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# Oil Demand Forecasting in Importing and Exporting Countries: AI-Based Analysis of Endogenous and Exogenous Factors

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**Abstract:** Given the prevalence of the digital world, artificial intelligence (AI) stands out as one of the most prominent technologies for demand prediction. Although numerous studies have explored energy demand forecasting using machine learning models, previous research has been limited to incorporating either a country's macroeconomic characteristics or exogenous elements as input variables. The simultaneous consideration of both endogenous and exogenous economic elements in demand forecasting has been disregarded. Furthermore, the stability of machine learning models for energy exporters and importers facing varying uncertainties has not been adequately examined. Therefore, this study aims to address these gaps by investigating these issues comprehensively. To accomplish this objective, data from 30 countries spanning the period from 2000 to 2020 was selected. In predicting oil demand, endogenous economic variables, such as carbon emissions, income level, energy price, gross domestic product (GDP), population growth, urbanization, trade liberalization, inflation, foreign direct investment (FDI), and financial development, were considered alongside exogenous factors, including energy sanctions and the COVID-19 pandemic. The findings indicate that among the input variables examined in demand forecasting, oil sanctions and the COVID-19 pandemic have had the most significant impact on reducing oil demand, while trade liberalization has proven to be the most influential factor in increasing oil demand. Furthermore, the support vector regression (SVR) model outperforms other models in terms of lower prediction error, as revealed by the error assessment of statistical models and AI in forecasting oil demand. Additionally, when comparing the stability of models in oil exporting and importing countries facing different levels of demand uncertainty, the SVR model demonstrates higher stability compared to other models.

**Keywords:** energy demand forecast; energy sanction; COVID-19 pandemic; artificial intelligence (AI)

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**Citation:** Zhu, H. Oil Demand Forecasting in Importing and Exporting Countries: AI-Based Analysis of Endogenous and Exogenous Factors. *Sustainability* **2023**, *15*, 13592. https://doi.org/10.3390/su151813592

Academic Editors: Seung-Hoon Yoo, Gerhard-Wilhelm Weber, Erfan Babaee Tirkolaee, Alireza Goli and Sadia Samar Ali

Received: 10 August 2023
Revised: 29 August 2023
Accepted: 31 August 2023
Published: 12 September 2023



## 1. Introduction

Oil demand forecasting plays a pivotal role in energy planning and decision-making for oil-importing and exporting countries alike. The ability to accurately and reliably predict future oil demand enables governments, energy companies, and other stakeholders to make well-informed decisions regarding production, consumption, pricing, and investment strategies [1]. Nevertheless, traditional forecasting methods commonly rely on linear models and historical data, which may not fully capture the intricate dynamics and interplay of endogenous and exogenous factors that impact oil demand [2].

The increasing volatility and uncertainty in global oil markets, along with the growing complexity of socio-economic and environmental factors, necessitate the adoption of more sophisticated and robust forecasting techniques. Artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools capable of analyzing vast and diverse datasets, identifying intricate patterns, and making accurate predictions. Leveraging AI-based analysis offers the potential to enhance the precision and reliability of oil demand forecasts, thereby facilitating more effective energy planning and decision-making. However, despite the advancements in AI and ML techniques, there remains a limited body of research specifically focusing on the AI-based analysis of endogenous and exogenous factors for oil demand forecasting in both importing and exporting countries [2]. Existing studies often concentrate on either importers or exporters individually, neglecting a comprehensive analysis of factors influencing oil demand in both types of countries. Furthermore, the integration of endogenous factors (such as economic indicators and energy policies) and exogenous factors (including geopolitical events and technological advancements) in AI-based forecasting models remains relatively unexplored. This study aims to address these gaps by conducting an in-depth analysis of oil demand forecasting in both importing and exporting countries using AI-based techniques. This study seeks to identify and incorporate a comprehensive set of endogenous and exogenous factors that influence oil demand patterns, drawing insights from the works of Swaminathan et al. [3], Moroff et al. [4], and Feizabadi et al. [5]. By developing and validating AI models that integrate these factors, this research aims to improve the accuracy, reliability, and robustness of oil demand forecasts. The findings of this study will provide valuable insights for policymakers, energy companies, and market participants, empowering them to make more informed decisions and devise proactive strategies in the evolving landscape of global oil markets [6]. Supply networks encompass suppliers, manufacturers, distributors, and customers, with customer demand being a significant disruption in the supply chain due to its stochastic nature. Accurate determination of demands in advance allows for better planning of production, raw material supply, and inventory management [1]. Companies currently operate in an unpredictable environment characterized by globalization, emerging markets, financial crises, pandemics, climate change, and supply constraints, posing challenges in forecasting future operations. These crises often result in demand shocks, making it challenging for companies to meet demand promptly while avoiding inventory increases due to decreased demand for specific products. The imbalance between supply and demand can cause severe disruptions in the supply chain. In such circumstances, the development of a demand forecasting model becomes crucial for enhancing efficiency and improving performance for manufacturers, distributors, and retailers [2]. Notably, Abbasimehr, Shabani, and Yousefi conducted a study proposing an optimized model that utilizes a Long Short-Term Memory (LSTM) network for demand forecasting in the Computers and Industrial Engineering field [7].

Demand forecasting serves as the foundation for all supply chain planning operations. Improving the accuracy of energy demand prediction can enhance the effectiveness of supply chain management by reducing inventory reserves [8]. The literature encompasses three different perspectives on energy demand prediction: short-term, medium-term, and long-term. Furthermore, there are model-driven and data-driven approaches to forecasting, and models can be static or dynamic, mathematical or experimental, univariate or multivariate, among other variations [9]. In data-driven methods, the relationship between energy demand and its causal variables is examined using statistical techniques, while model-oriented approaches determine and utilize this relationship [10]. Data-driven methods for energy demand forecasting can be categorized into two groups: autoregressive methods that rely solely on historical data for forecasting and causal methods that consider exogenous variables that can impact energy demand, such as temperature, economic conditions, and other relevant factors. Various data-based forecasting methods have been presented, including artificial neural networks [11], fuzzy logic [12], time series analysis [13], regression models [14], support vector machines [15], and genetic algorithms [16]. Demand forecasting is often approached as a time series problem, with researchers utilizing time series statistical methods such as autoregressive moving average (ARMA) models, Autoregressive Conditional Heteroscedastic (ARCH) models, and General Autoregressive Conditional Heteroscedastic (GARCH) models. Intelligent models such as artificial neural networks (ANN), support vector machines (SVM), K-nearest neighbors (KNN), and the Adaptive Neuro-Fuzzy Inference System (ANFIS) have also been employed for time series forecasting [7].

Artificial intelligence (AI) refers to the ability of computers to imitate human skills and communicate effectively [17]. It is a powerful technology that can be leveraged for demand forecasting, offering improved speed and accuracy in analysis [18]. With advancements in computer development, AI methods have rapidly evolved and demonstrated excellent results in prediction tasks due to their ability to perform nonlinear fitting and self-learning [19]. Machine learning (ML) is a subfield of AI that utilizes programmed algorithms to analyze input data and learn from it through supervised or unsupervised processes, enabling the prediction of output values within an acceptable range [20]. Several ML algorithms are commonly employed for demand forecasting, including Multilayer Perceptron (MLP), Radial Basis Functions (RBF), Bayesian Neural Network (BNN), Recurrent Neural Network (RNN), Support Vector Regression (SVR), Nearest Neighbor (NN) regression, and Long Short-Term Memory Neural Network (LSTM) [21].

Despite numerous studies in the field of energy demand forecasting utilizing ML models, previous research often limited the input elements for demand forecasting to macroeconomic characteristics or exogenous factors while neglecting the simultaneous role of endogenous and exogenous economic elements. Moreover, these studies did not investigate the stability of machine learning models in energy exporting and importing countries facing different uncertainties. Therefore, the objective of the present study is to bridge these existing gaps by considering a more comprehensive set of factors and examining the stability of machine learning models in both energy exporting and importing countries.

Oil sanctions can have a significant impact on the energy demand and overall economy of a country. Iran, for example, has faced multiple economic and non-economic sanctions due to international violations. With its abundant oil and gas resources, Iran heavily relies on oil revenue, which contributes to a substantial portion of its Gross Domestic Product (GDP), exports, and government funding. The sanctioning countries specifically targeted Iran's oil industry. As the world's third-largest oil-producing nation and the second-largest gas-producing nation, Iran plays a crucial role in the global energy market. Therefore, the effects of oil sanctions on Iran are of great importance considering the significance of Iran's oil industry and its impact on the country's economy [22].

In addition to sanctions, the COVID-19 pandemic has also had a notable impact on energy demand as an exogenous element. Various studies have demonstrated that the pandemic, which resulted in a significant increase in global fatalities, led to a decrease in oil demand and an increase in uncertainty surrounding oil supply and demand. Available data indicates that global oil demand in 2020 decreased by 9.3 million barrels per day compared to 2019. Researchers such as Ou et al. have shown that the pandemic resulted in reduced demand for motor fuel [23]. Wang and Zhang's research indicated that high-income nations experienced the most significant increase in energy consumption due to China's post-COVID-19 economic recovery, followed by middle-income countries [24]. However, the spillover effect of China's economic growth did not necessarily lead to increased energy consumption in lower and middle-income countries. Zhang et al. conducted a study in Sweden and found that the COVID-19 pandemic led to an increase in uncertainty regarding energy [25].

