 doi:10.20944/preprints201905.0346.v1

Carbon Dioxide Emissions Prediction of Five Middle Eastern Countries Using Artificial Neural Networks

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Abstract: Greenhouse gas (GHG) emissions contribute considerably to global warming and climate change. Since energy systems notably influence GHG emissions, such emissions can be modeled at the national level based on the energy sources utilized by a country. Economic activity also affects GHG emissions. In this work, an Artificial Neural Network (ANN) approach, Group Method of Data Handling (GMDH), is used for determining emissions of carbon dioxide, the most significant GHG, on the basis of shares of various energy sources used as primary energy supply and GDP as an indicator of economic activity. Five countries are considered as case studies: Iran, Kuwait, Qatar, Saudi Arabia and United Arab Emirates (UAE). Comparing the results achieved by the developed model and actual quantities shows that the ANN model has acceptable accuracy for predicting carbon dioxide emissions. The average absolute relative error and the R-squared values of the GMDH model are 2.3% and 0.9998, respectively. These values demonstrate the precision of the model in forecasting emissions of CO_2.

Keywords: Artificial Neural Network; Greenhouse gases; GMDH; Middle Eastern countries; Carbon dioxide emission

1. Introduction

Increases in industrial activities and improvements in quality of life are raising energy requirements. Various sources of energy are utilized for electricity generation, heating, desalination, cooling and other purposes (Alizadeh et al. 2016; Mohammad Hossein Ahmadi et al. 2017; M.H. Ahmadi, Ghazvini, et al. 2018). Among these, fossil fuels have the highest share in primary consumption. However, since these types of energy sources are limited and have unfavorable impacts on the environment, policies have been enacted in many countries to restrict their utilization. Renewable energy sources are more attractive than fossil fuels in terms of environmental impact and sustainability. The most commonly applied types of renewable energies are solar, wind and geothermal (Mohammad Hossein Ahmadi, Ramezanizadeh, et al. 2018; Ramezanizadeh, Nazari, et al. 2018; Mohammadi et al. 2017). Most renewable energy types can be used for electricity production (M.H. Ahmadi, Alhuyi Nazari, et al. 2018; Caliskan, Dincer, and Hepbasli 2013), while solar and geothermal can be also used for other applications such as HVAC (Haghighi Bardineh et al. 2018; Alhuyi Nazari et al. 2018). The use of renewable energy facilities for power production has risen in recent years (Mohammad Hossein Ahmadi, Ghazvini, et al. 2018; Mohammad Hossein Ahmadi, Ramezanizadeh, et al. 2018).

Since using fossil fuels impacts the environment unfavorably (Mirzaei et al. 2018; Anifantis, Colantoni, and Pascuzzi 2017; Ramezanizadeh et al. 2019), energy policy makers have proposes numerous policies to avoid increases and even reduce GHG emissions. Enhancing the efficiency of current power plants and systems, optimizing their operating condition and developing renewable-based energy systems are commonly incented (Mohammad H. Ahmadi, Jokar, et al. 2018; Naseri et al. 2017). Emissions of CO_2 for electricity generation are much greater for power plants using fossil fuels rather than renewable energy sources (O et al. 2011). For instance, by replacing current thermal power plants of Iran with 5000 MW PV for electricity production, it is possible to reduce emissions of carbon dioxide by up to 9.0 Mt per year, demonstrating the significant potential of renewable energies for decreasing GHG emissions (Dehghani Madvar et al. 2018).

Climate change is highly dependent on GHG emissions (Masson-Delmotte et al. 2018). Among the GHGs, carbon dioxide is the normally considered the most important and is considered in the focus of much work to prevent climate change. Various measures are presented in Paris agreement to reduce emissions of GHGs ("PARIS AGREEMENT" 2015). According to the scenarios presented by the IPCC (Masson-Delmotte et al. 2018), economic factors and the energy sector play key roles in emissions of carbon dioxide. Thus, exploring the impact of energy systems and economic factors on carbon dioxide emissions is important.

Numerous mathematical approaches have been introduced for modeling systems and related phenomena; among these the Artificial Neural Network (ANN) approach is one of the most accurate and powerful. The accuracy of ANN-based methods is much higher than conventional approaches, makes them advantageous. These types of algorithms can be employed for finding the relationship between some inputs and an output. ANN-based approaches are applicable in predicting the features of materials and the performance of engineering systems. For instance, Mohamadian et al. (Mohamadian, Eftekhar, and Haghighi Bardineh 2018a) used a GMDH ANN approach to model and predict the dynamic viscosity of a silver/water nanofluid. The accuracy of their model was very high based on the determined R-squared value which was 0.9996. In other study (Baghban et al. 2019), ANNs were used to determine the Nusselt number of nanofluids flow through a coil. The calculated R-squared value for this case was 0.979, indicating acceptable precision. Since ANNs have ability to consider the interactions of input variables with output of the model (Mohammad Hossein Ahmadi, Ahmadi, et al. 2018; Mohamadian, Eftekhar, and Haghighi Bardineh 2018b; Ramezanizadeh, Ahmadi, et al. 2018; Loni et al. 2017; Toghyani et al. 2016), these tools can be used for modeling environmental problems.

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To gain insights into the influence of each energy type on GHG emissions, mathematical modeling is an appropriate approach. With such models, sensitivity analyses can be carried out to better understand the effects of measures and policies to reduce GHG emissions. Among various machine learning approaches, GMDH is one of the most efficient and accurate. For example, Ahmadi et al. tested both GMDH and LSSVM methods in determining the thermal conductivity of a CuO/ethylene glycol nanofluid. The values of R-squared for these methods were 0.994 and 0.991, respectively. Due to the acceptable and reliable performance of GMDH in modeling different systems, it is an appropriate candidate for use in environment-related problems. In addition, the algorithm does not suffer from the overfitting (PHAM and LIU 1994). According to Rezaei et al. (Rezaei et al. 2018), carbon dioxide emissions of four Nordic countries were accurately assessed using the Group Method of Data Handling (GMDH) as an ANN-based approach. The R-squared value of the model was 0.998 and the maximum value of deviation between the output of the model and actual data was 4%, while approximately two-thirds of the data could be predicted with an error below 1%.

The Middle East region plays important role in providing energy to the world. In addition, since fossil fuel sources are abundant and the cost of energy is lower in these countries than in many other parts of the world and since many developing countries are located in this region, it is informative to investigate its energy-related issues. Middle Eastern countries accounted for approximately 6.3% of the world' CO_2 emissions in 2017 ("BP Statistical Review of World Energy" 2018). Up to now, there is not any mathematical model for predicting CO_2 of these countries, which play key role in world energy supply. In this regard, GMDH ANN, as an efficient and mathematical method, is employed to model the emissions of CO_2 in five Middle Eastern countries, Iran, Saudi Arabia, Qatar, UAE and Kuwait, all of which play important role in the global energy sector. This study aimed at proposing a comprehensive predictive model which would be applicable for all of the mentioned case studies.

Due to the significant dependency of environmental issues on energy systems, it is important to analyze emissions of carbon dioxide, one of the most important GHGs, based on utilized energy sources. The objective of the present study is to model the emission of CO_2 by using the shares of various types of energies, including oil, natural gas, coal and renewable sources, in primary energy consumption of the case studies. In addition, since economic activities affect CO_2 emission, GDP (as an indicator of economic activities) is considered as another input variable in order to propose a more accurate model. By employing the proposed model, it is possible to predict future CO_2 emissions according to the values of input data.

2. Method

Generally, one can use Volterra-Kolmogorov-Gabor (VKG) polynomials to model complex systems that include a set of data with multiple inputs and one output as:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots \quad (1)$$

Here, $x = (x_1, x_2, \ldots x_n)$ are input vectors, y is the output of the model and a_i are the polynomial coefficients. VKG polynomials are approximated using second-order polynomials. These quadratic polynomials are constructed based on the dual composition of network inputs. The GMDH algorithm is introduced using this idea as a learning method for modeling complex systems (Zoqi et al. 2016; Mohammad H Ahmadi et al. 2018).

