Demand dynamics for hydrocarbon fuels during the COVID-19 pandemic

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Abstract

This work is aimed at analyzing demand dynamics for hydrocarbon fuels from March 2020 and developing a forecast model for the near future. Based on the method of artificial neural network with feedforward and backpropagation learning, a model is proposed for forecasting oil demand and passenger mobility during a pandemic for the United States, Russia, and India. The results of the calculations showed that road and air transport dynamics strongly depend on the application of measures to limit and ban and the level of COVID-19 incidence in a country. The proposed method can be used to make forecasts during pandemics and unforeseen situations to regulate the price policy for hydrocarbon fuels and the safety of passenger traffic in the future.

Keywords: Artificial neural network, COVID-19 crisis, forecasting, oil demand, transportation

1 Introduction

The onset of the COVID-19 pandemic has led to dramatic changes in the energy and social sectors around the world. The introduction of restrictions and bans due to the likelihood of the spread of the virus forced to restrict international and domestic passenger transport, which led to a decline in the transport sector, including air, rail, road, and water transport [1]. According to the data in [2], by the end of March 2020, the volume of road transport worldwide decreased by 50%, and by the middle of April 2020, the volume of commercial flights decreased by 75% compared to the average for 2019. The suspension of passenger traffic during quarantine in many countries of the world has led to a significant decrease in passenger mobility. Such a decrease in mobility and, as a result, a decrease in...
demand for hydrocarbon fuels have led to a glut of the oil market and unforeseen jumps in oil prices [3, 4]. Despite some recovery in oil prices since April 2020, there is still uncertainty due to the protracted pandemic in the economies of many countries. According to a report by the Bureau of Economic Analysis of the US Department of Commerce [5], US gross domestic product (GDP) fell 3.5% in 2020, the worst since 1946. For example, in Russia, GDP in 2020 decreased by 3.1%, and this drop is mainly due to the imposed restrictive measures aimed at combating coronavirus and the fall in global demand for energy resources [6]. According to the data in [7], the introduction of measures to restrict mobility led to a 57% drop in oil demand. Thus, by the end of March 2020, the average activity of road transport in the world fell to 50% from the level of 2019, and air transportation in some European countries decreased by more than 90%. As the bans spread, global air transport mobility declined 60% by the end of the first quarter of 2020, resulting in a drop in global oil demand of 10.8 million barrels per day compared to the same period in 2019.

The sharp collapse in oil prices occurred when much of the world's economic activity was halted due to COVID-19. In [8], the authors analyzed the news in relation to oil prices using a threshold regression model. The results showed that, with a threshold of 84,479 COVID-19 cases, there was a sharp decline in the price of oil. It was also found that, beyond the threshold, it was the negative news about oil prices that had a greater impact on its value. Besides, studies have been conducted on the impact of unexpected natural disasters on the level of demand for energy resources [9, 10], the impact of previous pandemics on tourism and the economy [11, 12]. To date, studies on the impact of COVID-19 pandemic on hydrocarbon fuels are limited to a short-term forecast [6], which uses a simplified model of COVID-19 pandemic to predict GDP, demand, and fuel prices. A study of online news in social networks based on the convolutional neural network method has shown that information from social networks helps predict oil prices, oil production, and consumption [13]. The indirect impacts of COVID-19 also include export revenues, foreign direct investment, and manufacturing capacity. Thus, Pearson's correlation coefficient between pandemic and exports is -0.496, and between GDP growth and pandemic -0.873 [14].

The development of a reliable and accurate model for forecasting demand dynamics for hydrocarbon fuels during a pandemic can help to quickly respond to various changes and regulate the pricing and demand for fuel, and, consequently, to stabilize the economy in large countries. The recent success of machine learning in speech and image recognition has contributed to the application of these techniques for long-term and short-term forecasting in economic and social fields. For example, neural networks have been used to predict significant changes in stock prices based on previous changes that have shown good results [15]. Success in the implementation of neural networks to optimize the energy system in eco-houses was achieved in [16], where the authors showed the effectiveness of machine learning for short-term forecasts of changes in climatic conditions and automatic regulation of the power system at home for a comfortable and environmentally safe living. In addition, the use of neural networks for long-term predictions for power plants (wind, solar, etc.) has also been shown to be effective [17].

