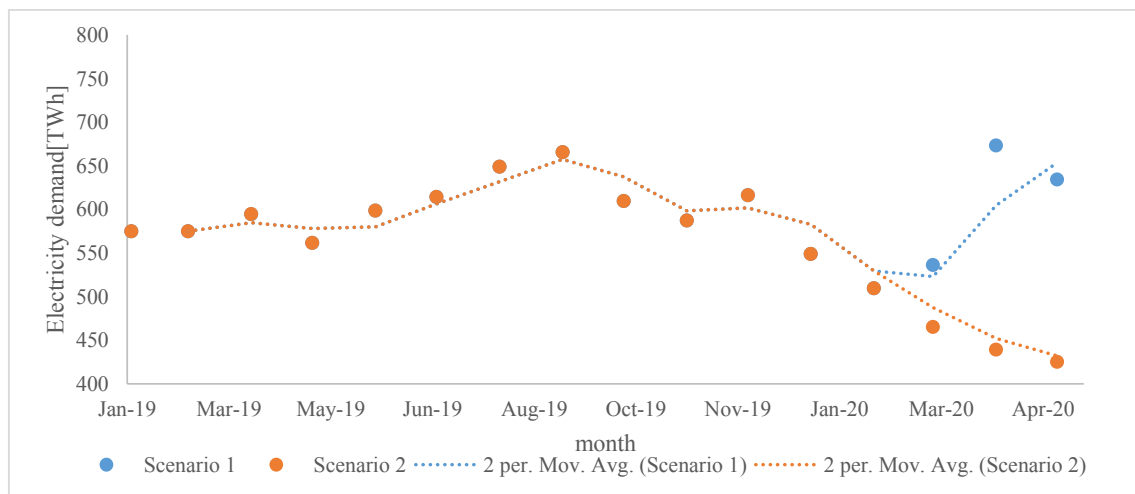


Fig. 4. Electricity demand forecast based on the model output with the assumptions of the first and second scenario.

While power consumption will only increase by 3.1 percent, compared to the initial forecast of 4.1 percent, as Zhou noted, “the main uncertainty is still under the speed of the virus spread,” the impact on the electricity sector will be relatively moderate across the later parts of 2020 [64–67]. In Hubei province, the virus-carrying center, the peak load – measuring power consumption – was 21 percent lower than planned by the end of January, as shown by data from Wood Mackenzie Energy Consulting [68]. Industrial productivity rates point to a significant decline in electricity consumption in China. Plastic processors work between 30% and 60% of their full potential, and according to another research study by ICIS China, the low level was expected to last until April 2020 [31]. ICIS data showed that knitting machines work in textile factories below ten percent capacity, the lowest in five years. China is the world's largest exporter of textiles and clothing [49] (See Fig. 9).

According to people with domestic knowledge of the country's energy industry, Chinese oil demand has fallen by about three million barrels a day, or 20% of total consumption, as the coronavirus is pushing the economy [21]. This fall is probably the most significant demand shock the oil market has suffered since the global financial crisis of 2008–2009 and the most sudden since the September 11, 2001 disaster. This situation has already forced OPEC and its allies to cut production and reduce prices to below zero in the time of pandemics [65].

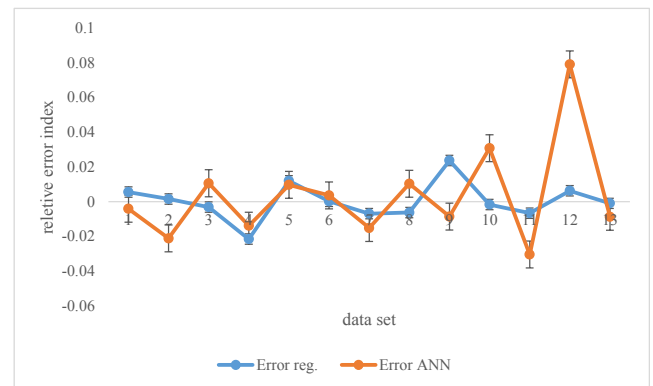


Fig. 6. petroleum demand relative error based on the model output for regressive and ANN models.

The World Bank data shows that the coronavirus damaged the Chinese economy severely in the last three months. Moreover, this caused about 1000 billion USD damage to the overall economy (–1.7% monthly Growth rate) [38] (See Fig. 10).