The GMDH neural network has a multi-layer and forward-oriented structure and consists of a set of neurons that connect the different input pairs through a quadratic polynomial. Each layer in this network consists of one or more processor units, each of which has two inputs

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and one output. These units play the role of model components and are considered as a quadratic polynomial, as follows:

$$\hat{\mathbf{y}} = \mathbf{G}(\mathbf{x_i}, \mathbf{x_j}) = \mathbf{a_0} + \mathbf{a_1 x_i} + \mathbf{a_2 x_j} + \mathbf{a_3 x_i^2} + \mathbf{a_4 x_j^2} + \mathbf{a_5 x_i x_j} \quad (2)$$

The unknown parameters of the GMDH algorithm are the polynomial coefficients of equation (2). To calculate the output value $\hat{y}_i$ for each input vector x= (x_1, x_2, …, x_n), the mean square error must be minimized:

$$\mathbf{e} = \frac{\sum_{i}^{M}(\mathbf{y_i} - \mathbf{G_i})^2}{\mathbf{M}} \rightarrow \mathbf{min} \quad (3)$$

To achieve the lowest error value, a partial derivative of equation (3) is used. By substituting from equation (2) in this partial derivative, a matrix equation ($Aa = y$) is obtained. In this equation, matrix A, $a = \{a_1.a_2.a_3.a_4.a_5\}$ and $Y = \{y_1. \dots . y_m.\}^T$ are in accordance with the following matrix:

$$\begin{bmatrix} \mathbf{1} & \mathbf{x_{1p}} & \mathbf{x_{1q}} & \mathbf{x_{1p}x_{1q}} & \mathbf{x_{1p}^2} & \mathbf{x_{1q}^2} \\ \mathbf{1} & \mathbf{x_{2p}} & \mathbf{x_{2q}} & \mathbf{x_{2p}x_{2q}} & \mathbf{x_{2p}^2} & \mathbf{x_{2q}^2} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \mathbf{1} & \mathbf{x_{Mp}} & \mathbf{x_{Mq}} & \mathbf{x_{Mp}x_{Mq}} & \mathbf{x_{Mp}^2} & \mathbf{x_{Mq}^2} \end{bmatrix}$$

This matrix is applied in order to solve the equation and determine the coefficient of the polynomials.

One approach for solving this matrix equation involves applying the Singular Value Decomposition (SVD) method. Then, the unknown a can be calculated as follows:

$$\mathbf{a} = (\mathbf{A^T A})^{-1}\mathbf{A^T} \quad (4)$$

where $A^T$is the transpose of matrix A. Using this solution method, the unknown a can always be calculated. If the matrix $A^T A$ is irreversible, the Thikhonov method is used to solve the equation.

In the design of the GMDH neural network, the goal is to prevent the divergence of the network and also to link the shape and structure of the network to one or more numerical parameters, in such a way that changing the parameter also changes the structure of the network. Evolutionary approaches such as genetic algorithms have received wide application in the design of ANNs, since they have unique capabilities for determining optimum values and are able to search in spaces with unpredictable features. In order achieve a general structure for the GMDH ANN, the utilization of the adjacent layer in the construction of the next layer should be removed. These types of neural networks are called generalized structure and are used to construct new layers from all previous layers (including the input layer) (Zoqi et al. 2016). More details on the procedures of GMDH are given elsewhere (Loni et al. 2018; Atashrouz, Pazuki, and Alimoradi 2014; Shahsavar et al. 2019).

One of the crucial points which must be taken into account in modeling a factor is consideration of the all factors influence on the output of the model. In this regard, the inputs of the model are selected according to the literature review and similar studies performed for the other regions of the world (Rezaei et al. 2018). In the current article, in order to model CO_2 emission of the considered countries, the data affecting this parameters are extracted from the BP report and WordBank website (“BP Statistical Review of World Energy” 2018; “IEA - Report” n.d.). In order to have adequate data to achieve a reliable model, data between 1990 and 2015 are extracted from the mentioned references. Afterwards, GMDH method is employed for estimating the emission of CO_2. More details about the input data, validation of the model and the criteria used for the model’s inputs are represented in the following section.

3. Results and discussion

Emissions of CO_2 have increased noticeably in recent years across the world and in the Middle East, as shown in Figure 1 and 2 respectively. Annual CO_2 emissions have increased globally from approximately 23,600 Mt in 2000 to about 33,400 Mt in 2017 (“BP Statistical Review of World Energy” 2018). During the same period, CO_2 emissions in Middle Eastern countries have increased from approximately 1,060 Mt to about 2,110 Mt as shown in Figure 2. In this period, the average annual growth rates in CO_2 emissions for the world and Middle

East have been approximately 2.2% and 4.6%, respectively. These values indicate the necessity of investigating environmental issues of Middle East. To better understand the trend in CO_2 emissions, values for the countries investigated here are presented for several years in Figure 3. The average annual growth rates in CO_2 emissions between 2000 and 2017 for Iran, Qatar, Saudi Arabia, UAE, and Kuwait are approximately 4.1%, 10.2%, 4.6%, 4.6% and 4.0%, respectively. These values are higher than global values.

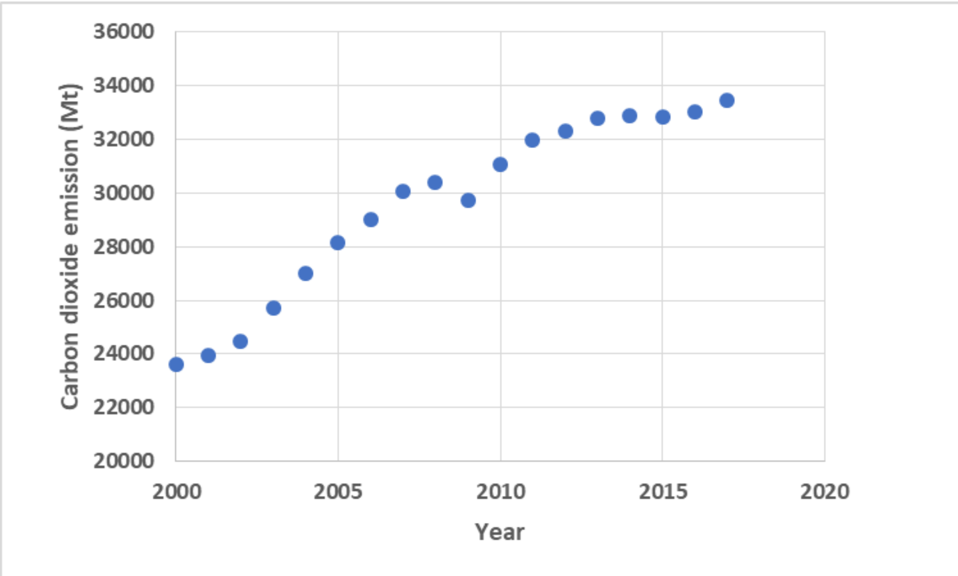

Figure 1. CO_2 emissions in the world ("BP Statistical Review of World Energy" 2018).