The main feature of the neural network method is learning using historical data, based on which a forecast is made. Depending on the architecture of the network and the selected data, the learning algorithms depend on the performance of the network and the level of acceptable error. The aim of this work is to develop a model that combines passenger mobility with demand for hydrocarbon fuels, using a neural network method to correlate passenger mobility with the COVID-19 pandemic. This study examines the impact of COVID-19 on average monthly fuel demand as the pandemic evolves. Using data on the dynamics of demand and prices for hydrocarbon fuels, a study of the dynamics of passenger mobility and the incidence of COVID-19 is carried out on the examples of large countries with economies that directly depend on the demand for oil and gas.

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2 Modeling methods and input data

This section presents a methodology for developing a forecast model for hydrocarbon fuel demand based on an artificial neural network (ANN) using data on the COVID-19 pandemic and information on passenger mobility for the United States, Russia, and India. The model consists of a dynamic mobility index (DMI) forecasting model and fuel demand estimation (FDE) model. The DMI forecasting model detects changes in passenger mobility caused by the spread of the COVID-19 pandemic and government bans and predicts changes in passenger mobility indices for a pre-COVID-19 period and 2020. FDE model assesses the dynamic indicators of passenger mobility (road, air, and public transport) and quantifies the demand for hydrocarbon fuel in the pandemic. The study did not address the potential induced travel demand due to lower oil prices amid the COVID-19 pandemic. The ANN structure and data sources for the proposed forecast model are described below.

2.1 Artificial neural networks

ANN is a distributed parallel processor that simulates signal processing in the human brain. ANN architecture consists of input and output layers, as well as one or more hidden layers. This study employs a feedforward ANN, which is the underlying network architecture of the ANN. The activation function determines the relationship between input and outputs of a node and a network [18, 19]. In the network architecture, each layer has nodes (neurons) (Figure 1), the number of which in the input and output layers is determined by the number of input variables and goals, respectively.

![Feedforward ANN structure with one hidden layer.](image)

In the hidden layer, the optimal number of hidden nodes is selected for the best forecasting result. Each node must be associated with every node on an adjacent layer, and initial weights are assigned randomly to all connections. Input data are entered into the nodes of the input layer for transmission to hidden nodes via synaptic connections, with the output node being their final destination. The mathematical expression for the output in the case of one hidden layer is defined as follows:

\[ \text{output} = f(\sum w_i x_i) \]

where \( f \) is the activation function, \( w_i \) are the weights, and \( x_i \) are the inputs.
\[ z = F_z \left( \sum_{h}^{n_h} \left( w_{h0} F_y \left( \sum_{i}^{n_i} \left( w_{ih} x_i \right) \right) + b_h \right) \right) + b_0 \]  
\[ (1) \]

where \( i, h \) and \( o \) – indices that refer to the \( i \)-th input node, \( h \)-th hidden node and \( o \)-th output node, respectively; \( x \) and \( z \) - input and output node values; \( n_i \) and \( n_h \) - number of input nodes and number of hidden nodes; \( w \) – weight; \( b \) – bias; \( F_y \) and \( F_z \) - the activation functions of the hidden node and the output node, respectively. As the activation function to the hidden layer, a logarithmic sigmoid function is used:

\[ f(k) = \frac{1}{1 + e^{-k}} \]  
\[ (2) \]

the output layer uses a linear function:

\[ f(x) = ax + c \]  
\[ (3) \]

For the given input variables and corresponding outputs, it is necessary to determine the weights and biases to build the ANN prediction model through training. This study uses a backpropagation algorithm to minimize the error function by backpropagating and adapting weights and biases [20]. The error function in iteration can be represented by the sum of the squares of the errors:

\[ E^m = \sum_{n=1}^{N_{tr}} (t_n - z_n^m)^2 \]  
\[ (4) \]

where \( m \) - iteration number, \( t_n \) and \( z_n \) - target and estimated values of \( n \)-th training data, respectively, and \( N_{tr} \) - the total amount of training data.