Indeed, studies have been conducted to examine the effects of exogenous variables such as the COVID-19 pandemic and oil sanctions on energy consumption and the economy. Ou et al. analyzed the impact of the COVID-19 pandemic on gasoline demand in the United States using a machine learning model. Their findings revealed a decrease in gasoline demand and lower prices in 2020 as a result of the pandemic [23]. Wang and Zhang investigated the influence of China's post-COVID-19 economic development on energy consumption and economic growth in other countries. Their research indicated that the recovery of China's economy can affect energy consumption in both high- and middle-income countries [24]. Zhang et al. examined residential structures in a specific region of Sweden and found that the COVID-19 pandemic had diverse impacts on energy consumption, leading to an increased need for electricity while reducing the demand for heating and cooling energy [25]. Regarding the effects of oil sanctions, Nakhli et al. conducted a study on the economic impact of oil sanctions on Iran. Their research highlighted that sanctions on oil exports, extraction technology, and foreign financing significantly affected Iran's economy [22]. The consequences of these sanctions included a decrease in oil demand and production, a decline in oil exports, reduced government budget financing, increased inflation, higher consumption costs, and a decrease in investment expenses.

These studies provide insights into the effects of exogenous variables, such as the COVID-19 pandemic and oil sanctions, on energy consumption and the associated economic implications. By considering these factors in demand forecasting models, energy planners and policymakers can better understand and address the uncertainties and challenges in the energy sector. Based on the presented materials, oil demand forecasting is based on machine learning models, considering exogenous elements, such as oil sanctions and pandemics, along with endogenous elements, including macroeconomic characteristics, in oil importing and exporting countries. The results indicate that, of the input variables considered in demand forecasting, the oil sanctions and the COVID-19 pandemic have had the greatest impact on reducing oil demand, while trade liberalization has had the greatest effect on increasing oil demand. Moreover, the SVR model performs better than other models because it has a lower prediction error, based on the findings of the error assessment of statistical models and AI to forecast oil demand. The comparison among the stability of models in oil exporting and importing countries that experience different levels of demand uncertainty shows the higher stability of the SVR model than other models. It opens with a general discussion of the variables' introduction and their relationship based on available theories. This section is followed by the methodology and the analysis of empirical findings. Finally, the paper outlines the conclusions.

The objective of this study is to compare the performance of statistical methods, specifically time-series analysis, and artificial intelligence (AI) methods in forecasting oil demand. We acknowledge the importance of clearly stating this objective to provide a comprehensive analysis of different forecasting techniques.

## 2. Literature Review

Machine learning models have indeed shown superior performance compared to traditional statistical models such as regression and time series analysis in predicting energy demand, making them increasingly popular in energy demand forecasting research. Researchers have utilized various machine learning algorithms to achieve high prediction accuracy and robustness. For example, Duan et al. proposed a prediction model called KELM-GMCC by optimizing the kernel extreme learning machine using the Generalized Maximum Correntropy Criterion. They demonstrated that their model outperformed existing models such as Back Propagation (BP), Support Vector Regression (SVR), and Extreme Learning Machine (ELM) in terms of prediction accuracy [19]. Maltais and Gosselin optimized machine learning models using model predictive control (MPC) and highlighted their high accuracy. They emphasized the effectiveness of these models in energy demand forecasting [26]. Zhang and Liang applied the Bayesian neural network model to predict the demand for refined oil products such as gasoline and diesel [27]. They showcased the capabilities of this model for accurately forecasting demand. In a case study by Nia et al. that reviewed articles in the field of energy demand forecasting, smart forecasting methods were found to reduce errors and costs, leading to increased profitability [9]. Abbasimehr et al. utilized a multi-layer Long Short-Term Memory (LSTM) forecasting method to predict demand in the furniture industry. They demonstrated that their proposed model outperformed a one-layer LSTM model and other smart models in terms of efficiency [7]. Huang et al. employed a combination of cointegration analysis and AI models to anticipate energy demand in China [28]. They showed that integrating econometric models with AI models improved the accuracy of the forecasts. Al-Fatah and Aramco aplied a hybrid approach of artificial intelligence techniques, including genetic algorithms, neural networks, and data mining (GANNATS), to predict oil demand in Saudi Arabia and China [29]. Brentun et al. suggested using support vector regression as one of the machine learning options for short-term water demand forecasting in Brazil. These studies highlight the effectiveness and advantages of machine learning models, such as optimized kernel extreme learning machines, Bayesian neural networks, multi-layer LSTM models, and support vector regression, in energy demand forecasting across different industries and regions [30].

Twumasi, and Twumasipredicted blood demand in a public hospital in Ghana using machine learning models and demonstrated that these models can be a suitable alternative to time series models for demand forecasting [21]. Kochak and Sharma employed a neural network model to predict demand in a retail supply chain from 2011 to 2013 [31]. Feizabadi et al. used a machine learning model to estimate demand in the Malaysian steel sector and then studied the influence of this projection on performance [5]. Ou et al. discovered a statistically significant difference in enhancing supply chain performance using conventional and machine learning-based demand forecasting approaches [23]. Moroff et al. compared the forecasting accuracy of statistical models and artificial intelligence in demand forecasting. They showed that in general, it is not possible to prove the superiority of one model over another with certainty, and the accuracy of forecasts depends on the type of demand and its structure [4]. Lashgari, et al. presented a demand forecasting model based on a meta-heuristic algorithm that was used to forecast transportation energy demand in Taiwan [32]. Huang et al. used the Recurrent Neural Network (RNN) model to forecast oil demand in China during the period of tourism growth in this country [33].

Fatima et al. employed a structural time series model and data from 1980 to 2015 to forecast oil demand in China [34]. They demonstrated that GDP, oil prices, and crude oil reserves all play a role in oil demand. Romero-Gelvez et al. used time series models, Support Vector Machines (SVM), and meta-heuristic algorithms to forecast demand in the oil business [35]. Anik and Rahman used Seemingly Unrelated Regression Estimation (SURE) and Ordinary Least Square Regression (OLS) to anticipate energy consumption in three sectors in Bangladesh: oil, natural gas, and coal [36]. They showed that as Bangladesh's economy grows, energy demand will continue to grow. It is expected that natural gas, which is the main source of energy in Bangladesh, will run out within the next two decades, and this will expose the country to external shocks and fluctuations in international energy markets [36]. Sánchez-Durán et al. predicted energy demand in Spain using econometric techniques, which showed that the growth of energy demand in this country is insignificant and will stabilized in the coming decades [37]. Rehman et al. used an autoregressive integrated moving average model (ARIMA) to forecast long-term energy demand in Pakistan [38]. Rehman et al. demonstrated that the industry sector has the highest energy demand, followed by the transportation and domestic sectors [38]. They also showed that oil is the most commonly used energy source, followed by natural gas. For forecasting the correlation between water and electrical energy consumption, Alhendi et al. underlined the significance of AI-based models [39]. Boamah et al. predicted energy demand in Ghana using linear regression, exponential, and exponential smoothing models and showed that energy demand would have an increasing trend [40]. Al-Musaylh et al. used three models, MARS, ARIMA, and SVR, to forecast electricity demand in Australia and proved the superiority of the MARS and SVR models in short-term demand forecasting [41]. Perea et al. (2018) used AI techniques to predict water demand and showed the predictability of these models compared to other models [42]. von Graevenitz, K., & Rottner analyzed Germany's energy usage trends between 2003 and 2017. Despite higher energy prices for the industrial sector during this period, they found that the economic crisis only had a temporary effect on reducing energy usage. Moreover, between 2003 and 2017, the level of pollution brought on by energy usage has been declining [43]. In examining the factors affecting energy consumption, Ma and Yang found that the financial pressure created by the reform of educational authority significantly increased the intensity of carbon emissions. It shows that governments will check carbon emissions in other ways if they feel financial pressure. Second, to reduce the fiscal pressure, local governments check energy-intensive enterprises and use their high production value and ability to collect taxes to increase production capacity and earn more tax revenues, which leads to high carbon emissions [44]. Kalimoldayev et al. conducted research on contemporary mathematical techniques for analyzing power consumption. They assessed the key benefits and drawbacks of the available modeling techniques and applied them to the energy systems of Kazakhstan and Ukraine. Furthermore, they identified the main factors affecting the dynamics of energy consumption and prepared a list of the main tasks that should be implemented to develop algorithms to forecast electricity demand for objects, industries, and different levels [45].

The goal of the passage is to highlight the importance of demand forecasting in supply chain management, particularly in the context of energy demand prediction. The passage discusses the challenges that companies face in forecasting demand due to the unpredictable nature of the environment they operate in and how inaccurate forecasting can lead to significant disruptions in the supply chain. The passage also highlights the different methods and approaches used in demand forecasting, including data-driven and model-oriented methods as well as statistical and intelligent models such as artificial neural networks and support vector machines. Finally, the passage emphasizes the potential of artificial intelligence and machine learning in improving the accuracy and speed of demand forecasting while also acknowledging the need for more comprehensive input elements in demand forecasting and the need to assess the stability of machine learning models in different contexts.

## 3. Research Methodology

Oil demand forecasting is discussed based on the SVR model. The support vector machine (SVM) model was originally designed by Vapnik for binary object classification and then extended to predict quantitative and qualitative numerical values in the form of support vector regression (SVR) [46]. The model structure involves fitting a regression function (SVR) to produce a model for qualitative or quantitative predictions or inserting the training data into a preset feature space to search for a hyperplane that best separates positive and negative training samples (SVM). A unique feature of SVM is that it works well in feature spaces of increasing dimensions to search for hyperplanes that linearly separate positive and negative training data. If linear separation is not possible in a feature space, the data are mapped to a higher-dimensional space where linear separation may be possible [47]. The primary value data utilized in the study was gathered from the electronic source of the gas oil company between Iran and China.