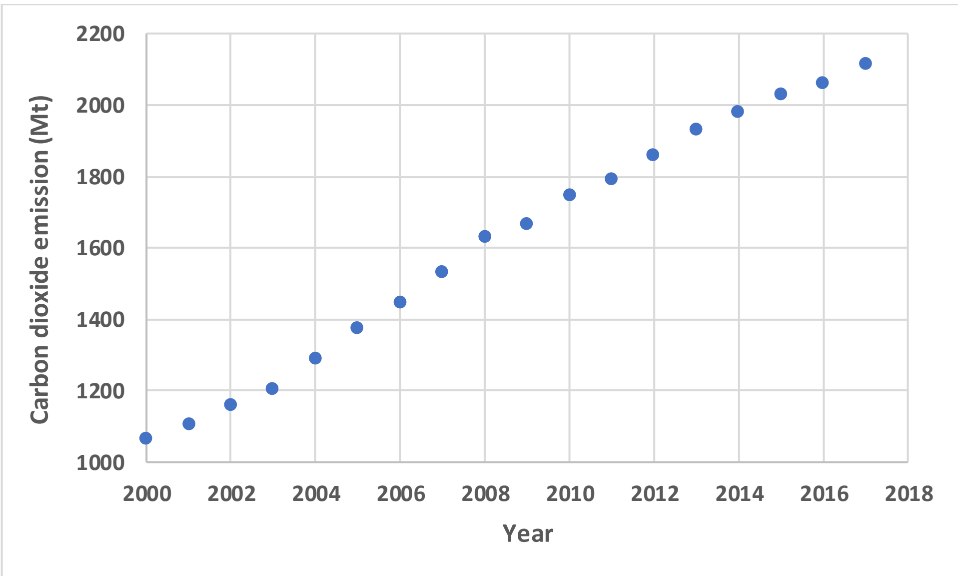

Figure 2. CO_2 emissions in the Middle East ("BP Statistical Review of World Energy" 2018).

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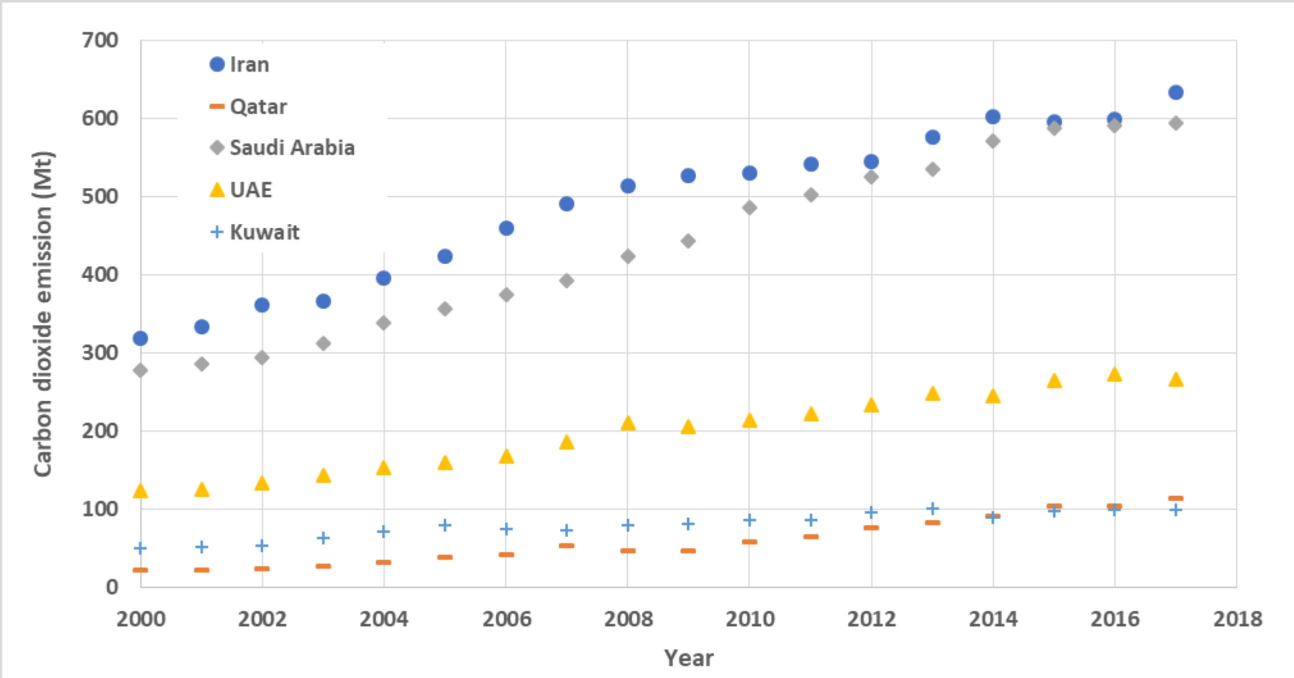

Figure 3. **CO_2** emissions for the investigated countries ("BP Statistical Review of World Energy" 2018).

CO_2 emissions are mainly caused by fossil fuel energy use; therefore, investigating the related values can provide useful insights into the corresponding environmental challenges. Primary Energy Consumption (PEC) between 2000 and 2017 of the world and Middle Eastern countries is illustrated in Figure 4 and Figure **5**, respectively. During this period, the PEC of the world increased from approximately 9,360 Mtoe to 13,500 Mtoe; while the PEC of the Middle East increased from 415 Mtoe to 897 Mtoe ("BP Statistical Review of World Energy" 2018). The average annual growth rates of PEC between these years were approximately 4.4% and 2.1% for the Middle East countries and the world, respectively. The average growth rate of energy consumption in Middle East is more than twice that of the world, mainly due to such factors as energy abundance, low efficiency, cost of energy and inappropriate use of energy.

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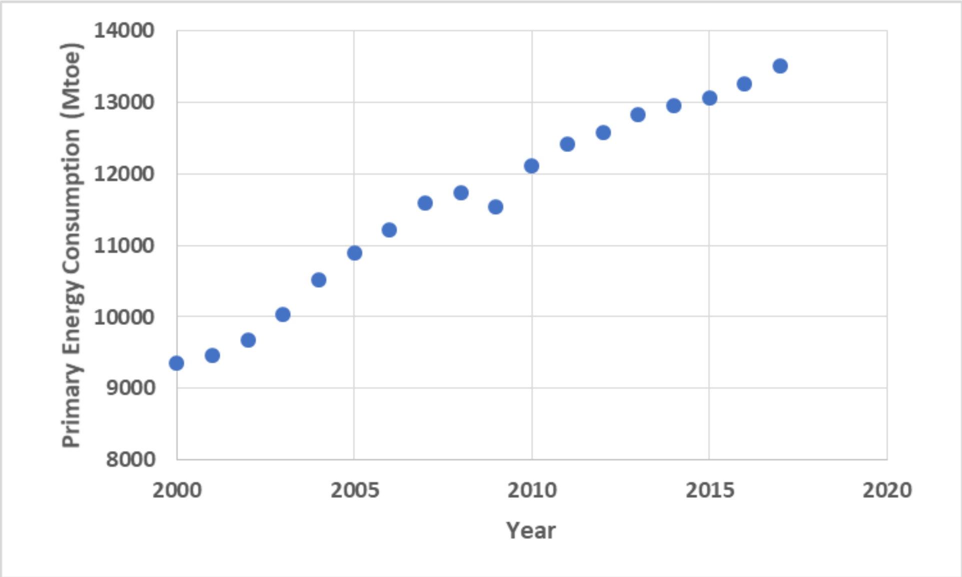

Figure 4. Primary energy consumption of the world ("BP Statistical Review of World Energy" 2018).

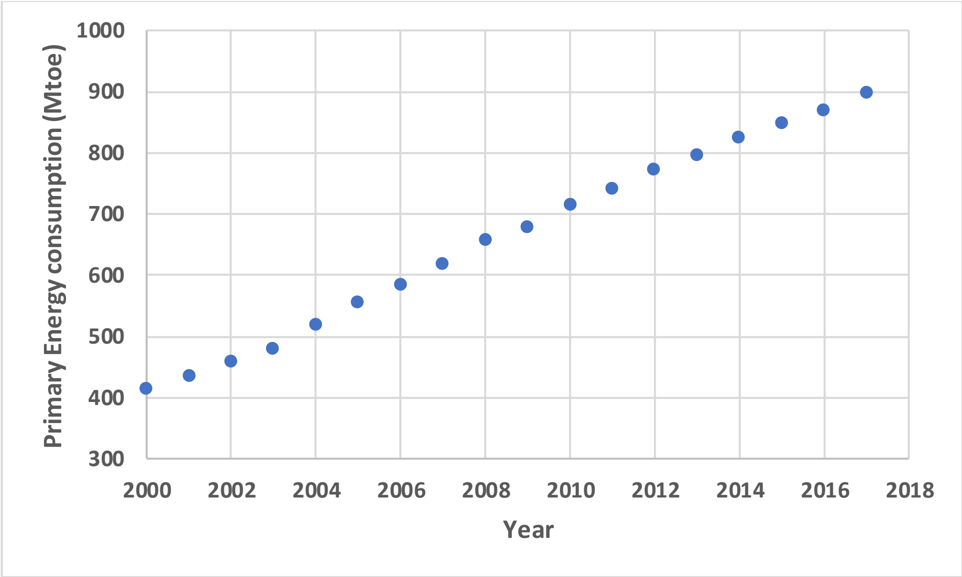

Figure 5. Primary energy consumption of Middle East countries ("BP Statistical Review of World Energy" 2018).