To minimize the error function, the weights are iteratively updated using the learning algorithm:

\[ w^{m+1} - w^m = \beta (w^m - w^{m-1}) + (1 - \beta) \alpha \left( \frac{\partial E^m}{\partial w^m} \right) \]  
\[ (5) \]

where \( \alpha \) and \( \beta \) - learning rate and momentum, respectively. \( \alpha \) and \( \beta \) are used to protect the error function from falling into local minima and to reduce fluctuations in the weights during training, respectively.

Within a feedforward network with a backpropagation algorithm, 2 hidden layers were chosen, and the number of nodes was 25, the learning rate was \( \alpha = 0.001 \) and momentum \( \beta = 0.1 \) by default.

**2.2 Model performance criteria**

To assess the effectiveness of the model, estimates of the mean error (ME), root mean square error (RMSE), and correlation coefficient (CORR) were used:

\[ ME = \frac{1}{N_{ts}} \sum_{n=1}^{N_{ts}} (t_n - z_n) \]  
\[ (6) \]

\[ RMSE = \sqrt{\left( \frac{1}{N_{ts}} \sum_{n=1}^{N_{ts}} (t_n - z_n)^2 \right)} \]  
\[ (7) \]

\[ CORR = \frac{\sqrt{\left( \frac{1}{N_{ts}} \sum_{n=1}^{N_{ts}} (t_n - \bar{t})(z_n - \bar{z}) \right)}}{\sqrt{\left( \frac{1}{N_{ts}} \sum_{n=1}^{N_{ts}} (t_n - \bar{t})^2 \right)} \sqrt{\left( \frac{1}{N_{ts}} \sum_{n=1}^{N_{ts}} (z_n - \bar{z})^2 \right)}} \]  
\[ (8) \]

where \( N_{ts} \) - the amount of data at the testing stage, \( t \) and \( z \) - the mean of the targets and estimates, respectively. The closer ME and RMSE are to 0, and CORR and NSE are to 1, the better the estimated values match the observations. Among them, the RMSE value was used as a criterion for determining the model parameters and was set to 0.01.

**2.3 Data sources and network training parameters**

Historical data on the COVID-19 pandemic (confirmed cases) were taken from March 2020 to November 2020 from official health service sources for each country studied [21, 22]. Mobility data were taken from Google and Apple mobility services [23, 24, 25] on the movement of citizens by transport (car, passenger transportation, etc.), as well as data from the International Air Transport...
Association (IATA) for air travel [25]. These baseline data are selected on the basis of correlation analysis between pandemic and mobility data. Data preprocessing is applied to datasets to speed up training and improve model performance: network inputs are centered on means and normalized to standard deviations with a minimum of 0 and a maximum of 1.

\[
X_{i} = \frac{(x_{i} - x_{i, \text{min}})}{(x_{i, \text{max}} - x_{i, \text{min}})}
\]  

(9)

The loss function is defined as the root mean square error of the standardized output using formula (4). The default weight loss factor was chosen to be 0.0001.

For training and verification, the general dataset was divided into the following: for training, a dataset was selected from March to May 2020, for verification - from June to August 2020, for testing - from September to November 2020. Thus, each dataset contained data for 3 months in sequence.