The support vector regression model consists of training data as (1).

$$P = \{(a_1, b_1),\ (a_2,\ b_2),\ \ldots,\ (a_N,\ b_N)\}; \tag{1}$$

where $a_i$ is the vector of true independent variables and $b_i$ is the value of its corresponding dependent variable. Hence, the regression equation is defined in the feature space based on (2).

$$z(a, \boldsymbol{w}) = (\boldsymbol{w}.\phi(a) + c); \tag{2}$$

where $\boldsymbol{w}$ is the weight vector, c is a constant value, and $\phi(a)$ is the feature function, and the symbol (.) indicates the dot product. The optimal value is obtained when (3) is minimized.

$$Q(f) = C\frac{1}{N}L_\varepsilon(b,\ z(a,\ w)) + \frac{1}{2}\left||W^2|\right|; \tag{3}$$

where:

$$L_\varepsilon(b,\ z(a,\ w)) = \left\{ \begin{array}{l} 0\,if\ |b - z(a,w)| \le \varepsilon \\ |b - z(a,w)| - \varepsilon\ o.w \end{array} \right. ; \tag{4}$$

In (3), LHS represents the experimental error, and $C$ represents a measure of optimization between the experimental error and the complexity of the model provided by the second term of the mentioned equation. (4) defines a loss function called the error-insensitive loss function (ε). The proposed optimization problem becomes a dual problem by combining the lagrangian coefficient $\beta$ and $\beta^*$. Only non-zero coefficients, along with their input vectors, $a_i$, are considered support vectors. The final form is based on (5).

$$z(\boldsymbol{a},\ \beta_i,\ \beta_i^*) = \sum_{i=1}^{N} (\beta_i - \beta_i^*)(\phi(a_i).\phi(a_j)) + c; \tag{5}$$

If the kernel function is defined as $K(x_i,\ x_j)$, the SVR function can be defined as (6).

$$z(\boldsymbol{a},\ \beta_i,\ \beta_i^*) = \sum_{i=1}^{N} (\beta_i - \beta_i^*)(K(a,\ ai)) + c; \tag{6}$$

where, $c$ is calculated by applying the Karush-Kan-Toker condition [48].

The input variables for demand forecasting include carbon emissions [49], income level [50], energy price [51], GDP [52], Population growth [53], urbanization [54], trade liberalization [55], inflation [53], FDI [56], financial development [52], energy sanction [22], and pandemic [24]. The R software (version of 4.2) and the libraries, including caret, e1071, ggplot, ggpubr, cluster, and gclus, were used for data analysis and model fitting.

We will provide a clear and detailed description of the experimental setup, including the selection of countries, the time period considered, and the specific variables used as input for the models. Moreover, we will emphasize the importance of considering both endogenous and exogenous economic factors in oil demand forecasting. Additionally, we will elaborate on the evaluation metrics used to assess the performance of the support vector regression (SVR) model and other models, providing a comprehensive analysis of the results.

The statistical population of the research includes oil-exporting and oil-importing countries. Importing countries include Latin America (Argentina, Chile, and Brazil), America, emerging Asia (Korea, Malaysia, the Philippines, Singapore), China, India, Japan, Australia, New Zealand, Turkey, and South Africa. The oil exporting countries include those from the Persian Gulf (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, the United Arab Emirates, Iraq, and Iran), as well as Algeria, Canada, Indonesia, Mexico, Nigeria, England, and Norway. Economic information for these countries was analyzed using data extracted from World Bank databases for the years 2000 to 2020. These data are formed as panel data based on a country-year framework. In cases where the data were not available for a period of time, the mean replacement method was used to replace the missing data. To understand whether the SVM model performs better than the traditional time series models or not, the results of fitting the SVM model were compared with the results of fitting the ARIMA, GLM, and SVR models. To compare the accuracy of these models, the RMSEA, MAPE, MAE, and MSE criteria, which are the criteria of model prediction error, were used.

The identification of model accuracy in this study involves comparing the performance of the SVM model to the ARIMA, GLM, and SVR models by fitting them to the same oil demand forecasting data. The prediction error of each model is evaluated using metrics such as RMSE, MAPE, MAE, and MSE. The SVM model is considered to have higher accuracy if it produces lower values for these metrics compared to the other models. The dataset used in this study includes panel data on oil exporting and importing countries from 2000 to 2020, with missing data imputed. The R software is used, along with various libraries, to fit and compare the models. In summary, the accuracy of the SVM model is determined by comparing its prediction errors with those of other models using standard metrics such as RMSE and MAPE, and the SVM model is considered more accurate if it produces lower errors.

## 4. Results

In this section, the collected data are analyzed. The descriptive statistics of the studied variables are shown in Table 1.

**Table 1.** Descriptive statistics of the studied variables.

| Variable | Count | Min | Max | Mean | Stdev |
|---|---|---|---|---|---|
| **Exporter** | 651.000 | 0.000 | 1.000 | 0.516 | 0.500 |
| **INCOME** | 651.000 | −66.762 | 51.415 | 6.047 | 11.941 |
| **$CO_2$** | 651.000 | 0.097 | 1.656 | 0.548 | 0.314 |
| **OILCONSUME** | 651.000 | 3.429 | 5.582 | 4.429 | 0.710 |
| **Openess** | 651.000 | 9.899 | 218.663 | 38.866 | 30.625 |
| **FDI** | 651.000 | −5.367 | 24.378 | 2.538 | 3.085 |
| **GDPGR** | 651.000 | −33.101 | 54.158 | 3.966 | 4.413 |
| **INF** | 651.000 | −10.067 | 254.949 | 5.658 | 12.961 |
| **OilPrice** | 651.000 | 0.000 | 64.078 | 10.234 | 13.828 |
| **Urbanization** | 651.000 | −1.758 | 17.763 | 2.542 | 2.215 |
| **POPGR** | 651.000 | −1.786 | 17.511 | 1.890 | 2.186 |
| **COVID** | 651.000 | 0.000 | 1.000 | 0.286 | 0.452 |
| **Sanction** | 651.000 | 0.000 | 1.000 | 0.429 | 0.495 |
| **OILCONSUMVOL** | 651.000 | 0.000 | 3.860 | 0.226 | 0.699 |

Source: Iran national and China national company.

Surveys show that 51% of the examined sample includes oil exporting countries, and the rest are oil-importing countries. Iraq has the highest level of per capita income growth, while Argentina has the lowest. Singapore has the lowest carbon dioxide emissions, whereas China produces the most. Singapore also has the lowest oil demand, while China has the greatest.

In terms of carbon emissions, China has the highest and Singapore has the lowest. China has the highest oil demand, whereas Singapore has the lowest demand. The growth of GDP experienced in Iraq was the highest and lowest amount of growth, followed by Argentina at the lowest level and Qatar at the highest level. The lowest level of inflation is in Iraq, and the highest level is in Venezuela. The level of urbanization in Qatar has the highest growth, and Venezuela has the lowest growth. Based on the studied variables, China's economy has a high level of oil consumption in terms of production and export. Japan's economy is a closed one that does not have many interactions in terms of trade, and its business activity is more in the field of exports than imports. Venezuela's economy is weak, characterized by high inflation and low economic growth, with little development. In contrast, Singapore's economy is growing, with a high level of trade and development. Singapore has also been successful in reducing environmental pollution. Figure 1 shows changes in the average of variables in the studied sample.

Surveys show that the trend of the COVID-19 pandemic and oil sanctions continues. Carbon emissions have decreased in recent years; this can be caused by the increase in the use of renewable energy around the world. The growth of FDI faced many fluctuations that did not follow a specific trend. GDP growth and per capita income growth in 2009 faced a significant decrease, and in 2008, inflation reached its highest level. This demonstrates that macroeconomic indices were at their most negative during the financial crisis, which lasted from 2007 to 2009. Since 2015, there has been a sharp decline in oil consumption, which can be attributed to factors such as oil sanctions and the COVID-19 epidemic. This decline followed a period of significant swings in consumption. Due to the decrease in oil demand, the price of oil reached its lowest level in 2015 and 2016. Regarding the global financial crisis and the COVID-19 pandemic, urbanization and population growth decreased. Thus, trade liberalization faced many fluctuations, and in recent years it has faced a significant decrease, which can be caused by the increase in terrorist attacks, deaths in terms of the

COVID-19 pandemic, the price of the dollar, the restrictions of government laws, and the global sanction.