The countries considered in the current work play key role in the global energy sector due to their notable shares of both oil and natural gas production. As shown in Figure 6, in 2017 these countries accounted for approximately 16% of the world's natural gas production. Iran has the highest share with 6.1% of global natural gas production and Qatar has the next highest share with 4.8%. Also in 2017, the countries considered here account for about 27% of world oil production, as illustrated in Figure *7*. Saudi Arabia accounts for the highest share of oil production with 12.8%, while Iran accounts for the next highest share with 5.3%. In part because the countries considered here are energy resource-rich regions, their energy costs are low.

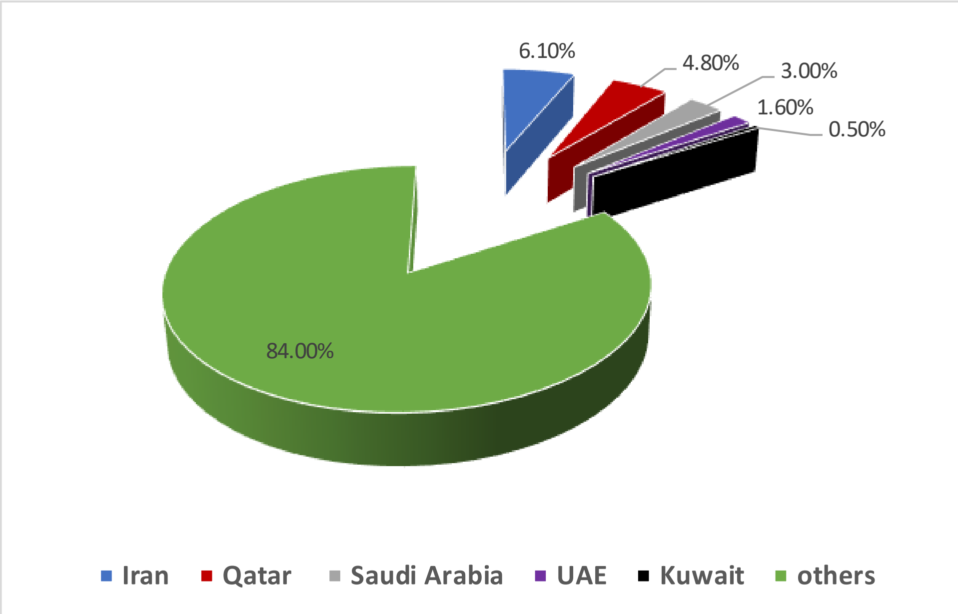

Figure 6. Shares of natural gas production attributable to the countries considered ("BP Statistical Review of World Energy" 2018).

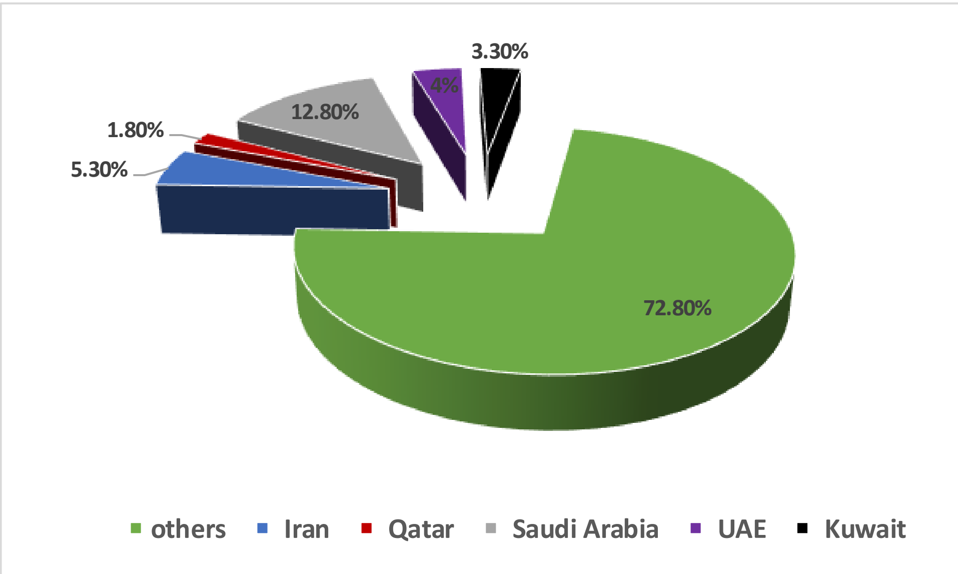

Figure 7. Shares of natural oil production attributable to the countries considered ("BP Statistical Review of World Energy" 2018).

In order to predict CO_2 emission of these countries, five input variables are considered: oil, natural gas, coal and renewable energy use as well as GDP. The latter is an indicator of economic activity. All data are obtained from Refs ("BP Statistical Review of World Energy" 2018; "IEA - Report" n.d.) between 1990 and 2015. The shares of gathered data utilized in

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training the NN and its testing and validation are defined according to related references (Mohammad H Ahmadi et al. 2018; Rezaei et al. 2018; Mohammad Hossein Ahmadi et al. 2019). 80% of the data are employed for training the network, while 20% are used for evaluating the trained network. Note that the data are divided randomly in order to prevent any bias, and no criteria are applied for selecting the data for training and testing the network.

By applying the GMDH ANN, the following regression model is obtained as:

$$CO_2 \text{ emission (Mt)} = 46.2068 + x_1^{1/3} * x_2^{1/3} *6.92072 + x_1 * x_2 *(-0.016363) + x_3^{1/3} * x_4^{1/3} *89.9774 + x_3^{1/3} *(-18.0261) + x_1 * x_3^{1/3} *(-0.528955) + x_1 * x_2^{1/3} *0.546926 + x_2 * x_2^{1/3} *0.422503 + x_1 * x_4^{1/3} *0.92734 + x_1^{2/3} *(-20.8425) + x_2^{1/3} * x_4^{1/3} *(-17.1947) + x_3^{2/3} *89.3559 + x_3 *(-133.129) + x_5^{1/3} *(-34.8123) + x_1^{1/3} * x_5^{1/3} *25.6853 + x_1^2 *0.00811567 + x_1 * x_5^{1/3} *(-0.147257) + x_5 *(-0.360737) + x_3^{1/3} * x_4^{1/3} *(-38.0333) + x_3 * x_1^{1/3} *26.6533 + x_1^{1/3} * x_4^{1/3} *(-11.7336)$$

Here, x_1, x_2, x_3 and x_4 denote consumptions of oil, natural gas, coal, and renewable (mtoe), respectively, and x_5 denotes the GDP of the countries (in billion USD). Several criteria are employed for assessment of the accuracy of the regression model (Kadiyala and Kumar 2012; M.-A. Ahmadi and Bahadori 2015). In the first step, actual data and calculated data with the model are compared (see Figure 8). As shown, the R-squared value of the proposed regression by GMDH is 0.9998. This determined value is higher than that obtained in a previous study performed for carbon dioxide emission prediction of some Nordic countries (Rezaei et al. 2018), which was 0.998. The majority of the estimated data by the model agree very well with actual data. The accuracy of the model indicates that appropriate variables are selected as input data in that they affect the model output, and the effectiveness of the model. Since the combustion of fuels produces a defined range of carbon dioxide, their consumptions must be considered to obtain an accurate model. Nonetheless, economic activities also influences GHGs emissions, so it is important that it be considered here.