As was mentioned in the results sector, the energy demand in the oil

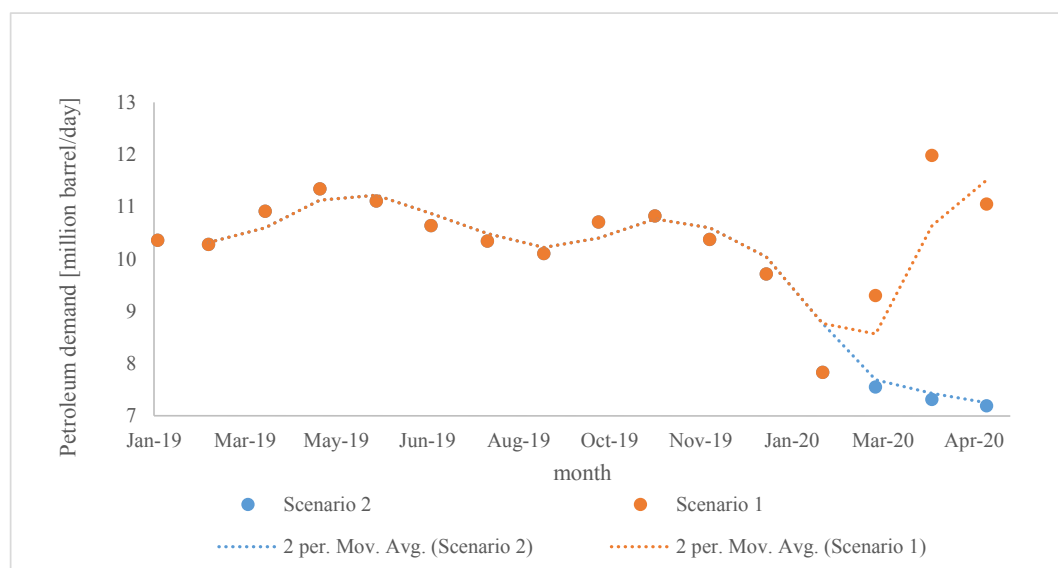


Fig. 5. Petroleum demand forecast based on the model output with the assumptions of the first and second scenario.

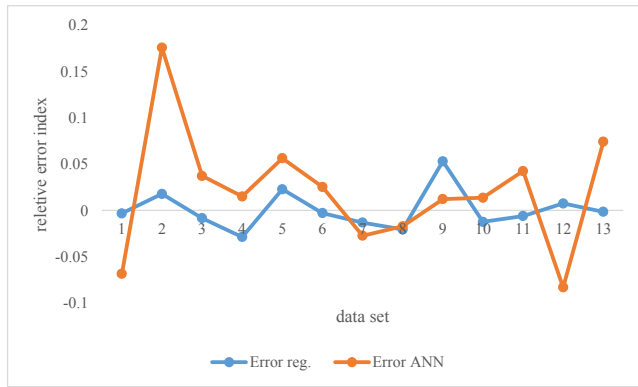


Fig. 7. Electricity demand relative error based on the model output for regressive and ANN models.

and electricity sector of China is estimated for two scenarios. The results show that the coronavirus, if be controlled, the country will recover to its former status quicker than it was predicted before in two months, and the electricity and petroleum demand will experience a minor peak by March–April 2020. However, if the coronavirus continues to spread, it will be more harmful to the energy and economy sectors [19].

In order to model and build a realistic picture of the social-economic impacts of the pandemic, we must address the environmental impacts of the coronavirus breakout to have a comprehensive picture of the situation [20]. To do so, we considered carbon emissions to model the environmental impacts of the energetic and economic aspects of the pandemic. In the last one hundred years, five great falls of carbon emissions have occurred. The first occurred in 1918–19 during the Spanish flow pandemics. This event caused a 480 million tonnes reduction of CO₂ emission, the second was WWII in 1944–45 with 850 million tonnes of CO₂ reduction, next one in 1980–81 when the great energy crisis occurred and caused 550 million tonnes of emission reduction, the fourth was during the recession and in 1991–92 more than 780 million tonnes of carbon emission reduced in this period. The financial crisis of 2008–9 was the fifth great fall of emissions, in which 400 million tons of carbon emission reduced [22]. Experts consider that the coronavirus pandemic can be the sixth and the greatest carbon fall

of the last century, with more than 2.2 billion tonnes of the reduction. According to the findings of this paper, this prediction is an optimistic view, but 1.8–2.0 billion tonnes is likely. However, it too early to conclude that this pandemic has had either a negative or positive effect on climate change and the environment. Considering the previous great falls in the carbon emissions, it is a short time event, and almost always after the end of the severeness, the emissions rapidly increase (revenge emission) to even higher amounts than the pre-event levels [23]. But even with these experiences, there are other factors that can affect the emissions path, as the coronavirus outbreak in China was followed by an oil shock, and, unlike the energy crisis of 1980–81, there are plenty of current energy alternatives to diversify energy supply streams. Considering the mentioned facts, the current structure of the global energy economy is highly dependent on energy security and reliable energy sources. Unlike the other similar situations, it is likely that the petroleum demand and also carbon emissions do not increase to the pre-corona virus outbreak's level, considering the dynamism of a globalized world with additional collateral impacts. On the other hand, the pandemic and the fall of the oil price may lean societies towards an improved the renewable energy market, with the need for resiliency on the sector and on the economy in general, similar to what happened in Germany by the late 2019 and early 2020 [24]. This has also been arguably evidenced by the early impacts of the coronavirus on renewable energy growth in power capacity, which has affected the sector but no completely halt it although the analysis of the full effects of the pandemic will require further data as the global situation continues to progress [68,69].