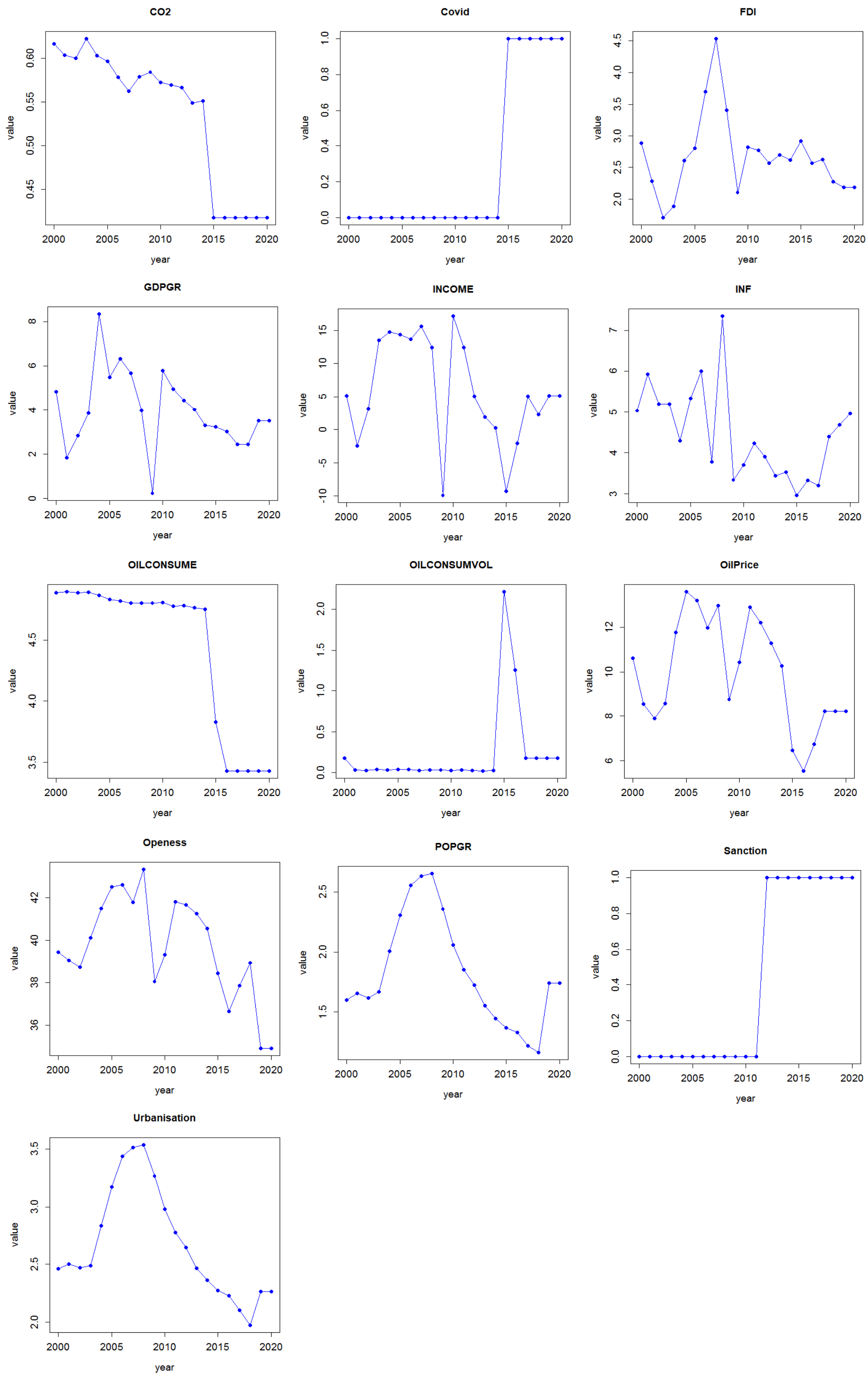


**Figure 1.** Changes in the average of the variables in the sample of the studied countries.

The correlation diagram among the variables is shown in Table 2 for a better understanding of the relationships among them.

**Table 2.** Correlation diagram between variables.

| | Exporter | INCOME | $CO_2$ | OILCONSUME | Openess | FDI | GDPGR | INF | OilPrice | Urbanisation | POPGR | COVID | Sanction |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Exporter** | 1 | −0.004 | 0.08 ** | 0.022 | −0.004 | 0.085 ** | −0.007 | 0.094 ** | 0.54 *** | 0.326 *** | −0.094 ** | 0 | 0 |
| **INCOME** | | 1 | 0.129 *** | 0.189 *** | −0.005 | 0.042 | 0.423 *** | 0.032 | 0.13 *** | 0.01 | −0.012 | −0.251 *** | −0.316 *** |
| **$CO_2$** | | | 1 | 0.516 *** | −0.002 | −0.117 *** | 0.198 *** | 0.054 | 0.289 *** | 0.293 *** | −0.139 *** | −0.262 *** | −0.214 *** |
| **OILCONSUME** | | | | 1 | 0.012 | 0.07 * | 0.163 *** | −0.067 * | 0.159 *** | 0.246 *** | 0.113 *** | −0.83 *** | −0.627 *** |
| **Openess** | | | | | 1 | −0.064 | 0.094 ** | −0.077 ** | 0.136 *** | 0.161 *** | −0.135 *** | −0.046 | −0.027 |
| **FDI** | | | | | | 1 | −0.029 | −0.048 | −0.017 | −0.028 | 0.069 * | −0.036 | −0.032 |
| **GDPGR** | | | | | | | 1 | −0.011 | 0.195 *** | 0.3 *** | −0.114 *** | −0.126 *** | −0.137 *** |
| **INF** | | | | | | | | 1 | 0.057 | −0.031 | 0.022 | 0.027 | 0.022 |
| **OilPrice** | | | | | | | | | 1 | 0.415 *** | 0.017 | −0.136 *** | −0.1 ** |
| **Urbanisation** | | | | | | | | | | 1 | −0.113 *** | −0.133 *** | −0.144 *** |
| **POPGR** | | | | | | | | | | | 1 | −0.112 *** | −0.127 *** |
| **COVID** | | | | | | | | | | | | 1 | 0.73 *** |
| **Sanction** | | | | | | | | | | | | | 1 |

"***": 99% CI, "**": 95% CI, "*": 90% CI. Source: Iran and China National oil company

According to the results of the correlation test shown in Table 1, the COVID-19 pandemic and the oil sanctions have the greatest impact on lowering demand for oil.

The reason for the decrease in oil demand as a result of the COVID-19 pandemic can be attributed to several factors. Firstly, travel restrictions have led to a decrease in the use of fuel by airplanes, and a slowdown in industrial activities has also contributed to the decrease in demand for oil. The second reason is the reaction of stock market to the corona virus, as the result the global economy reaction to oil is affected, which will reduce the global demand for oil.

Oil consumption is greater in nations with increasing carbon emissions, and vice versa. Increasing urbanization has a great effect on carbon emissions and oil prices. Urbanization growth has a direct relationship with economic growth. In oil-exporting countries, oil prices are higher.

In the following, the SVM model was used to forecast oil demand. The actual and predicted values of the oil demand based on the variables considered are shown in Figure 2.

The weight values obtained from model fitting are shown in Table 3.

The coefficients obtained from fitting the model listed in Table 2 show that in most cases, the increase in per capita income, FDI rate, inflation, oil price, oil sanctions, and COVID-19 pandemic led to a decrease in oil demand. There is a clear correlation between oil consumption and several factors, including GDP growth, trade liberalization, carbon emissions, urbanization, and population growth. Among these input factors, urbanization had the least influence on oil consumption. However, factors such as the COVID-19 pandemic, trade liberalization, oil sanctions, and carbon emissions had a significant effect on oil demand. To check the accuracy of the model and the importance of the inputs considered in this study, the results obtained from the SVR model with the results of the SVM model fitting without input variables and referring to previous values of the dependent variable, the generalized linear regression model, and the autoregressive moving average (ARMA) are compared. The results of model fitting and forecasting in the 30 countries studied are shown in Figure 3. For each country, the forecast was separately made, and an overview of the calculations is presented in Figure 3.

To accurately evaluate the prediction error of the model, four indicators, namely the mean absolute percentage error (MAPE), mean squared error (MSE), mean absolute error (MAE), and root mean square error (RMSE), were used to evaluate the prediction accuracy.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{y_i}, \tag{7}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2, \tag{8}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|, \tag{9}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}, \tag{10}$$

where $y_i$ is the actual value of ith sample and $\hat{y}_i$ is the predicted value of the i-th sample based on the desired model. The model with the lowest error values is more reliable [57]. The results of calculating the criteria for thirty sample countries based on the four studied models are shown in Table 4.