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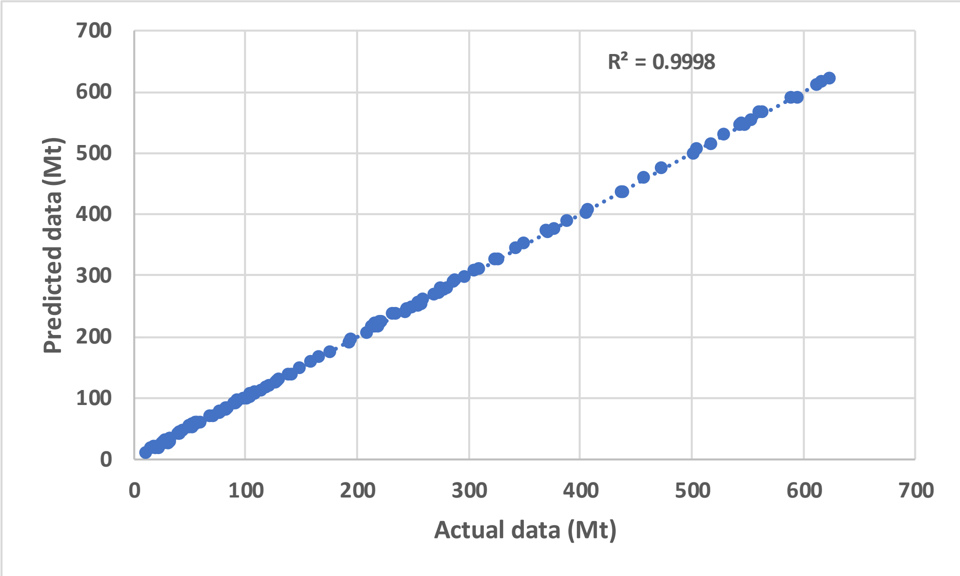

Figure 8. Carbon dioxide emissions determined by the model vs actual data.

Relative error is another criterion applicable for the assessment of model accuracy. In Figure 9, the relative error of the model on the basis of the data index is presented. The maximum error of the model in predicting carbon dioxide emissions is 23%, while the error of more than 88% of predicted data are in the bound of ±5%. The average absolute error of the model for all data is approximately 2.3% which also supports an acceptable level of accuracy for the model. This low value of average error is an indicator of the high accuracy of the model and its reliability in forecasting CO_2 emissions of the investigated countries.

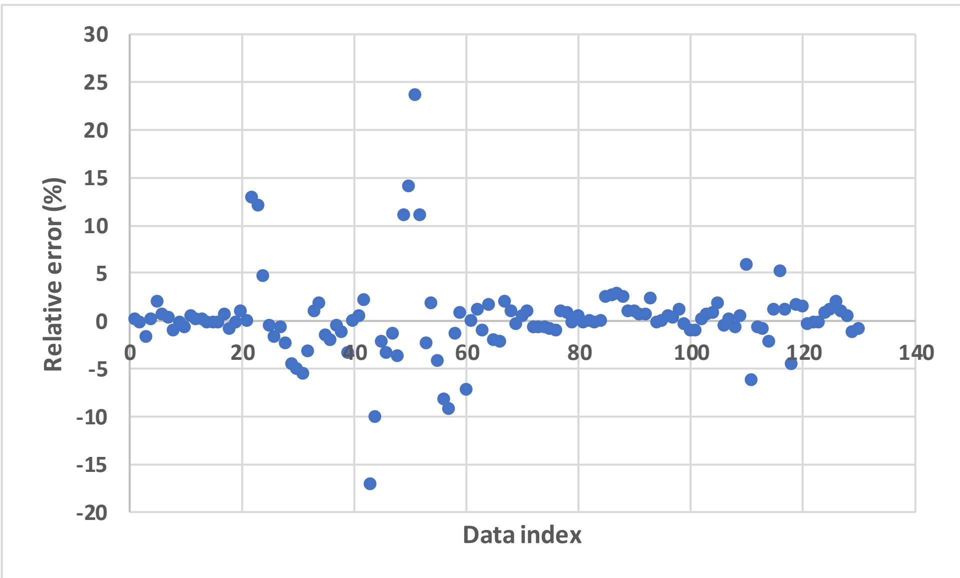

Figure 9. Relative error of the model in predicting emissions of carbon dioxide.

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Finally, the actual values and the outputs of the model, based on the data index, are compared. As depicted in Figure 10, the outputs of the model are very similar to the actual data obtained from reliable references. Thus, the proposed model by employing GMDH ANN is an accurate and reliable approach for predicting carbon dioxide emissions of the considered Middle Eastern countries. Since there are no similar mathematical models for the investigated countries, the accuracy of the model cannot be compared with other studies; however, according to the utilized statistical criteria, the model has acceptable accuracy and can be reliably applied for predicting CO_2 emissions in future years.

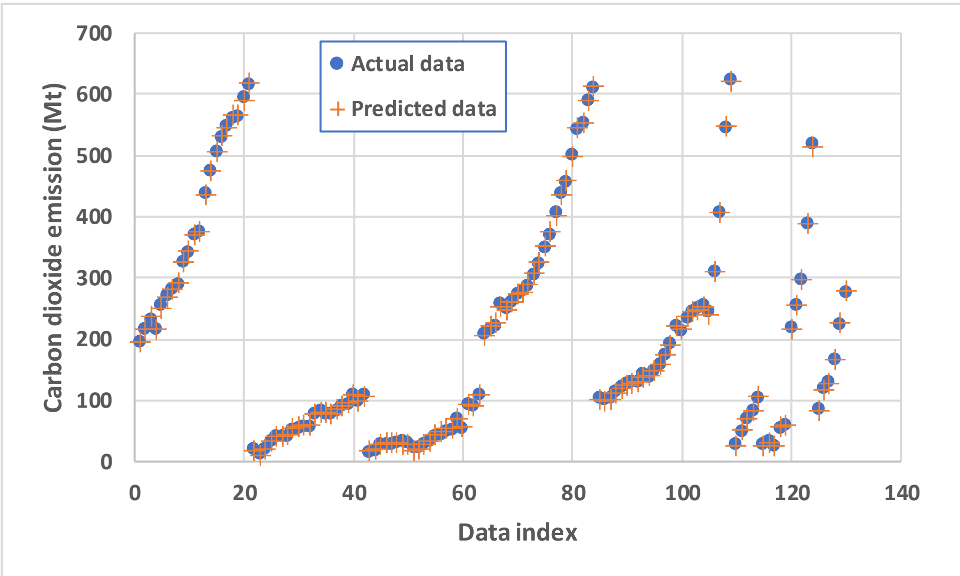

Figure 10. Comparison of GMDH output and actual data for emissions of carbon dioxide.

In order to gain insight into the impact of the various utilized input variables, the emissions of CO_2 versus each input variable are illustrated for Iran, one of the considered countries, in Figure 11 to Figure 12. There, emissions of CO_2 are observed to increase significantly with the consumption of various fossil fuels. In addition, it is confirmed that utilizing renewable energies instead of fossil fuels results in lower CO_2 emissions.