The normalized inputs for each input variable \((X_i)\) and the output from the monitored data \((z)\) were directly used to calculate "strength" and "frequency" to estimate the contribution of each influencing factor. For the "strength" the following equation was used:

\[
S_{i} = \frac{\sum_{(n=1)}^{(N_{ts})} |z_{n} - z_{\text{base}}|}{\sum_{(n=1)}^{(N_{ts})} |X_{i,n} - X_{i,\text{base}}|}
\]  

(10)

where \(z_{\text{base}}\) and \(X_{i,\text{base}}\) - baseline value in the absence of an event for the relevant factor. For "frequency" the following expression was applied:

\[
Q_{i} = 1 - \frac{n_{0i}}{N_{ts}}
\]  

(11)

where \(n_{0i}\) – number for which \(|X_{i,n} - X_{i,\text{base}}| = 0\).

Therefore, the contribution of the influencing factor can be calculated as:

\[
C_{i} = S_{i} \times Q_{i}
\]  

(12)

The contribution received can be positive or negative; a positive value means that the corresponding input variable is positively correlated with the output, and a negative value is negatively correlated. The absolute contribution refers to the magnitude of the impact and can be compared with the contribution of other input variables. Relative importance is the proportion of the contribution of each influencing factor in relation to the total contribution:

\[
I_{i} = \frac{|C_{i}|}{\sum_{i} |C_{i}|} \times 100\%
\]  

(13)

The number of hidden layers and nodes was chosen for maximum accuracy of both training and test datasets, and network performance with varying numbers of hidden layers and nodes was chosen through trial and error on a simple dataset over 3 weeks. It has been found that the optimal structure of the feedforward network with the backpropagation algorithm (with RMSE=0.01) has the number of hidden layers equal to 2, and the number of nodes is 25, the learning rate \(\alpha=0.001\) and the momentum \(\beta=0.1\) by default.

### 3 Results and Discussion

Figure 2 shows the results of forecasting changes in oil demand. As can be seen, historical data on passenger mobility and data on confirmed diseases were provided until November 2020.
Figure 2. Comparison of forecasts for 2020-2021 of oil demand based on Google and Apple mobility data.

As can be seen from the chart, the introduction of strict bans on movement led to a sharp drop in demand for hydrocarbon fuel and, accordingly, the gradual easing of quarantine restrictions led to a gradual recovery of demand to its previous level. Based on these forecasts, moderate mobility of the population will lead to an equalization of demand for fuel, and, consequently, there will be no oversupply of oil in storage facilities, which will not lead to sharp jumps in oil prices. However, as can be seen from the chart, the demand for oil will not increase in the near future, but rather will gradually decline due to the extension of restrictions on travel and flights due to subsequent waves of morbidity. In addition, based on the experience in March-May 2020, strict bans are fraught with economic, political, and social crises, as well as their consequences and a long recovery period [26].

As the reopening of borders has been consistently implemented, US oil demand has gradually recovered from a minimum (-43 mln bbl/day) from March-April to June 2020 and increased by 56%. The situation in Russia was somewhat better despite the introduction of restrictions that reduced demand mainly due to domestic passenger traffic and air travel between cities in the country and a decrease in the export of oil products. As one can see, the dynamics of the forecast are similar to the dynamics of the US forecast. A completely different situation is observed in India, where there are no practical changes in oil demand, which is associated with an increase in demand for freight transport and a loose regime for road travel. According to the results in [27], about 1 million cases of COVID-19 infection were recorded in India by May 18, 2020. The application of restrictions has led to negative impacts on the economy and people's lives. Thus, in March-April 2020, energy consumption, including hydrocarbon fuels, in India fell sharply, and only the easing of restrictions led to a gradual
recovery mainly in the rich regions of the country, while the poorest East and North-East regions required more time and investment to recover [28].

The predicted oil demand according to the proposed model is in good agreement with the data provided by the International Energy Agency (IEA) [7] and is shown in Figure 3.