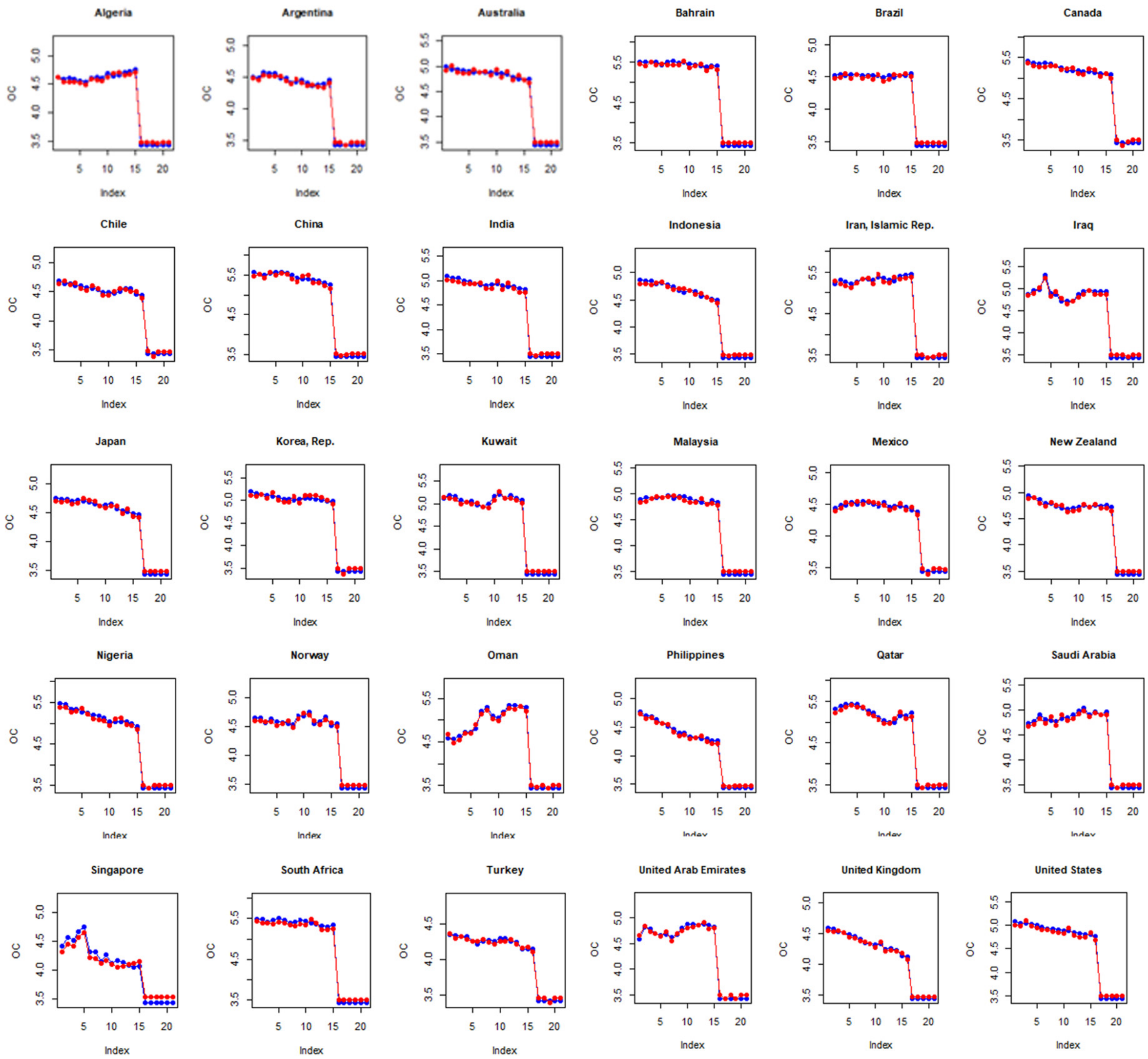


**Figure 2.** Actual (blue) and predicted (red) values of average oil consumption based on the SVM model.

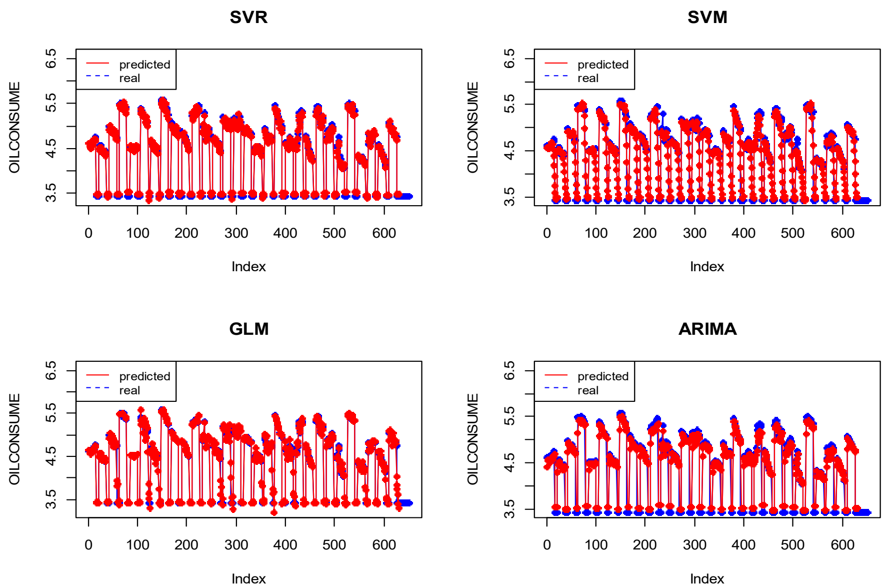


**Figure 3.** Actual and predicted values of average oil consumption based on statistical models and AI.

**Table 3.** Estimation of weight parameters in the SVR model.

| | INCOME | $CO_2$ | Openess | FDI | GDPGR | INF | OilPrice | Urbanisation | POPGR | COVID | Sanction |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Algeria** | 1.85 | 7.89 | 1.99 | 0.04 | 1.44 | 0.23 | 5.35 | 2.26 | −0.64 | −7.39 | −2.93 |
| **Argentina** | −2.05 | 6.05 | −0.46 | 1.84 | −0.95 | −3.94 | −1.40 | −3.22 | 0.51 | −12.20 | −4.96 |
| **Australia** | −1.08 | −5.82 | −3.63 | −8.68 | −3.76 | 0.73 | −4.88 | −8.01 | 0.37 | −8.33 | −4.37 |
| **Bahrain** | −0.09 | 7.33 | 2.96 | −1.87 | 2.04 | −2.30 | −1.80 | 0.77 | −2.10 | −8.77 | −4.63 |
| **Brazil** | 2.06 | −8.66 | −2.81 | 0.83 | 3.83 | 2.62 | −2.48 | 1.32 | −2.66 | −9.28 | −3.03 |
| **Canada** | −3.22 | −1.65 | 2.39 | 6.13 | −0.35 | −3.86 | −4.28 | −7.13 | −8.02 | −6.72 | −5.06 |
| **Chile** | −9.18 | 0.63 | 5.97 | 0.17 | 5.42 | −1.52 | −7.56 | −9.24 | −3.35 | −5.15 | −4.25 |
| **China** | 2.96 | 6.77 | 0.72 | −2.98 | 3.66 | −0.83 | −2.26 | 4.04 | −3.04 | −7.67 | −3.04 |
| **India** | 1.07 | 7.30 | −1.68 | −3.60 | −0.42 | 1.38 | −2.76 | 2.94 | −2.04 | −7.28 | −3.01 |
| **Indonesia** | 1.59 | 5.19 | 2.92 | −2.29 | 1.23 | 2.16 | −1.09 | 6.23 | −1.40 | −10.18 | −4.15 |
| **Iran** | 0.70 | 8.37 | −1.33 | −0.60 | −1.06 | 0.94 | 5.21 | −0.63 | 2.49 | −7.95 | −3.14 |
| **Iraq** | 1.19 | 7.47 | 3.11 | 0.52 | −1.86 | 1.82 | 1.34 | 1.00 | 1.94 | −7.98 | −3.75 |
| **Japan** | −6.36 | −5.66 | −6.42 | 1.39 | −4.12 | −1.76 | −6.52 | 0.18 | 3.45 | −6.11 | −4.54 |
| **Korea, Rep.** | −8.44 | 4.50 | 9.06 | −13.94 | −0.05 | −3.03 | −7.05 | 2.70 | 6.24 | −7.17 | −7.44 |
| **Kuwait** | 1.03 | 8.01 | 0.25 | −0.14 | 1.65 | 0.64 | 4.01 | 2.10 | 0.29 | −8.17 | −4.77 |
| **Malaysia** | 0.53 | 8.37 | 4.66 | 2.07 | −0.35 | −0.19 | −0.25 | 3.80 | −0.20 | −8.75 | −3.57 |
| **Mexico** | −5.13 | 4.54 | −20.46 | 3.37 | 1.36 | 3.40 | 0.63 | −0.06 | 10.35 | −4.10 | −3.89 |
| **New Zealand** | −6.70 | −6.61 | 2.81 | −2.07 | 1.12 | −4.60 | −7.35 | −3.39 | 3.67 | −7.44 | −5.16 |
| **Nigeria** | 2.60 | −0.62 | 0.35 | −1.69 | 4.24 | 1.23 | 4.67 | 4.00 | 3.30 | −7.49 | −4.82 |
| **Norway** | −6.55 | −6.79 | 0.68 | 2.50 | −1.41 | −3.73 | 1.31 | −1.40 | 2.53 | −8.21 | −4.46 |
| **Oman** | 0.02 | 7.84 | 2.31 | −0.11 | 0.80 | 1.63 | 5.00 | 2.11 | −1.50 | −7.18 | −3.28 |
| **Philippines** | 0.96 | 4.43 | 2.89 | −1.97 | −0.98 | 1.57 | −4.14 | −0.66 | −1.65 | −10.13 | −4.02 |
| **Qatar** | 1.34 | 5.90 | 2.36 | 0.28 | 1.95 | 0.90 | 4.55 | 2.63 | −2.85 | −8.20 | −2.58 |
| **Saudi Arabia** | 1.15 | 6.92 | 2.04 | 0.61 | −0.09 | 2.20 | 4.75 | 4.21 | −0.97 | −7.18 | −3.95 |
| **Singapore** | 6.39 | −0.41 | 172.08 | −2.35 | 5.89 | 0.90 | 0.00 | 0.09 | 4.68 | −2.52 | −2.52 |
| **South Africa** | 1.27 | 8.30 | −1.57 | 0.42 | 1.73 | 0.88 | −3.61 | 0.82 | −1.58 | −8.42 | −4.72 |
| **Turkey** | −8.70 | 0.17 | −3.93 | 5.49 | 4.77 | 0.09 | −2.32 | 8.01 | −0.36 | −11.23 | −6.95 |
| **United Arab Emirates** | −1.79 | 5.28 | 0.59 | −1.76 | −1.01 | 1.36 | 5.74 | 2.33 | 0.77 | −9.47 | −4.79 |
| **United Kingdom** | −1.07 | −5.58 | −7.42 | 1.18 | −1.38 | −4.78 | −4.64 | −5.77 | 1.55 | −7.16 | −5.95 |
| **United States** | 1.31 | −1.73 | −5.38 | −1.33 | 2.41 | −8.05 | −7.02 | −2.12 | 2.61 | −10.36 | −5.64 |

Source: Iran and China national oil company.

Based on the obtained error values listed in Table 3, the SVM model has the lowest prediction error value for demand forecasting. Moreover, the ARIMA model is more accurate than the SVM model in time series forecasting. When independent variables are included in the model, the intelligent model has higher predictive power compared to the statistical model. However, when only the history of the input variable is used to forecast its future, time series models perform better and have lower error rates. The Mann-Whitney test was used to check whether the studied models have different accuracy in oil-importing and exporting countries. For this purpose, it was first evaluated whether there is a significant difference in the level of demand uncertainty in oil-importing and exporting countries, and then the difference in prediction error of models in oil-importing and exporting countries was studied. The test results are shown in Tables 5 and 6, respectively.