5. Conclusion

Currently, the novel Coronavirus epidemic is still underway, preventing a comprehensive study of its full impact. As Commissioner Gentilonius pointed out on February 26, 2020, while China's weight gain in the world economy since the outbreak of SARS in 2003 has undoubtedly had an impact, it is too early to assess this and provide a comprehensive study forecasts for China and its impacts on the other regions like EU or Australia. However, given China's containment measures and preventive measures taken by the rest of the world, the first attempt has been made to estimate the likely impact on the economy in the medium and long term. As noted, the first visible impact on the health sector and the lack of capacity to deal with the

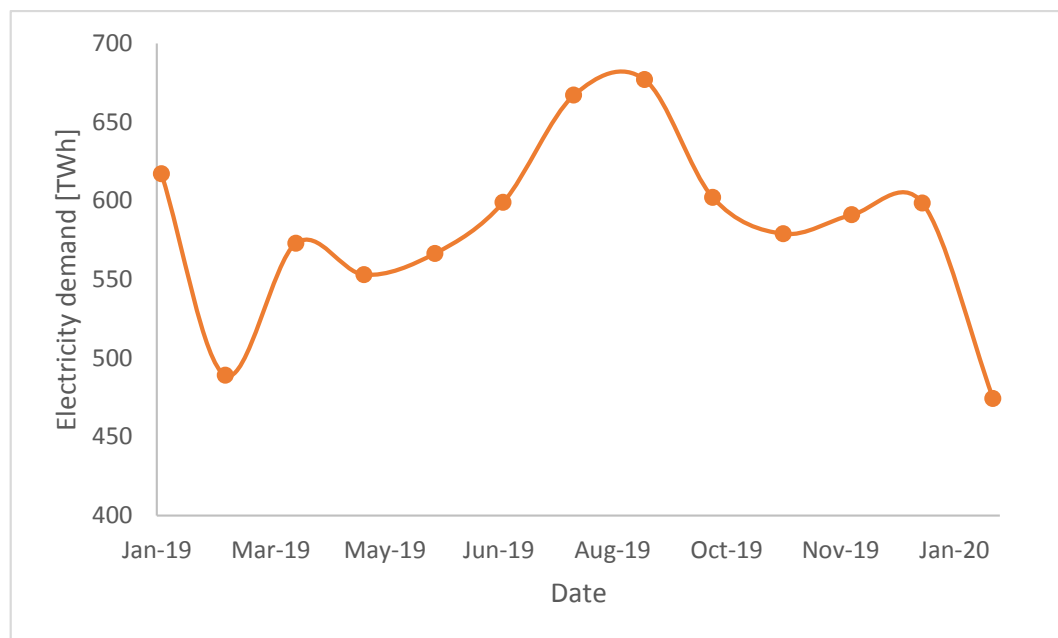


Fig. 8. Mean monthly Electricity demand in TWh.

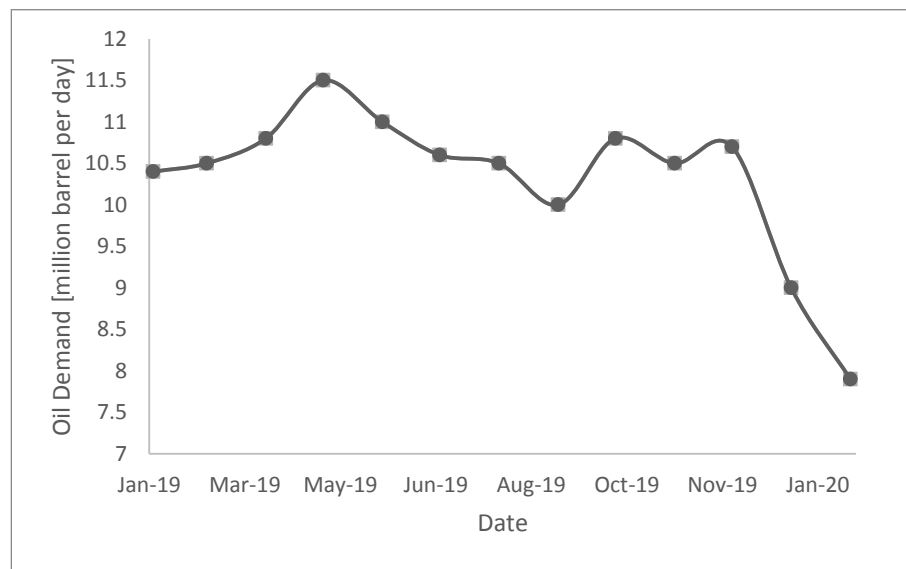


Fig. 9. Mean monthly oil demand in Million barrel per day.