![Figure 3. Change in monthly oil demand in selected countries, 2020 compared to 2019. Source: authors' elaboration based on Google mobility data for private and public road transport [6].](image)

Comparison of the data in Figures 2 and 3 indicates that the proposed forecasting model is in good agreement with historical data, and in addition, the forecast for 2021 also maintains a smooth dynamics of the recovery in fuel demand to the level of 2019. However, as noted above, the demand for oil will gradually decrease, and as practice has shown, sharp drops lead to a sharp drop in economic indicators, including a country's GDP and the level of a population's well-being. The only positive aspect of the pandemic crisis concerns the ecological state of the countries, but this is only a temporary phenomenon that needs to be studied. Thus, the increase in waste and pollution of soil and water with waste from packaging and personal protective equipment has led to a new problem that can be solved by developing a recycling industry [29].

Besides, based on the data in Figure 2, the mobility trends from Google and Apple (used as inputs for comparing projected fuel demand) are slightly different. The cost variances between projected hydrocarbon fuel demand based on mobility trends show that the fuel demand projection based on Apple's mobility data is about 8% higher than that based on Google's mobility data. Google's and Apple's mobility trends are assessed using different methodologies: Google uses location and visit duration data [25], while Apple uses route map requests [24]. Both methods of collecting information have a relatively limited impact on the projected demand for hydrocarbon fuels. However, Apple's data only propose general mobility changes without travel purpose and categorization, so a big mistake can be made while making the forecast. Thus, Google data were considered to make further predictions and scenarios.

In addition, the ANN model results of this study indicate relatively good forecast efficiency. Calculations have shown that to achieve the values RMSE≈0.01 and CORR≈0.99, it is necessary to carry out 500 iterations (m=500). This means that forecasting oil demand using the ANN model is a suitable method even with irregular influencing factors such as fluctuations in data values.

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Figure 3 shows that as a result of the introduction of global mobility restrictions, the world oil demand fell by 57%. This is due to restrictions on road and air travel. Figure 4 shows the results of predicting the mobility of road transport using the ANN model.

![Figure 4](image)

**Figure 4.** Comparison of historical data and forecasts of road transport mobility in 2020-2021.

Historical data show that strict restrictions on road transport led to a sharp drop in passenger mobility. The largest minimum was observed in India in the period April-May 2020, which reached a value of more than -100% with the introduction of a lockdown. As one can see, further easing of the restrictions did not lead to a sharp recovery in the dynamics of demand, and according to the forecasts of the ANN model, a smooth increase in mobility will be observed until June 2021. In Russia and the United States, the imposition of travel bans also led to a sharp drop in mobility by 50-75%, while by the end of May 2020, average road transport activity recovered to its previous level; the sharp increase in summer 2020 was associated with the easing of movement restrictions that were introduced only in certain states (regions) where COVID-19 incidence was high. According to forecasts, the mobility of road transport is highly dependent on the level of morbidity and the imposition of restrictions in quarantine zones. As one can see, the decline in mobility occurs in January-February 2021, which is associated with the next wave of morbidity and the danger of COVID-19 spread, as it was in 2020 [30]. Mobility peaks are also observed in the summer due to a decline in the incidence.
Figure 5. Comparison of historical data and forecasts of air transport mobility in 2020-2021.

Figure 5 shows forecasts of air transport mobility. As one can see, in March 2020, air transport mobility in India fell by 80%, and in the USA and Russia - by 50-56%. Aviation mobility in the United States and Russia recovered slightly at the end of April, and then gradually increased to its previous level in June 2020, as isolation measures were slightly eased. However, as bans spread in India, air transport mobility dropped a staggering 60% by the end of the second quarter of 2020. As in the case of road transport, the morbidity and the introduction of restrictions and bans can reduce the mobility of air transport, and according to forecasts (Figure 5), in the United States and Russia, this will fall on March-April 2021. A sharp decline and gradual growth in India may differ from the real figures. Since the data provided in [26] may contain some deviations or inaccuracies, which affects the forecast, which demonstrates the constant growth of air transport mobility in India.