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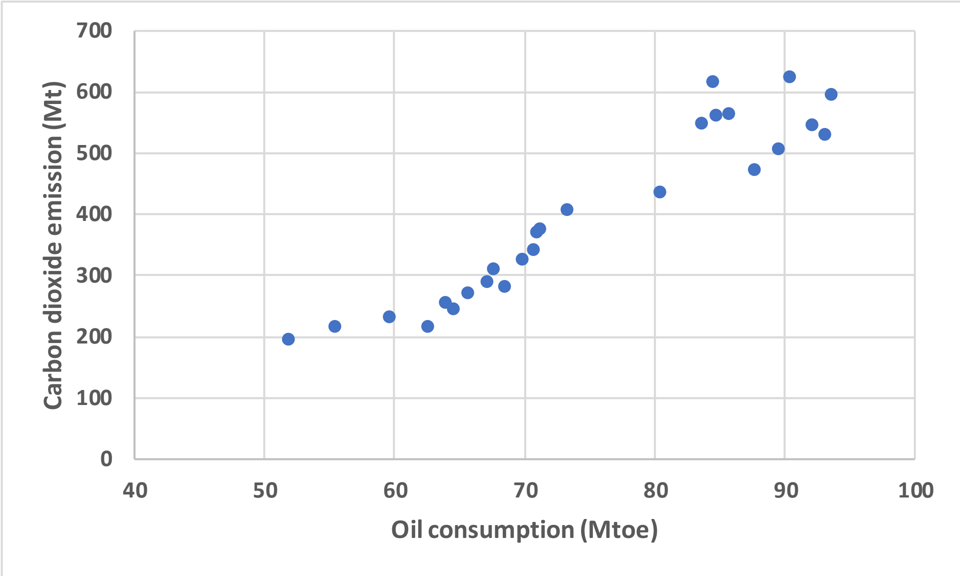

Figure 11. CO_2 emission vs oil consumption in Iran between 2000 and 2017 ("BP Statistical Review of World Energy" 2018).

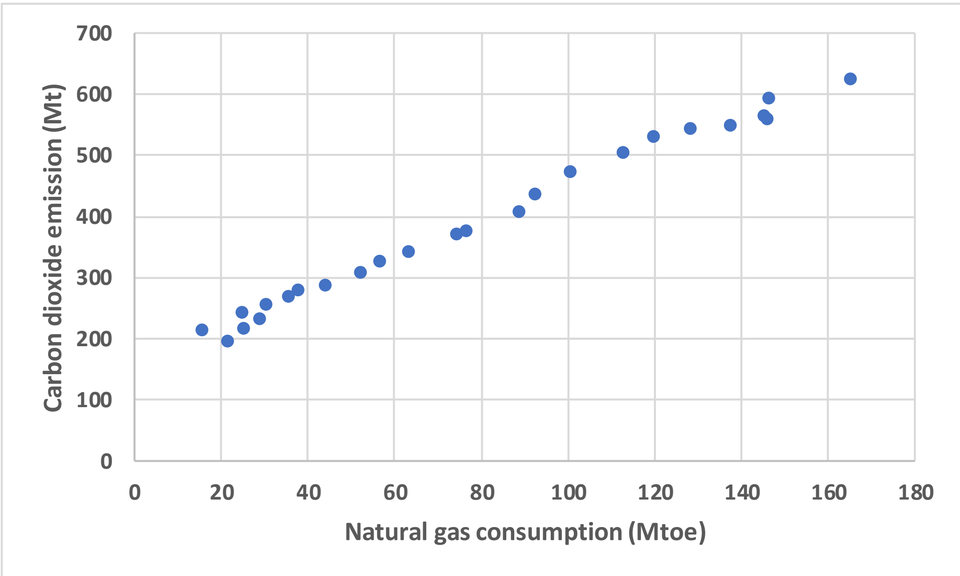

Figure 12. CO_2 emission vs natural gas consumption in Iran between 2000 and 2017 ("BP Statistical Review of World Energy" 2018).

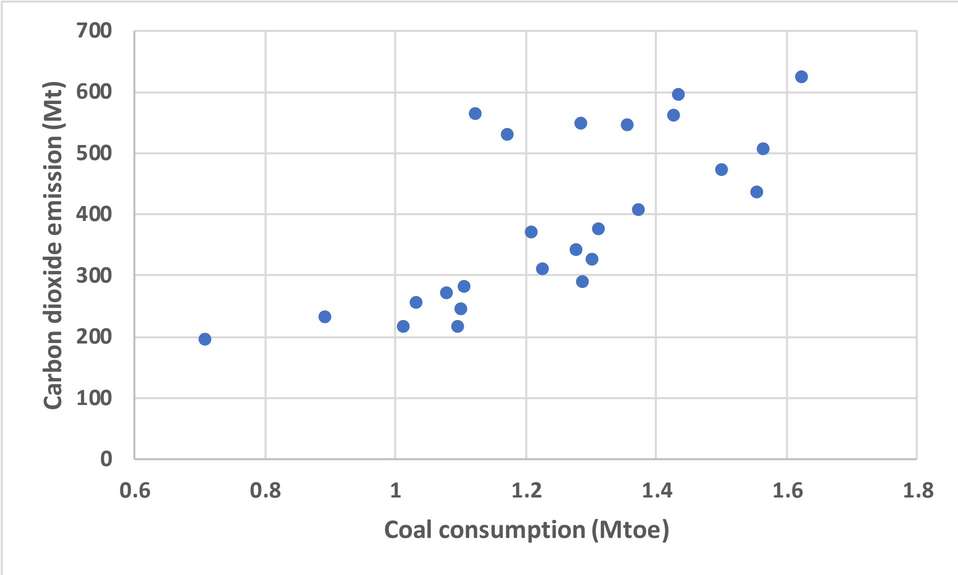

Figure 13. CO_2 emission vs coal consumption in Iran between 2000 and 2017 ("BP Statistical Review of World Energy" 2018).

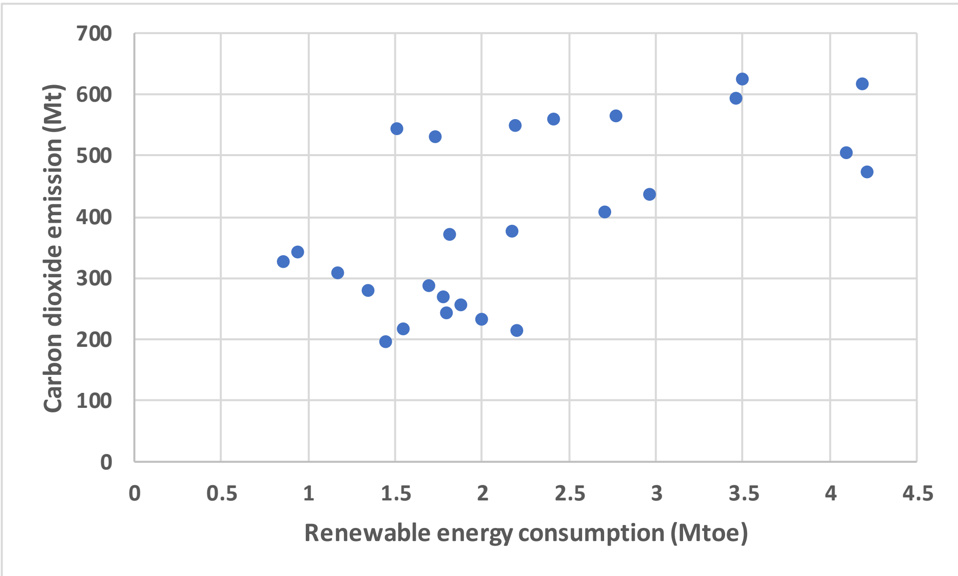

Figure 14. CO_2 emission vs renewable energy consumption in Iran between 2000 and 2017 ("BP Statistical Review of World Energy" 2018).