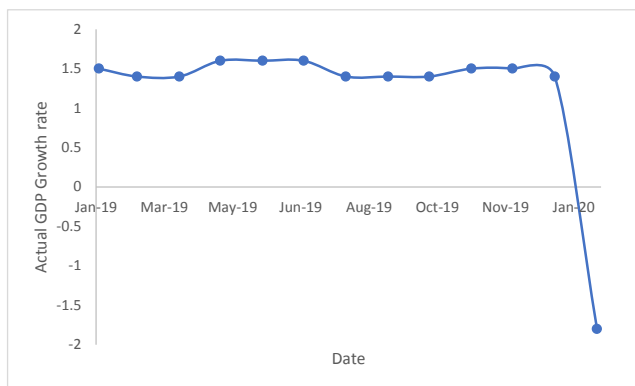


Fig. 10. Mean monthly GDP Growth rate in China [38].

volume of infections, which prompted officials to build other hospitals in days. Another major impact includes reduction or closure of transportation systems and social events, such as the Chinese New Year (when much Chinese return home for the holidays), as well as containment measures around several Chinese cities.

The main contribution of this paper is in developing a method for investigation of the periods that historical trends become inaccurate and useless because of the described global crisis (i.e., pandemics, economic collapses, etc.). As it was mentioned, trend shift phenomena caused by the pandemic makes all of the models developed using the historical trends useless and inaccurate. Thus, the long-term trend analysis decreases the inaccuracy of the model, and short periods increase the uncertainty of the model because of the smaller data sets for model training and test process. For this season, the present method and analysis can be used to help the researchers in the investigation of such uncertain times. It is suggested that it may be for other global trend shifts, not only exclusive to pandemics, such as economic crisis or peak-oil phenomenon. Doing so would continue to further the literature and impact of this field of study. Furthermore, the methods applied for this study are developed using classical econometric models and, therefore, can be used for investigating trend shifts, regardless of where such shifts occur or what are its fundamental assumptions. Thus, there are no regional and problem characteristic limitations for the trend-shift analysis implementation in other cases.

Since the crisis is not ended yet, there is not complete data to study

the crisis comprehensively and investigate its full range and multi-dimensional impacts. However, there are recommendations from this study can be summarized as:

1. According to the quarantine and shutting down of the industries, the importance of electricity and eCommerce is highlighted, and businesses with more developed eCommerce infrastructures have shown more resilience to the economic shock caused by the epidemic situation. Some suggestions can be made for the future of energy portfolio and sustainable development of the countries considering this fact [30,70]:
 - Those Countries without developed electricity infrastructure and internet communication are more vulnerable to the social and economic aspects of the epidemic situations and should develop their electricity and internet industries [31,71].
 - The coronavirus situation has shown that renewable electricity because of its decentralized nature is more suitable for the situation, which can be a reliable source during the worst chaotic situations [29,72].
 - The energy demand reduction during the coronavirus outbreak has shown that the conventional electricity sources are not flexible enough to manage the crisis without a significant fall in the overall efficiency and imposing pressure on the distribution and generation system [28,72,73].
 - Also, renewable electricity because of its availability in most regions is more reliable than fossil fuel, which in the case of a problematic epidemic situation in the oil and gas producing countries, may become unavailable or significant shortages occur [31,74].
2. According to fall of oil price to the pre21st century level which makes 10% of the global oil production infeasible for production and refinement process, oil-producing countries should try to cooperate in the crisis to control the energy market, thus the energy security level of the consumers of their oil products to prevent more significant economic harsh situations [32,73,75,76].