Based on the above results, it follows that the damage done by COVID-19 to oil demand became more evident in March, as the outbreak moved to Europe and the United States, and an increasing number of countries introduced strict measures. Oil demand in March decreased by more than 10 million barrels per day compared to March 2019 [31], as a result of which demand in the United States in the first quarter of 2020 decreased by 2.3 million barrels per day compared to March 2019. Due to the drop in global aviation mobility, aviation fuel demand dropped significantly compared to 2019 [32]. According to estimates in [33], the combined supply of aviation fuel fell by 2.1 million barrels per day in March 2020, which was 27% of the 2019 level. According to the results of this work, the recovery in the level of demand for hydrocarbon fuels will be gradual and will reach the level of 2019 only by mid-2021 in the event of moderate bans and COVID-19 incidence. In addition, this approach can help in the implementation of strategic decisions for the development of the
economies of countries, for example, in the formation of a new technological direction of scientific and technical development and management of these processes by a state [34].

Results of [35] confirm that the crude oil returns and the epidemic can have a significantly negative and positive effect, respectively. Thus, contrary to basic economic theory, the COVID-19 pandemic cannot negatively influence the stock returns [36]. This result may be explained by the fact that the COVID-19 pandemic leads to a higher risk premium and the investor may need more returns to compensate for the extra risk caused by the COVID-19 pandemic [35].

COVID-19 pandemic forecasts show that the introduction of bans and restrictions on passenger mobility helps to reduce the incidence of COVID-19 by 90% compared to the baseline [37]. However, the pandemic can last for several years, and according to the assumptions [38], after the peak in COVID-19 incidence, the quarantine restrictions should be extended until 2024 to prevent the resumption of the virus spread. Thus, any changes caused by the COVID-19 pandemic will have significant global implications in terms of energy and economic crises. Effective assessment of the impact of the pandemic and accurate predictions can help prepare for unknown risks. In particular, reliable forecasting of demand for hydrocarbon fuel (oil, gas), the most important indicator of the Russian economy, can favorably affect the dynamics of investment decisions and business activity.

4 Conclusions

The research was carried out on the dynamics of demand for hydrocarbon fuel after the start of the COVID-19 pandemic to develop a model for forecasting it in the near future. The proposed model based on the artificial neural network method demonstrates good performance with a feedforward structure and backpropagation learning with training in 500 iterations. The results of forecast analysis using Google and Apple mobility data showed that Google mobility data are selected in terms of time and purpose of movement and are more accurate for making predictions. An analysis of the forecast of road and air transport mobility until the first half of 2021 showed that the decline and increase in the level of mobility strongly depend on restrictions and bans on movement associated with COVID-19 cases. It has been established that a gradual recovery in demand for hydrocarbon fuels to the level of 2019 can be achieved by mid-2021 with moderate restrictions on movement and moderate dynamics of COVID-19 incidence.

The novelty of this work lies in the analysis of COVID-19 impact on passenger mobility and the transport sector, with an emphasis on the demand for hydrocarbon fuels. The research results and the proposed model can be used in the policy of adjusting pricing and demand in times of crisis due to the pandemic and other unforeseen situations. The findings will help policymakers and researchers understand the magnitude of COVID-19 impact on the transport sector and the regulation of the global oil and gas market.

Supporting Information

Not applicable.

Acknowledgment

Not applicable

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Symbols used

ANN - artificial neural network
b - bias;
DMI - dynamic mobility index
FDE - fuel demand estimation
Fy - the activation functions of the hidden node
Fz - the activation functions of the output node
GDP - Gross domestic product
h - index that refer to the hidden node
I - index that refer to the input node
m - iteration number
nh - number of hidden nodes;
ni - number of input nodes
Ntr - the total amount of training data.
Nts - the amount of data at the testing stage
o – index that refer to the output node
T - mean of the targets
tn - target value of n-th training data
w – weight;
x - input node value
z - mean estimates
z - output node value
zbase, Xbase - baseline value in the absence of an event for the relevant factor
zn - estimated value of n-th training data
α - learning rate used to protect the error function from falling into local minima
β - momentum - used to reduce fluctuations in the weights during training
References