**Table 4.** Oil demand prediction errors according to different models in the 30 studied countries.

| | SVR | | | | SVM | | | | GLM | | | | ARIMA | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | RMSEA | MAPE | MAE | MSE | RMSEA | MAPE | MAE | MSE | RMSEA | MAPE | MAE | MSE | RMSEA | MAPE | MAE | MSE |
| Algeria | 0.05 | 0.01 | 0.05 | 0.00 | 0.21 | 0.03 | 0.12 | 0.04 | 0.01 | 0.00 | 0.01 | 0.00 | 0.29 | 0.03 | 0.14 | 0.08 |
| Argentina | 0.04 | 0.01 | 0.04 | 0.00 | 0.15 | 0.02 | 0.09 | 0.02 | 0.02 | 0.00 | 0.01 | 0.00 | 0.23 | 0.03 | 0.11 | 0.05 |
| Australia | 0.06 | 0.01 | 0.05 | 0.00 | 0.19 | 0.03 | 0.12 | 0.04 | 0.22 | 0.03 | 0.12 | 0.05 | 0.29 | 0.02 | 0.11 | 0.08 |
| Bahrain | 0.07 | 0.02 | 0.07 | 0.01 | 0.30 | 0.04 | 0.18 | 0.09 | 0.02 | 0.00 | 0.01 | 0.00 | 0.43 | 0.04 | 0.19 | 0.18 |
| Brazil | 0.04 | 0.01 | 0.04 | 0.00 | 0.17 | 0.03 | 0.11 | 0.03 | 0.01 | 0.00 | 0.00 | 0.00 | 0.24 | 0.03 | 0.11 | 0.06 |
| Canada | 0.07 | 0.01 | 0.06 | 0.00 | 0.25 | 0.03 | 0.15 | 0.06 | 0.19 | 0.03 | 0.15 | 0.04 | 0.36 | 0.03 | 0.14 | 0.13 |
| Chile | 0.05 | 0.01 | 0.04 | 0.00 | 0.16 | 0.02 | 0.10 | 0.02 | 0.11 | 0.02 | 0.08 | 0.01 | 0.22 | 0.02 | 0.09 | 0.05 |
| China | 0.08 | 0.02 | 0.07 | 0.01 | 0.28 | 0.04 | 0.17 | 0.08 | 0.01 | 0.00 | 0.01 | 0.00 | 0.40 | 0.03 | 0.16 | 0.16 |
| India | 0.06 | 0.01 | 0.06 | 0.00 | 0.21 | 0.03 | 0.13 | 0.04 | 0.01 | 0.00 | 0.01 | 0.00 | 0.31 | 0.03 | 0.12 | 0.09 |
| Indonesia | 0.05 | 0.01 | 0.04 | 0.00 | 0.16 | 0.02 | 0.10 | 0.02 | 0.01 | 0.00 | 0.01 | 0.00 | 0.24 | 0.02 | 0.09 | 0.06 |
| Iran | 0.07 | 0.01 | 0.07 | 0.01 | 0.32 | 0.04 | 0.19 | 0.10 | 0.01 | 0.00 | 0.01 | 0.00 | 0.44 | 0.04 | 0.22 | 0.19 |
| Iraq | 0.06 | 0.01 | 0.06 | 0.00 | 0.25 | 0.04 | 0.17 | 0.06 | 0.02 | 0.00 | 0.02 | 0.00 | 0.35 | 0.04 | 0.19 | 0.12 |
| Japan | 0.05 | 0.01 | 0.05 | 0.00 | 0.15 | 0.02 | 0.10 | 0.02 | 0.16 | 0.02 | 0.10 | 0.03 | 0.23 | 0.02 | 0.09 | 0.05 |
| Korea, Rep. | 0.07 | 0.01 | 0.06 | 0.00 | 0.24 | 0.03 | 0.15 | 0.06 | 0.22 | 0.03 | 0.15 | 0.05 | 0.34 | 0.03 | 0.14 | 0.12 |
| Kuwait | 0.06 | 0.01 | 0.06 | 0.00 | 0.26 | 0.04 | 0.16 | 0.07 | 0.01 | 0.00 | 0.01 | 0.00 | 0.37 | 0.04 | 0.17 | 0.13 |
| Malaysia | 0.06 | 0.01 | 0.05 | 0.00 | 0.22 | 0.03 | 0.13 | 0.05 | 0.02 | 0.00 | 0.01 | 0.00 | 0.31 | 0.03 | 0.13 | 0.09 |
| Mexico | 0.04 | 0.01 | 0.04 | 0.00 | 0.15 | 0.02 | 0.09 | 0.02 | 0.15 | 0.02 | 0.08 | 0.02 | 0.21 | 0.02 | 0.09 | 0.04 |
| New Zealand | 0.05 | 0.01 | 0.05 | 0.00 | 0.20 | 0.03 | 0.12 | 0.04 | 0.18 | 0.03 | 0.12 | 0.03 | 0.28 | 0.03 | 0.11 | 0.08 |
| Nigeria | 0.07 | 0.02 | 0.07 | 0.01 | 0.23 | 0.03 | 0.15 | 0.05 | 0.02 | 0.00 | 0.02 | 0.00 | 0.33 | 0.03 | 0.13 | 0.11 |
| Norway | 0.05 | 0.01 | 0.05 | 0.00 | 0.17 | 0.03 | 0.11 | 0.03 | 0.14 | 0.03 | 0.11 | 0.02 | 0.25 | 0.03 | 0.13 | 0.06 |
| Oman | 0.07 | 0.01 | 0.06 | 0.00 | 0.31 | 0.05 | 0.21 | 0.09 | 0.04 | 0.01 | 0.03 | 0.00 | 0.41 | 0.05 | 0.23 | 0.17 |
| Philippines | 0.04 | 0.01 | 0.04 | 0.00 | 0.12 | 0.02 | 0.08 | 0.02 | 0.01 | 0.00 | 0.01 | 0.00 | 0.19 | 0.02 | 0.07 | 0.04 |
| Qatar | 0.07 | 0.01 | 0.07 | 0.01 | 0.29 | 0.04 | 0.18 | 0.08 | 0.04 | 0.01 | 0.03 | 0.00 | 0.39 | 0.04 | 0.18 | 0.15 |
| Saudi Arabia | 0.06 | 0.01 | 0.06 | 0.00 | 0.23 | 0.03 | 0.14 | 0.05 | 0.03 | 0.00 | 0.02 | 0.00 | 0.34 | 0.04 | 0.17 | 0.11 |
| Singapore | 0.09 | 0.02 | 0.08 | 0.01 | 0.12 | 0.02 | 0.09 | 0.02 | 0.11 | 0.02 | 0.07 | 0.01 | 0.18 | 0.03 | 0.12 | 0.03 |
| South Africa | 0.08 | 0.02 | 0.08 | 0.01 | 0.29 | 0.04 | 0.17 | 0.08 | 0.01 | 0.00 | 0.01 | 0.00 | 0.42 | 0.04 | 0.18 | 0.18 |
| Turkey | 0.03 | 0.01 | 0.03 | 0.00 | 0.11 | 0.02 | 0.06 | 0.01 | 0.11 | 0.02 | 0.06 | 0.01 | 0.16 | 0.02 | 0.07 | 0.03 |
| United Arab Emirates | 0.05 | 0.01 | 0.04 | 0.00 | 0.22 | 0.03 | 0.14 | 0.05 | 0.02 | 0.00 | 0.02 | 0.00 | 0.31 | 0.03 | 0.15 | 0.09 |
| United Kingdom | 0.04 | 0.01 | 0.03 | 0.00 | 0.10 | 0.02 | 0.07 | 0.01 | 0.07 | 0.01 | 0.06 | 0.01 | 0.16 | 0.02 | 0.06 | 0.02 |
| United States | 0.06 | 0.01 | 0.06 | 0.00 | 0.20 | 0.03 | 0.13 | 0.04 | 0.21 | 0.03 | 0.14 | 0.05 | 0.29 | 0.02 | 0.11 | 0.09 |
| Error Average | 0.058 | 0.013 | 0.055 | 0.004 | 0.209 | 0.031 | 0.130 | 0.047 | 0.074 | 0.012 | 0.050 | 0.011 | 0.299 | 0.029 | 0.133 | 0.096 |

Source: Iran and China national oil company.

**Table 5.** Mann-Whitney test results for comparing demand uncertainty in oil importing and exporting countries.

| | OILCONSUMVOL |
|---|---|
| Mann-Whitney U | 44,825.500 |
| Wilcoxon W | 94,595.500 |
| Z | −3.418 |
| Asymp. Sig. (2-tailed) | 0.001 |

Source: Iran and China national company.

**Table 6.** Mann-Whitney test results for comparing accuracy in oil exporter and importer group.

| | ARIMA | SVM | GLM | SVR |
|---|---|---|---|---|
| Mann-Whitney U | 44,065.000 | 48,625.000 | 47,819.500 | 51,702.500 |
| Wilcoxon W | 93,835.000 | 98,395.000 | 97,589.500 | 101,472.500 |
| Z | −3.720 | −1.791 | −2.127 | −0.508 |
| Asymp. Sig. (2-tailed) | 0.000 | 0.073 | 0.033 | 0.612 |

Source: Iran and China national company.

The results listed in Table 4 indicate a significant difference between the uncertainty level of demand in oil exporting and importing countries, as the significance level of the test is less than 0.05. The negative value of the statistic suggests that the demand uncertainty level is higher in oil exporting countries than in oil importing countries. One of the reasons for this difference is oil price fluctuations. Oil price changes lead to a redistribution of income between oil importers and exporters, increasing the real exchange rate and thereby weakening the price competition of domestic production. Moreover, in oil-exporting countries, oil price fluctuations significantly affect public finances. Even if some governments try to limit its scale by creating stabilization funds, the effectiveness of this policy is not always there.

Based on the results in Table 6, the significance value of the Mann-Whitney test for the ARIMA and GLM models is less than 0.05, and the value of the statistic is negative, which indicates that there is a significant difference between the error of the model in two groups of oil exporters and importers in the mentioned models. Based on these findings, the forecast error in oil-exporting countries, which face more uncertainties, is higher than in oil-importing countries. The results also suggest that the ARIMA and GLM models are unstable in terms of the uncertainty level of the oil demand variable. Therefore, the intelligent model is more stable than the statistical model.

Table 7 presents a comprehensive literature review on the topic of "Oil Demand Forecasting in Importing and Exporting Countries: AI-Based Analysis of Endogenous and Exogenous Factors." The purpose of this literature review is to examine and summarize the key findings of relevant studies that have investigated the application of AI-based analysis in forecasting oil demand, considering both endogenous and exogenous factors.