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Appendix A

See, [Tables A1 and A2](#)

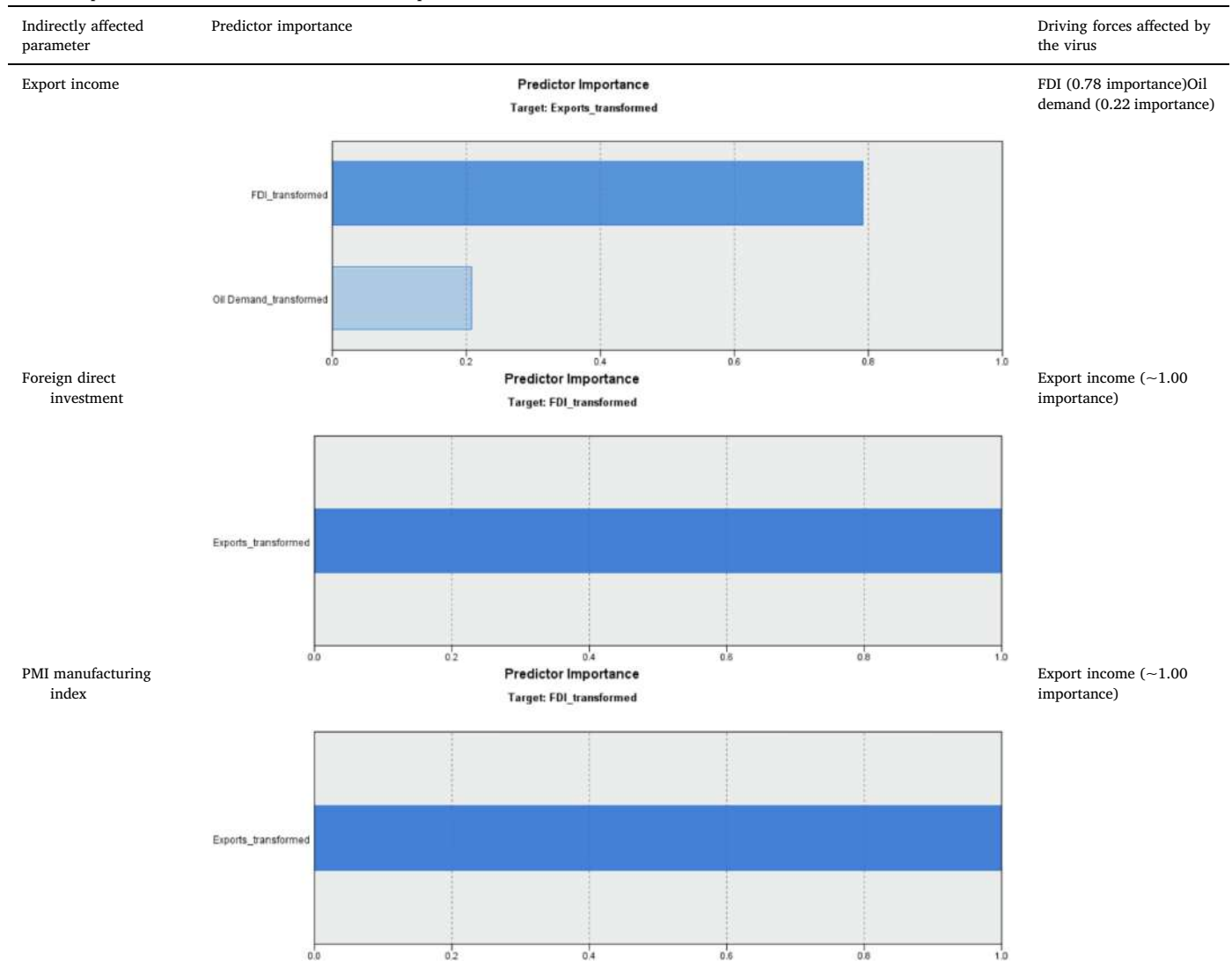
Table A1

instructions for model result interpretation (equations are being developed by the authors).

Parameter	Description
slopes or coefficients regression	This coefficient of the parameter shows the impact of that parameter on the dependent variable and this impact is called the elasticity of the dependent variable toward independent variables for example if the coefficient for independent parameter A is estimated 0.6 it means that the 1% increase in the A causes 0.6% increase in the dependent parameter.
Sensitivity index of the ANN model	This index shows the sensitivity or the dependence amount of the dependent variable toward the independent parameters for example if the dependent variable's sensitivity toward the parameter A be estimated 0.6% it means that the 1% increase in the parameter A causes a 0.6% increase in the amount of the dependent variable.

Table A2

indirect impacts of the coronavirus in the term of the parameters mentioned in [Table 6](#).