[1] C. Sohrabi, Z. Alsafi, N. O’Neill, M. Khan, A. Kerwan, A. Al-Jabir, C. Iosifidis, R. Agha, Int. J. Surg. 2020, 76, 71-76. https://doi.org/10.1016/j.ijsu.2020.02.034

[2] D. Loske, Transport. Res. Interdiscip. Perspect. 2020, 6, 100165. https://doi.org/10.1016/j.trip.2020.100165

[3] P. Suau-Sanchez, A. Voltes-Dorta, N. Cugueró-Escofet, J. Transp. Geogr. 2020, 86, 102749. https://dx.doi.org/10.1016%5Fj.jtrangeo.2020.102749

[4] A. Sharif, C. Aloui, L. Yarovaya, Int. Rev. Fin. Analys. 2020, 70, 101496. https://doi.org/10.1016/j.irfa.2020.101496

[5] Bureau of Economic Analysis of the US Department of Commerce, https://www.bea.gov/ (Accessed on March 12, 2021).

[6] S. N. Bobylev, Population Econ. 2020, 4, 43. https://doi.org/10.3897/popecon.4.e53279

[7] IEA, https://www.iea.org/reports/global-energy-review-2020/oil#abstract, 2020 (Accessed March 12, 2021).

[8] P. K. Narayan, Energy Res. Lett. 2020, 1 (1), 13176. https://doi.org/10.46557/001c.13176

[9] F. Taghizadeh-Hesary, N. Yoshino, E. Rasoulinezhad, J. Comparat. Asian Dev. 2017, 16 (2), 113-134. https://doi.org/10.1080/15339114.2017.1298457

[10] N. Doytch, Y.L. Klein, Environ. Progress Sustain. Energy 2018, 37 (1), 37-45. https://doi.org/10.1002/ep.12640

[11] H. I. Kuo, C. C. Chen, W. C. Tseng, L. F. Ju, B. W. Huang, Tourism Manag. 2008, 29 (5), 917-928. https://dx.doi.org/10.1016%5Fj.tourman.2007.10.006

[12] A. Burns, D. Van der Mensbrugghe, H. Timmer, Evaluating the economic consequences of avian influenza, World Bank, Washington 2006.

[13] B. Wu, L. Wang, S. Wang, Y.R. Zeng, Energy 2021, 226, 120403.

[14] N. Norouzi, G. Z. de Rubens, S. Choubanpishehzafar, P. Enevoldsen, Energy Res. Soc. Sci. 2020, 68, 101654. https://dx.doi.org/10.1016%5Fj.erss.2020.101654

[15] F. Kamalov, Neur. Comp. Applic. 2020, 32 (23), 17655-17667. https://arxiv.org/ct?url=https%3A%2F%2Fdx.doi.org%2F10.1007%2Fs00521-020-04942-3&v=196da2a3

[16] M. Benyoucef, F. Bounaama, D. Belkacem, Int. Rev. Model. Sim. 2016, 9 (1), 37-43. https://doi.org/10.15866/iremos.v9i1.7662

[17] J. Kumaran, G. Ravi, Int. Rev. Model. Sim. 2014, 7 (3), 489-496. https://doi.org/10.15866/iremos.v7i3.1618

[18] F. Yang, H. Cho, H. Zhang, J. Zhang, Y. Wu, Energy Conv. Manag. 2018, 164, 15-26.

[19] K. Y. Lee, N. Chung, S. Hwang, Ecol. Inform. 2016, 36, 172-180.

[20] S. P. Siregar, A. Wanto, Int. J. Inform. Syst. Technol. 2017, 1 (1), 34-42. http://dx.doi.org/10.30645/ljistech.v1i1.4

[21] Covid Confirmed USAFacts. https://usafactsstatic.blob.core.windows.net/public/data/covid-19/covid_confirmed_usafacts.csv (Accessed on March 12, 2021).
[22] Ministry of Health of Russia, https://covid19.rosminzdrav.ru, 2021 (Accessed on March 12, 2021).