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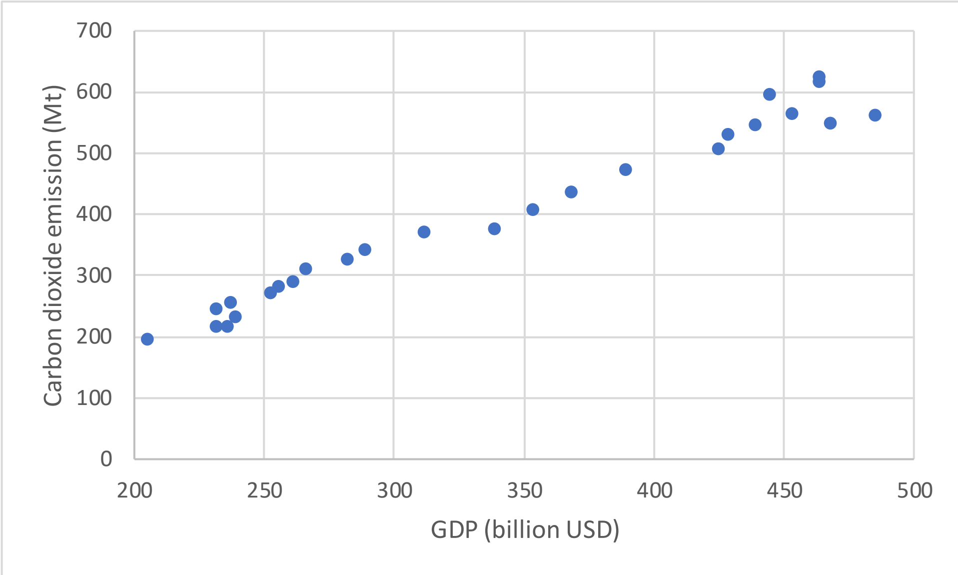

Figure 15. CO_2 emission vs GDP in Iran between 2000 and 2017 ("BP Statistical Review of World Energy" 2018).

4. Conclusion

In the present work, a GMDH ANN is used to determine emissions of carbon dioxide, the most important GHG, for five Middle Eastern countries, including Iran, Qatar, Saudi Arabia, United Arab Emirates and Kuwait. Consumption of fossil fuels, including coal, oil and natural gas, in addition to renewable energy sources are utilized as input variables for training the network. Also, GDP is considered as an input, as an indicator of economic activity, to improve the accuracy of the model. The ANN model is successfully trained for the prediction of carbon dioxide emissions according to the statistical assessment of the model. The values of R-squared and average absolute error of the models are 0.9998 and 2.3%, respectively. The accuracy of the proposed regression is attributed to the appropriate selection of input variables and the effectiveness of the applied method.

Author Contributions: All authors contributed equally to the paper.

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

References

Ahmadi, M.H., M. Alhuyi Nazari, R. Ghasempour, F. Pourfayaz, M. Rahimzadeh, and T. Ming. 2018. "A Review on Solar-Assisted Gas Turbines." *Energy Science and Engineering*. https://doi.org/10.1002/ese3.238.

Ahmadi, M.H., M. Ghazvini, M. Sadeghzadeh, M. Alhuyi Nazari, R. Kumar, A. Naeimi, and T. Ming. 2018. "Solar Power Technology for Electricity Generation: A Critical Review." *Energy Science and Engineering*. https://doi.org/10.1002/ese3.239.

Ahmadi, Mohammad-Ali, and Alireza Bahadori. 2015. "A LSSVM Approach for Determining Well Placement and Conning Phenomena in Horizontal Wells." *Fuel* 153 (August): 276–83. https://doi.org/10.1016/J.FUEL.2015.02.094.

Ahmadi, Mohammad H., Mohammad Ali Jokar, Tingzhen Ming, Michel Feidt, Fathollah Pourfayaz, and Fatemeh Razi Astaraei. 2018. "Multi-Objective Performance Optimization of Irreversible Molten Carbonate Fuel Cell–Braysson Heat Engine and Thermodynamic Analysis with Ecological Objective Approach." *Energy* 144 (February): 707–22. https://doi.org/10.1016/J.ENERGY.2017.12.028.

Ahmadi, Mohammad H, Fatemeh Hajizadeh, Mohammad Rahimzadeh, Mohammad B Shafii, and Ali J Chamkha. 2018. "Application GMDH Artificial Neural Network for Modeling of Al 2 O 3 / Water and Al 2 O 3 / Ethylene Glycol Thermal Conductivity." *International Journal of Heat and Technology* 36 (3): 773–82.

Ahmadi, Mohammad Hossein, Mohammad Ali Ahmadi, Mohammad Alhuyi Nazari, Omid Mahian, and Roghayeh Ghasempour. 2018. "A Proposed Model to Predict Thermal Conductivity Ratio of Al2O3/EG Nanofluid by Applying Least Squares Support Vector Machine (LSSVM) and Genetic Algorithm as a Connectionist Approach." *Journal of Thermal Analysis and Calorimetry*, February, 1–11. https://doi.org/10.1007/s10973-018-7035-z.

Ahmadi, Mohammad Hossein, Mohammad Ali Ahmadi, Mirhadi S. Sadaghiani, Mahyar Ghazvini, Sadegh Shahriar, and Mohammad Alhuyi Nazari. 2017. "Ground Source Heat Pump Carbon Emissions and Ground-Source Heat Pump Systems for Heating and Cooling of Buildings: A Review." *Environmental Progress & Sustainable Energy*, November. https://doi.org/10.1002/ep.12802.

Ahmadi, Mohammad Hossein, Mahyar Ghazvini, Milad Sadeghzadeh, Mohammad Alhuyi Nazari, Ravinder Kumar, Abbas Naeimi, and Tingzhen Ming. 2018. "Solar Power Technology for Electricity Generation: A Critical Review." *Energy Science & Engineering* 6 (5): 340–61. https://doi.org/10.1002/ese3.239.

Ahmadi, Mohammad Hossein, Mahdi Ramezanizadeh, Mohammad Alhuyi Nazari, Giulio Lorenzini, Ravinder Kumar, and Ravindra Jilte. 2018. "Applications of Nanofluids in Geothermal: A Review." *Mathematical Modelling of Engineering Problems* 5 (4): 281–85. https://doi.org/10.18280/mmep.050402.

Ahmadi, Mohammad Hossein, Milad Sadeghzadeh, Amir Hossein Raffiee, and Kwok-wing Chau. 2019. "Applying GMDH Neural Network to Estimate the Thermal Resistance and Thermal Conductivity of Pulsating Heat Pipes." *Engineering Applications of Computational Fluid Mechanics* 13 (1): 327–36.

https://doi.org/10.1080/19942060.2019.1582109.

Alhuyi Nazari, M., M.H. Ahmadi, R. Ghasempour, M.B. Shafii, O. Mahian, S. Kalogirou, and S. Wongwises. 2018. "A Review on Pulsating Heat Pipes: From Solar to Cryogenic Applications." *Applied Energy* 222. https://doi.org/10.1016/j.apenergy.2018.04.020.

Alizadeh, Hossein, Roghayeh Ghasempour, Fatemeh Razi Astaraei, and Mohammad Alhuyi Nazari. 2016. "Numerical Modeling of PV Cooling by Using Pulsating Heat Pipe." In *The 3rd International Conference and Exhibition on Solar Energy ICESE-2016*. Tehran.

Anifantis, Alexandros Sotirios, Andrea Colantoni, and Simone Pascuzzi. 2017. "Thermal Energy Assessment of a Small Scale Photovoltaic, Hydrogen and Geothermal Stand-Alone System for Greenhouse Heating." *Renewable Energy* 103: 115–27. https://doi.org/10.1016/j.renene.2016.11.031.

Atashrouz, Saeid, Gholamreza Pazuki, and Younes Alimoradi. 2014. "Estimation of the Viscosity of Nine Nanofluids Using a Hybrid GMDH-Type Neural Network System." *Fluid Phase Equilibria* 372: 43–48. https://doi.org/10.1016/j.fluid.2014.03.031.

Baghban, Alireza, Mostafa Kahani, Mohammad Alhuyi Nazari, Mohammad Hossein Ahmadi, and Wei-Mon Yan. 2019. "Sensitivity Analysis and Application of Machine Learning Methods to Predict the Heat Transfer Performance of CNT/Water Nanofluid Flows through Coils." *International Journal of Heat and Mass Transfer* 128 (January): 825–35. https://doi.org/10.1016/J.IJHEATMASSTRANSFER.2018.09.041.