References

- [1] COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), available online in <https://coronavirus.jhu.edu/map.html>.
- [2] A. Amarawickrama, L.C. Hunt, Electricity demand for sri lanka: a time series analysis, *SEEDS* (2007).
- [3] A. Aqeel, M.S. Butt, The relationship between energy consumption and economic growth in Pakistan, *Asia-Pacific Dev. J.* 8 (2001) 101–110.
- [4] Considerations for quarantine of individuals in the context of containment for coronavirus disease (COVID-19), WHO, available online in https://apps.who.int/iris/bitstream/handle/10665/331497/WHO-2019-nCoV-IHR_Quarantine-2020.2-eng.pdf, 2020.
- [5] J. Kaplan, L. Frias, M. McFall-Johnsen, Countries around the world are reopening — here's our constantly updated list of how they're doing it and who remains under lockdown, available online in <https://www.businessinsider.com/countries-on-lockdown-coronavirus-italy-2020-3?r=US&IR=T>, 2020.

- [6] Coronavirus Travel Restrictions, Across the Globe, The New York Times, available online in <https://www.nytimes.com/article/coronavirus-travel-restrictions.html>.
- [7] The Great Lockdown: Worst Economic Downturn Since the Great Depression, available online in <https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/>.
- [8] N. Norouzi, M. Fani, Z. Karami Ziarani, The fall of oil Age: a scenario planning approach over the last peak oil of human history by 2040, *J. Petrol. Sci. Eng.* 188 (2020) 106827, <https://doi.org/10.1016/j.petrol.2019.106827>.
- [9] T. Bakirtas, S. Karbuz, M. Bildirici, An Econometric Analysis of Electricity Demand in Turkey, *METU Studies in Development*, 2000.
- [10] R.D. Bandaranaike, M. Munasighe, The demand for electricity service and the quality of supply, *Energy J.* 4 (1983) 49–71.
- [11] B. Cheng, An Investigation of cointegration and causality between energy consumption and economic growth, *J. Energy Dev.* 21 (1995) 73–84.
- [12] The world largest economies, available online in <https://www.nasdaq.com/articles/the-5-largest-economies-in-the-world-and-their-growth-in-2020-2020-01-22>.
- [13] IEA, *Global Energy Review 2020*, IEA, Paris, 2020.
- [14] L. Xu, N. Chen, Z. Chen, Will China make a difference in its carbon intensity reduction targets by 2020 and 2030? *Appl. Energy* 203 (2017) 874–882, <https://doi.org/10.1016/j.apenergy.2017.06.087>.
- [15] Y. Wang, H. Li, Q. Song, Y. Qi, The consequence of energy policies in China: a case study of the iron and steel sector, *J. Energy Dev.* 117 (2017) 66–73, <https://doi.org/10.1016/j.resconrec.2015.07.007>.
- [16] Y. Chen, Z. Wang, Z. Zhong, CO₂ emissions, economic growth, renewable and non-renewable energy production and foreign trade in China, *Renewable Energy* 131 (2019) 208–216, <https://doi.org/10.1016/j.renene.2018.07.047>.
- [17] Coronavirus leads to 'staggering' drop in global energy demand, available online in <https://www.ft.com/content/ee88c064-2fac-4a08-aad5-59188210167b>.
- [18] What the future may hold for oil amidst COVID-19, available online in <https://www.weforum.org/agenda/2020/04/the-week-when-oil-cost-minus-38-a-barrel-what-it-means-whats-coming-next>, April 26 2020.
- [19] M.W. Gardner, S.R. Dorling, Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences, *Atmos. Environ.* 32 (1998) 2627–2636, [https://doi.org/10.1016/S1352-2310\(97\)00447-0](https://doi.org/10.1016/S1352-2310(97)00447-0).
- [20] D.C. Park, M.A. El-Sharkawi, R.J. Marks, L.E. Atlas, M.J. Damborg, Electric load forecasting using an artificial neural network, *IEEE Trans. Power Syst.* 6 (1991) 442–449, <https://doi.org/10.1109/59.76685>.
- [21] M.T. Hagan, H.B. Demuth, M. Beale, *Neural Network Design*, 1995.
- [22] M. Fani, N. Norouzi, Using social and economic indicators for modelling, sensitivity analysis and forecasting the gasoline demand in the transportation sector: an ANN approach in a case study for Tehran metropolis, Iran, *J. Energy* (2019).
- [23] R.F. Engle, C.W.J. Granger, Cointegration and error correction: representation estimation, and testing, *Econometrica* 55 (1987) 251–276.
- [24] G. Erdal, The causality between energy consumption and economic growth in Turkey, *Energy Policy* 36 (2008) 3838–3842.
- [25] H. Khalifa, M. Ghali, Energy use and output growth in Canada: a multivariate cointegration analysis, *Energy Econ.* 26 (2005) 225–238.