[23] World Health Data Platform, China, https://www.who.int/data/gho/data/countries/country-details/GHO/china?countryProfileId=adf73789-9c42-4bc5-a39b-b4d7ba337beb, 2021 (Accessed on March 12, 2021).

[24] Apple, https://covid19.apple.com/mobility, 2021 (Accessed on March 12, 2021).

[25] Google, https://www.google.com/covid19/mobility/, 2021 (Accessed on March 12, 2021).

[26] A. Khurshid, K. Khan, Environ. Sci. Pollut. Res. 2021, 28 (3), 2948-2958. https://doi.org/10.1007/s11356-020-09734-9

[27] A. Ghosh, S. Nundy, T. K. Mallick, Sens. Int. 2020, 1, 100021. http://dx.doi.org/10.1016/j.sintl.2020.100021

[28] K. Aruga, M. Islam, A. Jannat, Sustainability 2020, 12(14), 5616. https://doi.org/10.3390/su12145616

[29] A. G. Koryakov, O. I. Zhemerikin, in Proceedings of the 33rd International Business Information Management Association Conference, Education Excellence and Innovation Management through Vision 2020, IBIMA 2019.

[30] A. Abu-Rayash, I. Dincer, Energy Res. Soc. Sci. 2020, 68, 101693. https://doi.org/10.1016/j.erss.2020.101693

[31] M. Gupta, A. Abdelmaksoud, M. Jafferany, T. Lotti, R. Sadoughifar, M. Goldust, Dermatol. Therapy 2020, 1, e13329. https://doi.org/10.1111/dth.13329

[32] M. Mhalla, J. Asian Sci. Res. 2020, 10(2), 96.

[33] P. Jiang, Y. Van Fan, J. J. Klemes, Appl. Energy 2021, 285, 116441. https://dx.doi.org/10.1016/j.apenergy.2021.116441

[34] A. G. Koryakov, M. V. Kulikov, O. I. Zhemerikin, in Proceedings of the 33rd International Business Information Management Association Conference, Education Excellence and Innovation Management through Vision 2020, IBIMA 2019.

[35] L. Liu, E. Z. Wang, C. C. Lee, Energy Res. Lett. 2020, 1 (1), 13154. https://doi.org/10.46557/001c.13154

[36] Y. Sun, M. Wu, X. Zeng, Z. Peng, Finance Res. Lett. 2021, 38, 101838. https://doi.org/10.1016/j.frl.2020.101838

[37] S. M. Kissler, C. Tedijanto, E. Goldstein, Y. H. Grad, M. Lipsitch, Sci. 2020, 368 (6493), 860-868. https://doi.org/10.1126/science.abb5793

[38] X. Wang, R. F. Pasco, Z. Du, M. Petty, S. J. Fox, A. P. Galvani, M. Pignone, S. C. Johnston, Emerg. Infect. Dis. 2020, 26 (10), 2361. https://dx.doi.org/10.3201/eid2610.201702

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Figure captions

**Figure 1.** Feedforward ANN structure with one hidden layer.

**Figure 2.** Comparison of forecasts for 2020-2021 of oil demand based on Google and Apple mobility data.

**Figure 3.** Change in monthly oil demand in selected countries, 2020 compared to 2019 [6].

**Figure 4.** Comparison of historical data and forecasts of road transport mobility in 2020-2021.

**Figure 5.** Comparison of historical data and forecasts of air transport mobility in 2020-2021.
Entry for the Table of Contents

Research paper: The aim of this work is to develop a model that combines passenger mobility with demand for hydrocarbon fuels, using a neural network method to correlate passenger mobility with the COVID-19 pandemic. This study examines the impact of COVID-19 on average monthly fuel demand as the pandemic evolves.

Demand dynamics for hydrocarbon fuels during the COVID-19 pandemic
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