**Table 7.** Oil Demand Forecasting in Importing and Exporting Countries: AI-Based Analysis of Endogenous and Exogenous Factors.

| Study | Key Findings |
|---|---|
| Al-Fattah et al. [29] | - Utilized AI-based analysis for oil demand forecasting in importing and exporting countries.<br>- Found that incorporating endogenous factors, such as economic indicators and energy policies, improved forecast accuracy.<br>- Identified exogenous factors such as geopolitical events and technological advancements as significant drivers of oil demand. |
| Romero-Gelvez [35] | - Conducted an AI-based analysis of oil demand forecasting in exporting countries.<br>- Demonstrated that machine learning models outperformed traditional statistical models in predicting oil demand.<br>- Highlighted the importance of considering both endogenous and exogenous factors for accurate forecasts. |
| Liu et al. [58] | - Examined the impact of AI-based analysis on Natural gas consumption forecasting in both importing and exporting countries.<br>- To the medium-term and short-term forecasting, AI-based models present the best performance.<br>- Suggested that AI-based forecasting can enhance energy planning and decision-making in the oil sector. |
| Huang et al. [33] | - Explored the role of machine learning techniques in oil demand forecasting for importing countries.<br>- Identified the need for advanced AI models to capture the complex dynamics and interplay of factors influencing oil demand.<br>- Emphasized the potential of AI-based analysis in improving forecast accuracy and supporting energy-related policy decisions. |

## 5. Discussion and Conclusions

Accurate forecasting is among the necessities of supply chain development, communication development, and improvement of decision-making, depending on providing a correct forecast of the future. Since demand is an external factor that has an effect on a company's operations, understanding the factors that influence demand and utilizing that information to make predictions about future demand is crucial to a business's success in a highly competitive market. Improving the accuracy of demand forecasting can lead to better supply chain management by preventing producers from oversupplying and incurring additional production costs. Conversely, inaccurate forecasts can result in unnecessary costs in purchasing, transportation, human resources, service level, and inventory. Therefore, having an accurate demand forecasting tool is essential for producers. In the digital age, the development of AI techniques has made it possible for manufacturers to improve their performance in the global arena, and one of the cases in which AI techniques can be used is forecasting. Numerous studies employed this approach to anticipate demand in various areas in light of this problem. In this work, oil demand forecasting in oil exporting and importing nations was carried out using AI approaches, and the prediction accuracy of statistical tools and AI techniques was compared. To achieve this purpose, data from 30 countries around the world were selected for the period from 2000 to 2020. To forecast oil demand, both endogenous and exogenous economic variables were considered. Endogenous variables included carbon emissions, income levels, energy prices, GDP, population growth, urbanization, trade liberalization, inflation, FDI, and financial development. Exogenous factors such as energy sanctions and the COVID-19 pandemic were also included. Demand forecasting was conducted based on four SVR, SVM, GLM, and ARIMA models, and the results were compared with each other using the forecasting error evaluation indicators, including MAPE, MSE, MAE, and RMSE.

Surveys showed that among the input elements considered in demand forecasting, the oil sanctions, and COVID-19 pandemic had the greatest impact on reducing oil demand. Thus, trade liberalization has the greatest effect on increasing oil demand. It implies that exogenous elements can increase oil demand fluctuations more than endogenous elements. Moreover, government policies regarding the development of imports and exports can increase the tendency to expand oil exchanges. So, it stands to reason that better demand forecasting may be achieved by taking into account both endogenous and external factors simultaneously.

In addition, the results showed that the sanctions can be a factor in reducing the demand for and price of oil. Sanctions against countries can be a destructive factor from an economic perspective, which leads to a decrease in the level of public income and a decrease in economic growth in the sanctioned country.

Comparing the prediction error of statistical models and AI in oil demand forecasting, the Support Vector Regression (SVR) model outperformed the other models with a lower prediction error. Additionally, when evaluating the stability of models in oil exporting and importing countries that experience different levels of demand uncertainty, the SVR model showed higher stability compared to other models used. These results show that using AI models to consider input variables in demand forecasting and not relying only on demand history for future forecasting is more successful than other models in demand forecasting. Therefore, using these models in demand forecasting can improve supply chain management. These results are consistent with the studies of Romero-Gelvez et al. [35] and Al-Musaylh et al. [41].

Moreover, in assessing the qualification of models in oil exporter and importer countries using the Mann-Whitney test, the results showed that there is a significant difference between the error of models in the two groups of oil exporters and importers in the mentioned models. Based on these findings, the forecast error in oil-exporting countries, which face more uncertainties, is higher than in oil-importing countries. The results also suggest that the ARIMA and GLM models are unstable in terms of the uncertainty level of the oil demand variable. Therefore, the intelligent model is more stable than the statistical model.

Sanctions and the COVID-19 pandemic have disrupted exchanges for oil-exporting nations, which rely heavily on oil sales for their budgets. To cope with the crisis, these countries should consider strategies to increase income from non-oil sources. Improving marketing techniques and global market entry methods can help achieve this goal. They should discover the country's potential production capacity through strong field research. Thus, countries should actualize their potential to overcome the crisis by means of the following:

- Increasing low-interest loans for production development
- Monitoring business activities,
- Increasing the value of national currency
- Recognizing the needs of global markets
- Increasing the number of businessmen in the target countries
- And strengthening business relationships through strong commercial diplomacy
- Providing consulting services for business enterprises
- Positive visualizing, and introducing domestic capabilities in other countries
- Introducing foreign capacities to domestic producer

## 6. Limitation and Future Research

To increase the generalizability of the results and reduce the limitations of this study, an attempt was made to include most of the economic indicators affecting oil demand in the research model. However, this study is limited by the lack of information regarding country-specific behavioral traits, which were not taken into account in the current investigation. As a result, the capacity to generalize the findings is limited. Future researchers are suggested to investigate the role of behavioral variables in oil demand following the principles of behavioral economics to help address this limitation. Based on the objectives of the present study, which are the forecasting of oil demand, the present study can be useful for energy suppliers, industrialists, analysts, energy planners, and governments in oil exporting and importing countries.

**Funding:** This research received no external funding.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Sharma, R.; Singhal, P. Demand forecasting of engine oil for automotive and industrial lubricant manufacturing company using neural network. *Mater. Today Proc.* **2019**, *18*, 2308–2314. [CrossRef]
2. Mediavilla, M.A.; Dietrich, F.; Palm, D. Review and analysis of artificial intelligence methods for demand forecasting in supply chain management. *Procedia CIRP* **2022**, *107*, 1126–1131. [CrossRef]
3. Swaminathan, K.; Venkitasubramony, R. Demand forecasting for fashion products: A systematic review. *Int. J. Forecast.* **2023**, *in press*. [CrossRef]
4. Moroff, N.U.; Kurt, E.; Kamphues, J. Machine Learning and statistics: A Study for assessing innovative demand forecasting models. *Procedia Comput. Sci.* **2021**, *180*, 40–49. [CrossRef]
5. Feizabadi, J. Machine learning demand forecasting and supply chain performance. *Int. J. Logist. Res. Appl.* **2022**, *25*, 119–142. [CrossRef]
6. Coussement, K.; Lessmann, S.; Verstraeten, G. A comparative analysis of data preparation algorithms for customer churn prediction: A case study in the telecommunication industry. *Decis. Support Syst.* **2017**, *95*, 27–36. [CrossRef]
7. Abbasimehr, H.; Shabani, M.; Yousefi, M. An optimized model using LSTM network for demand forecasting. *Comput. Ind. Eng.* **2020**, *143*, 106435. [CrossRef]
8. Kumar, A.; Shankar, R.; Alijohani, N. A big data driven framework for demand- driven forecasting with effects of marketing-mix variables. *Ind. Mark. Manag.* **2019**, *90*, 493–507. [CrossRef]
9. Nia, A.R.; Awasthi, A.; Bhuiyan, N. Industry 4.0 and demand forecasting of the energy supply chain: A literature review. *Comput. Ind. Eng.* **2021**, *154*, 107128.
10. Dorin, P.; Kim, J.; Wang, K.W. Vibration energy harvesting system with coupled bistable modules. *Act. Passiv. Smart Struct. Integr. Syst.* **2019**, *XIII*, 81–94.
11. Khashei, M.; Bijari, M. A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. *Appl. Soft Comput.* **2011**, *11*, 2664–2675. [CrossRef]
12. Çevik, H.H.; Çunkaş, M. Short-term load forecasting using fuzzy logic and ANFIS. *Neural Comput. Appl.* **2015**, *26*, 1355–1367. [CrossRef]
13. Box, G.E.; Jenkins, G.M.; Reinsel, G.C.; Ljung, G.M. *Time Series Analysis: Forecasting and Control*; John Wiley & Sons: Hoboken, NJ, USA, 2015.