- [26] C.J. Kim, C.R. Nelson, *Business Cycles Turning Points. A new coincident index and tests of duration dependence based on a dynamic factor model with regime switching*, *Rev. Econ. Stat.* 80 (1998) 188–201.
- [27] J.S. Rounqvist, P. Enevoldsen, Timescale classification in wind forecasting: a review of the state-of-the-art, *J. Forecasting* (2020) 1–12, <https://doi.org/10.1002/for.2657>.
- [28] J. Runge, R. Zmeureanu, Forecasting energy use in buildings using artificial neural networks: a review, *Energies* 12 (2019) 3254.
- [29] J. Reynolds, M.W. Ahmad, Y. Rezgui, J.-L. Hippolyte, Operational supply and demand optimisation of a multi-vector district energy system using artificial neural networks and a genetic algorithm, *Appl. Energy* 235 (2019) 699–713, <https://doi.org/10.1016/j.apenergy.2018.11.001>.
- [30] J.S. Rounqvist, P. Enevoldsen, G. Xydis, High-resolution electricity spot price forecast for the Danish power market, *Sustainability* 12 (2020), <https://doi.org/10.3390/su12104267>.
- [31] C. Richter, Some limitations of regional econometric models, *Ann. Reg. Sci.* 6 (1972) 28–34, <https://doi.org/10.1007/BF01285511>.
- [32] D. Freedman, From association to causation via regression, *Adv. Appl. Math.* (1997).
- [33] J.H. Goldthorpe, *On sociology: Numbers, Narratives, and the Integration of Research and Theory*, Oxford University Press, Oxford, 2000.
- [34] J.M. Keynes, *Professor Tinbergen's method*, *Econ. J.* (1939).
- [35] J.M. Keynes, *Comment*, *Econ. J.* (1940).
- [36] I.A. Moosa, *Econometric analysis: loopholes and shortcomings*, *Econometrics as a Con Art Exposing the Limitations and Abuses of Econometrics*, Edward Elgar Publishing, Cheltenham, UK, 2017, <https://doi.org/10.4337/9781785369957.00009>.
- [37] C.C. Lee, Ch.P. Chang, Structural breaks, energy demand, and economic growth revisited: evidence from Taiwan, *J. Energy Econ.* 27 (2005) 857–872.
- [38] GDP growth of China, available online in <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG>.
- [39] Energy demand of China, available online in <https://www.iea.org/countries/china>.
- [40] Corona Virus Death cases, available online in <https://www.worldometers.info/coronavirus/country/china/>.
- [41] Manufacturing PMI in China, available online in <https://tradingeconomics.com/china/manufacturing-pmi>.
- [42] Export income of the China, available online in <https://tradingeconomics.com/china/exports>.
- [43] China Foreign Direct Investment, available online in <https://tradingeconomics.com/china/foreign-direct-investment>.
- [44] China Industrial Production, available online in <https://tradingeconomics.com/china/industrial-production>.
- [45] Shanghai Composite Index, available online in <https://www.marketwatch.com/investing/index/shcomp?countrycode=cn>.
- [46] J. Durbin, G.S. Watson, Testing for serial correlation in least squares regression. II, *Biometrika* 38 (1951) 159–177.
- [47] A. Masih, Energy consumption and real income temporal causality, results for a multi-country study based on cointegration and error-correction techniques, *Energy Econ.* 18 (1996) 165–183.
- [48] A.M. Masih, R. Masih, On the temporal causal relationship between energy consumption real income and prices: some new evidence from Asian energy dependent NICS based on a multivariate cointegration vector error correction approach, *J. Policy Model.* 19 (1997) 17–440.
- [49] M. Mehrara, Energy consumption and economic growth: the case of oil exporting countries, *Energy Policy* 35 (2007) 2939–2945.
- [50] Shane Barks, Verification and Adjustment of Regional Regression Models for Urban Storm-runoff Quality Using Data Collected in Little Rock, Arkansas, U.S. Department of the Interior, U.S. Geological Survey, 1995.
- [51] P.K. Narayan, R. Smyth, Electricity consumption employment and real income Australia evidences from multivariate granger causality tests, *Energy Policy* 33 (2004) 1109–1116.
- [52] M.H. Pesaran, Y. Shin, R. Smith, Bounds testing approach to the analysis of level relationships, *J. Appl. Econ.* 16 (2001) 289–326.
- [53] P.C.B. Phillips, Understanding spurious regressions in econometrics, *J. Economet.* 33 (1986) 311–340.