"BP Statistical Review of World Energy." 2018.

Caliskan, Hakan, Ibrahim Dincer, and Arif Hepbasli. 2013. "Energy, Exergy and Sustainability Analyses of Hybrid Renewable Energy Based Hydrogen and Electricity Production and Storage Systems: Modeling and Case Study." *Applied Thermal Engineering* 61 (2): 784–98. https://doi.org/10.1016/j.applthermaleng.2012.04.026.

Dehghani Madvar, Mohammad, Mohammad Alhuyi Nazari, Jamal Tabe Arjmand, Alireza Aslani, Roghayeh Ghasempour, and Mohammad Hossein Ahmadi. 2018. "Analysis of Stakeholder Roles and the Challenges of Solar Energy Utilization in Iran." *International Journal of Low-Carbon Technologies* 13 (4): 438–51. https://doi.org/10.1093/ijlct/cty044.

Haghighi Bardineh, Yashar, Fatemeh Mohamadian, Mohammad Hossein Ahmadi, and Nazila Akbarianrad. 2018. "Medical and Dental Applications of Renewable Energy Systems." *International Journal of Low-Carbon Technologies* 13 (4): 320–26. https://doi.org/10.1093/ijlct/cty040.

"IEA - Report." n.d. Accessed April 15, 2018. http://www.iea.org/statistics.

Kadiyala, A, and A Kumar. 2012. *Guidelines for Operational Evaluation of Air Quality*

Models. LAP LAMBERT Academic Publishing. https://www.morebooks.de/store/gb/book/guidelines-for-operational-evaluation-of-air-quality-models/isbn/978-3-8465-3277-5.

Loni, Reyhaneh, E. Askari Asli-Ardeh, B. Ghobadian, M.H. Ahmadi, and Evangelos Bellos. 2018. “GMDH Modeling and Experimental Investigation of Thermal Performance Enhancement of Hemispherical Cavity Receiver Using MWCNT/Oil Nanofluid.” *Solar Energy* 171 (September): 790–803. https://doi.org/10.1016/J.SOLENER.2018.07.003.

Loni, Reyhaneh, Alibakhsh Kasaeian, Kazem Shahverdi, Ezzatollah Askari Asli-Ardeh, Barat Ghobadian, and Mohammad H. Ahmadi. 2017. “ANN Model to Predict the Performance of Parabolic Dish Collector with Tubular Cavity Receiver.” *Mechanics & Industry* 18 (4): 408. https://doi.org/10.1051/meca/2017016.

Masson-Delmotte, Valérie, Panmao Zhai, Hans-Otto Pörtner, Debra Roberts, Jim Skea, Priyadarshi R Shukla, Anna Pirani, et al. 2018. “Global Warming of 1.5°C.” https://report.ipcc.ch/sr15/pdf/sr15_spm_final.pdf.

Mirzaei, Mojtaba, Mohammad Hossein Ahmadi, Mohammad Mobin, Mohammad Alhuyi Nazari, and Reza Alayi. 2018. “Energy, Exergy and Economics Analysis of an ORC Working with Several Fluids and Utilizes Smelting Furnace Gases as Heat Source.” *Thermal Science and Engineering Progress* 5 (March): 230–37. https://doi.org/10.1016/j.tsep.2017.11.011.

Mohamadian, Fatemeh, Leila Eftekhar, and Yashar Haghighi Bardineh. 2018a. “Applying GMDH Artificial Neural Network to Predict Dynamic Viscosity of an Antimicrobial Nanofluid.” *Mashhad University of Medical Sciences* 5 (4): 217–21. https://doi.org/10.22038/NMJ.2018.05.00005.

———. 2018b. “Applying GMDH Artificial Neural Network to Predict Dynamic Viscosity of an Antimicrobial Nanofluid.” *Nanomedicine Journal* 5 (4): 217–21. https://doi.org/10.22038/NMJ.2018.05.00005.

Mohammadi, Amin, Mohammad H. Ahmadi, Mokhtar Bidi, Fatemeh Joda, Antonio Valero, and Sergio Uson. 2017. “Exergy Analysis of a Combined Cooling, Heating and Power System Integrated with Wind Turbine and Compressed Air Energy Storage System.” *Energy Conversion and Management* 131 (January): 69–78. https://doi.org/10.1016/J.ENCONMAN.2016.11.003.

Naseri, Ali, Mokhtar Bidi, Mohammad H. Ahmadi, and R. Saidur. 2017. “Exergy Analysis of a Hydrogen and Water Production Process by a Solar-Driven Transcritical CO2 Power Cycle with Stirling Engine.” *Journal of Cleaner Production* 158 (August): 165–81. https://doi.org/10.1016/J.JCLEPRO.2017.05.005.

O, Edenhofer, Pichs-Madruga R, Sokona Y, Seyboth K, Kadner S, Zwickel T, Eickemeier P, et al. 2011. *Renewable Energy Sources and Climate Change Mitigation: Special Report* *of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

"PARIS AGREEMENT." 2015.

PHAM, D. T., and X. LIU. 1994. "Modelling and Prediction Using GMDH Networks of Adalines with Nonlinear Preprocessors." *International Journal of Systems Science* 25 (11): 1743–59. https://doi.org/10.1080/00207729408949310.

Ramezanizadeh, Mahdi, Mohammad Ali Ahmadi, Mohammad Hossein Ahmadi, and Mohammad Alhuyi Nazari. 2018. "Rigorous Smart Model for Predicting Dynamic Viscosity of Al2O3/Water Nanofluid." *Journal of Thermal Analysis and Calorimetry* 1. https://doi.org/10.1007/s10973-018-7916-1.

Ramezanizadeh, Mahdi, Mohammad Alhuyi Nazari, Mohammad Hossein Ahmadi, and Lingen Chen. 2019. "A Review on the Approaches Applied for Cooling Fuel Cells." *International Journal of Heat and Mass Transfer* 139 (August): 517–25. https://doi.org/10.1016/J.IJHEATMASSTRANSFER.2019.05.032.

Ramezanizadeh, Mahdi, Mohammad Alhuyi Nazari, Mohammad Hossein Ahmadi, Giulio Lorenzini, Ravinder Kumar, and Ravindra Jilte. 2018. "A Review on the Solar Applications of Thermosyphons." *Mathematical Modelling of Engineering Problems* 5 (4): 275–80. https://doi.org/10.18280/mmep.050401.

Rezaei, Mohammad Hossein, Milad Sadeghzadeh, Mohammad Alhuyi Nazari, Mohammad Hossein Ahmadi, and Fatemeh Razi Astaraei. 2018. "Applying GMDH Artificial Neural Network in Modeling CO2 Emissions in Four Nordic Countries." *International Journal of Low-Carbon Technologies* 13 (3): 266–71. https://doi.org/10.1093/ijlct/cty026.

Shahsavar, Amin, Shoaib Khanmohammadi, Arash Karimipour, and Marjan Goodarzi. 2019. "A Novel Comprehensive Experimental Study Concerned Synthesizes and Prepare Liquid Paraffin-Fe3O4 Mixture to Develop Models for Both Thermal Conductivity & Viscosity: A New Approach of GMDH Type of Neural Network." *International Journal of Heat and Mass Transfer* 131: 432–41. https://doi.org/10.1016/j.ijheatmasstransfer.2018.11.069.

Toghyani, Somayeh, Mohammad H. Ahmadi, Alibakhsh Kasaeian, and Amir H. Mohammadi. 2016. "Artificial Neural Network, ANN-PSO and ANN-ICA for Modelling the Stirling Engine." *International Journal of Ambient Energy* 37 (5): 456–68. https://doi.org/10.1080/01430750.2014.986289.

Zoqi, Mohammad Javad, Mohammad Ghamgosar, Moslem Ganji, and Saeed Fallahi. 2016. "Application of GMDH and Genetic Algorithm in Fraction in Biogas from Landfill Modeling." *J.Env. Sci. Tech.* 18 (3): 1–12.