14. Johannesen, N.J.; Kolhe, M.; Goodwin, M. Relative evaluation of regression tools for urban area electrical energy demand forecasting. *J. Clean. Prod.* **2019**, *218*, 555–564. [CrossRef]
15. Chen, R.; Rao, Z.; Liao, S. Hybrid LEAP modeling method for long-term energy demand forecasting of regions with limited statistical data. *J. Cent. South Univ.* **2019**, *26*, 2136–2148. [CrossRef]
16. Bouktif, S.; Fiaz, A.; Ouni, A.; Serhani, M.A. Optimal deep learning lstm model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. *Energies* **2018**, *11*, 1636. [CrossRef]
17. Dirican, C. The impacts of robotics, artificial intelligence on business and economics. *Procedia Soc. Behav. Sci.* **2015**, *195*, 564–573. [CrossRef]
18. Toorajipour, R.; Sohrabpour, V.; Nazarpour, A.; Oghazi, P.; Fischl, M. Artificial intelligence in supply chain management: A systematic literature review. *J. Bus. Res.* **2021**, *122*, 502–517. [CrossRef]
19. Duan, J.; Hou, Z.; Fang, S.; Lu, W.; Hu, M.; Tian, X.; Wang, P.; Ma, W. A novel electricity consumption forecasting model based on kernel extreme learning machine-with generalized maximum correntropy criterion. *Energy Rep.* **2022**, *8*, 10113–10124. [CrossRef]
20. Wakefield, K. A Guide to Machine Learning Algorithms and Their Application. Undated, SAS. Com. 2013. Available online: https://www.sas.com/en_gb/insights/articles/analytics/machine-learning-algorithms.html (accessed on 1 June 2023).
21. Twumasi, C.; Twumasi, J. Machine learning algorithms for forecasting and backcasting blood demand data with missing values and outliers: A study of Tema General Hospital of Ghana. *Int. J. Forecast.* **2022**, *38*, 1258–1277. [CrossRef]
22. Nakhli, S.R.; Rafat, M.; Dastjerdi, R.B.; Rafei, M. Oil sanctions and their transmission channels in the Iranian economy: A DSGE model. *Resour. Policy* **2021**, *70*, 101963. [CrossRef]
23. Ou, S.; He, X.; Ji, W.; Chen, W.; Sui, L.; Gan, Y.; Lu, Z.; Lin, Z.; Deng, S.; Bouchard, J.; et al. Machine learning model to project the impact of COVID-19 on US motor gasoline demand. *Naure. Energy* **2020**, *5*, 666–673.
24. Wang, Q.; Zhang, F. What does the China's economic recovery after COVID-19 pandemic mean for the economic growth and energy consumption of other countries? *J. Clean. Prod.* **2021**, *295*, 126265. [CrossRef]
25. Zhang, X.; Pellegrino, F.; Shen, J.; Copertaro, B.; Huang, P.; Saini, P.K.; Lovati, M. A preliminary simulation study about the impact of COVID-19 crisis on energy demand of a building mix at a district in Sweden. *Appl. Energy* **2020**, *280*, 115954. [CrossRef] [PubMed]
26. Maltais, L.G.; Gosselin, L. Energy management of domestic hot water systems with model predictive control and demand forecast based on machine learning. *Energy Convers. Manag.* **2022**, *15*, 100254. [CrossRef]
27. Zhang, W.; Liang, Y. Regional Demand Forecasting of Refined Oil under Alternative Energy Market's Competition. *J. Clean Energy Technol.* **2019**, *7*, 56–59. [CrossRef]
28. Huang, J.; Tang, Y.; Chen, S. Energy demand forecasting: Combining cointegration analysis and artificial intelligence algorithm. *Math. Probl. Eng.* **2018**, *2018*, 5194810. [CrossRef]
29. Al-Fattah, S.M.; Aramco, S. Application of the artificial intelligence GANNATS model in forecasting crude oil demand for Saudi Arabia and China. *J. Pet. Sci. Eng.* **2021**, *200*, 108368. [CrossRef]
30. Brentan, B.M.; Luvizotto, E., Jr.; Herrera, M.; Izquierdo, J.; Pérez-García, R. Hybrid regression model for near real-time urban water demand forecasting. *J. Comput. Appl. Math.* **2017**, *309*, 532–541. [CrossRef]
31. Kochak, A.; Sharma, S. Demand forecasting using neural network for supply chain management. *Int. J. Mech. Eng. Robot. Res.* **2015**, *4*, 96–104.
32. Lashgari, A.; Hosseinzadeh, H.; Khalilzadeh, M.; Milani, B.; Ahmadisharaf, A.; Rashidi, S. Transportation energy demand forecasting in Taiwan based on metaheuristic algorithms. *Energy Sources Part A Recovery Util. Environ. Eff.* **2022**, *44*, 2782–2800. [CrossRef]
33. Huang, Y.; Li, S.; Wang, R.; Zhao, Z.; Huang, B.; Wei, B.; Zhu, G. Forecasting Oil Demand with the Development of Comprehensive Tourism. *Chem. Technol. Fuels Oils* **2021**, *57*, 299–310. [CrossRef]
34. Fatima, T.; Xia, E.; Ahad, M. Oil demand forecasting for China: A fresh evidence from structural time series analysis. *Environ. Dev. Sustain.* **2019**, *21*, 1205–1224. [CrossRef]
35. Romero-Gelvez, J.I.; Villamizar, E.F.; Garcia-Bedoya, O.; Cuartas, J.A.H. Demand Forecasting for Inventory Management using Limited Data Sets: A Case Study from the Oil Industry. In Proceedings of the ICAI Workshops: At the Third International Conference on Applied Informatics 2020, Ota, Nigeria, 29–31 October 2020; pp. 111–119.
36. Anik, A.R.; Rahman, S. Commercial energy demand forecasting in Bangladesh. *Energies* **2021**, *14*, 6394. [CrossRef]
37. Sánchez-Durán, R.; Luque, J.; Barbancho, J. Long-term demand forecasting in a scenario of energy transition. *Energies* **2019**, *12*, 3095. [CrossRef]
38. Rehman, S.A.U.; Cai, Y.; Fazal, R.; Das Walasai, G.; Mirjat, N.H. An integrated modeling approach for forecasting long-term energy demand in Pakistan. *Energies* **2017**, *10*, 1868. [CrossRef]
39. Alhendi, A.A.; Al-Sumaiti, A.S.; Elmay, F.K.; Wescaot, J.; Kavousi-Fard, A.; Heydarian-Forushani, E.; Alhelou, H.H. Artificial intelligence for water–energy nexus demand forecasting: A review. *Int. J. Low-Carbon Technol.* **2022**, *17*, 730–744. [CrossRef]
40. Boamah, V. Forecasting the Demand of Oil in Ghana: A Statistical Approach. *Manag. Sci. Bus. Decis.* **2021**, *1*, 29–43. [CrossRef]
41. Al-Musaylh, M.S.; Deo, R.C.; Adamowski, J.F.; Li, Y. Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Adv. Eng. Inform.* **2018**, *35*, 1–16. [CrossRef]
42. Perea, R.G.; Poyato, E.C.; Montesinos, P.; Díaz, J.A.R. Optimisation of water demand forecasting by artificial intelligence with short data sets. *Biosyst. Eng.* **2019**, *177*, 59–66. [CrossRef]

43. von Graevenitz, K.; Rottner, E. Energy Use Patterns in German Manufacturing from 2003 to 2017. *Jahrbücher Für Natl. Und Stat.* 2023. Available online: https://www.degruyter.com/document/doi/10.1515/jbnst-2022-0031/html (accessed on 1 June 2023).
44. Ma, E.; Yang, X. Financial Pressure, Energy Consumption and Carbon Emissions: A Quasi-Natural Experiment Based on the Educational Authority Reform. *China Financ. Econ. Rev.* **2022**, *11*, 44–65. Available online: https://www.degruyter.com/document/doi/10.1515/cfer-2022-0022/html (accessed on 1 June 2023).
45. Kalimoldayev, M.; Drozdenko, A.; Koplyk, I.; Marinich, T.; Abdildayeva, A.; Zhukabayeva, T. Analysis of modern approaches for the prediction of electric energy consumption. *Open Eng.* **2020**, *10*, 350–361, Published by De Gruyter. Available online: https://www.degruyter.com/document/doi/10.1515/eng-2020-0028/html (accessed on 1 June 2023). [CrossRef]
46. Vapnik, V.N. An overview of statistical learning theory. *IEEE Trans. Neural Netw.* **1999**, *10*, 988–999. [CrossRef]
47. Rodríguez-Pérez, R.; Bajorath, J. Evolution of Support Vector Machine and Regression Modeling in Chemoinformatics and Drug Discovery. *J. Comput.-Aided Mol. Des.* **2022**, *36*, 355–362. [CrossRef] [PubMed]
48. Parveen, N.; Zaidi, S.; Danish, M. Support vector regression model for predicting the sorption capacity of lead (II). *Perspect. Sci.* **2016**, *8*, 629–631. [CrossRef]
49. Lin, S.J.; Lu, I.J.; Lewis, C. Grey relation performance correlations among economics, energy use and carbon dioxide emission in Taiwan. *Energy Policy* **2007**, *35*, 1948–1955. [CrossRef]
50. Chaudhry, A.A. A Panel Data Analysis of Electricity Demand in Pakistan. *Lahore J. Econ.* **2010**, *15*, 75–106. [CrossRef]
51. Mustapha, N.H.N.; Ismail, R. Factors affecting energy demand in developing countries: A dynamic panel analysis. *Int. J. Energy Econ. Policy* **2013**, *3*, 1–6.
52. Saidi, K.; Hammami, S. The impact of $CO_2$ emissions and economic growth on energy consumption in 58 countries. *Energy Rep.* **2015**, *1*, 62–70. [CrossRef]
53. Sadiq, M.; Ou, J.P.; Duong, K.D.; Van, L.; Ngo, T.Q.; Bui, T.X. The influence of economic factors on the sustainable energy consumption: Evidence from China. *Econ. Res.-Ekon. Istraživanja* **2022**, *36*, 1751–1773. [CrossRef]
54. Salim, R.; Rafiq, S.; Shafiei, S.; Yao, Y. Does urbanization increase pollutant emission and energy intensity? Evidence from some Asian developing economies. *Appl. Econ.* **2019**, *51*, 4008–4024. [CrossRef]
55. Ogunsola, A.J.; Tipoy, C.K. Determinants of energy consumption: The case of African oil exporting countries. *Cogent Econ. Financ.* **2022**, *10*, 2058157. [CrossRef]
56. Kim, S. The effects of foreign direct investment, economic growth, industrial structure, renewable and nuclear energy, and urbanization on Korean greenhouse gas emissions. *Sustainability* **2020**, *12*, 1625. [CrossRef]
57. Al-Fattah, S.M. Artificial intelligence approach for modeling and forecasting oil-price volatility. *SPE Reserv. Eval. Eng.* **2019**, *22*, 817–826. [CrossRef]
58. Liu, J.; Wang, S.; Wei, N.; Chen, X.; Xie, H.; Wang, J. Natural gas consumption forecasting: A discussion on forecasting history and future challenges. *J. Nat. Gas Sci. Eng.* **2021**, *90*, 103930. [CrossRef]