- [54] D.I. Stern, A multivariate cointegration analysis of the role of energy in the us macroeconomy, *Energy Econ.* 22 (2000) 267–283.
- [55] J.H. Stock, Asymptotic properties of least squares estimators of cointegrating vectors, *Econometrica* 55 (1987) 1035–1056.
- [56] Y. Wolde-Rufael, Energy demand and economic growth: the African experience, *J. Policy Model.* 27 (2005) 891–903.
- [57] H.Y. Yang, A note on the Causal Relationship between Energy and GDP in Taiwan, *Energy Econ.* 22 (2000).
- [58] D.E. Bloom, D. Cadarette, J.P. Sevilla, The economic risks and impacts of Epidemics, *Int. Monetary Fund, F&D Mag.* (2018).
- [59] V.Y. Fan, D.T. Jamison, L.H. Summers, Pandemic risk: how large are the expected losses? *Bull. World Health Organ.* (2018).
- [60] D. Kostova, C.H. Cassell, J.T. Redd, D.E. Williams, T. Singh, L.D. Martel, R.E. Bunnell, Long-distance effects of epidemics: assessing the link between the 2014 West Africa Ebola outbreak and US exports and employment, *Health Econ.* (2019).
- [61] L. Suganthi, A.A. Samuel, Energy models for demand forecasting—a review, *Renewable Sustainable Energy Rev.* 16 (2012) 1223–1240, <https://doi.org/10.1016/j.rser.2011.08.014>.
- [62] World Bank Group, *From Panic and Neglect to Investing in Health Security: Financing Pandemic Preparedness at a National Level*, World Bank Group, 2017.
- [63] World Bank Group, *Pandemic Preparedness Financing – Status update*, World Bank, 2019.
- [64] From mild to wild: Coronavirus impact on China's power and renewables sector, available online in <https://ihsmarkit.com/research-analysis/from-mild-to-wild-coronavirus-impact-on-chinas-power-renewabl.html>.
- [65] K.R. Smith, available online at: <http://www.kirksmith.org/publications/2019/8/7/energy-and-air-pollution-benefits-of-household-fuel-policies-in-northern-china>, 2020.
- [66] S. Evans, GLOBAL EMISSIONS website, available online in: <https://www.carbonbrief.org/analysis-coronavirus-set-to-cause-largest-ever-annual-fall-in-co2-emissions>, April 2020.
- [67] The Big Deal to Cut Oil Production May Not Be Big Enough, available online in <https://www.nytimes.com/2020/04/13/business/economy/coronavirus-oil-opec-trump.html>.
- [68] Coronavirus power and renewables market impact update, available online in <https://www.woodmac.com/our-expertise/focus/Power-Renewables/coronavirus-power-and-renewables-market-impact-update/>.
- [69] N. Norouzi, G. Kalantari, The sun food-water-energy nexus governance model A case study for Iran, *Water-Energy Nexus* 3 (2020) 72–80, <https://doi.org/10.1016/j.wen.2020.05.005>.
- [70] N. Norouzi, S. Talebi, M. Fani, H. Khajepour, Heavy oil thermal conversion and refinement to the green petroleum: a petrochemical refinement plant using the sustainable formic acid for the process, *Biointerface Res. Appl. Chem.* 10 (5) (2020) 6088–6100, <https://doi.org/10.33263/BRIAC105.60886100>.
- [71] N. Norouzi, G. Kalantari, S. Talebi, Combination of renewable energy in the refinery with carbon emissions approach, *Biointerface Res. Appl. Chem.* 10 (4) (2020) 5780–5786, <https://doi.org/10.33263/BRIAC104.780786>.
- [72] S. Ghasemian, A. Faridzad, P. Abbaszadeh, et al., An overview of global energy scenarios by 2040: identifying the driving forces using cross-impact analysis method, *Int. J. Environ. Sci. Technol.* (2020), <https://doi.org/10.1007/s13762->

- 020-02738-5 In press.
- [73] N. Norouzi, M. Fani, The impacts of the novel corona virus on the oil and electricity demand in Iran and China, *J. Energy Manage. Technol.* 4 (4) (2020) 36–48, <https://doi.org/10.22109/jemt.2020.222593.1232>.
- [74] S. Talebi, N. Norouzi, Entropy and exergy analysis and optimization of the VVER nuclear power plant with a capacity of 1000 MW using the firefly optimization algorithm, *Nucl. Eng. Technol.* (2020), <https://doi.org/10.1016/j.net.2020.05.011>
- In press.
- [75] N. Norouzi, 4E Analysis and design of a combined cycle with a geothermal condensing system in Iranian Moghan diesel power Plant, *Int. J. Air-Cond. Refrig.* (2020), <https://doi.org/10.1142/S2010132520500224> In press.
- [76] M.I. Meltzer, N.J. Cox, K. Fukuda, The economic impact of pandemic influenza in the United States: priorities for intervention, *Emerg. Infect. Dis.* 5 (5) (1999) 659–671, <https://doi.org/10.3201/eid0505.990507>.