Prediction of Potential Carbon Dioxide Emissions of Selected Emerging Economies Using Artificial Neural Network

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Abstract: Tackling future global emissions of carbon dioxide is a daunting task. Different black box models have been used to determine the trajectories of CO₂ emissions and other carbon stocks. Trajectories are important because climate modelers use them to project future climate under higher atmospheric CO₂ concentrations. In this paper, fully connected two-layer feed-forward neural network with tangent activation function that comes with hidden neurons as well as linear output neurons was used. The study applied classical nonlinear least squares algorithm such as LM (Levenberg-Marquardt), to predict potential emissions of selected emerging economies. Building the model on the basis of input variables such as crop production, livestock production, trade imports, trade exports, economic growth, renewable and nonrenewable energy consumption. These variables are considered to affect the ecosystems of high rising economic power states. The main idea is to ensure that emerging economies have a clear understanding of expected future emissions so that appropriate measures can be implemented to mitigate its impact. Data for the analysis were obtained from 1971 to 2013 from World Development Indicators and FAOSTAT database. Results indicate an achievement of training performance at epoch 11 when the value of the MSE (Mean Square Error) is 0.0003345 which indicates that the model errors are less than 0.05. Hence, the study concluded that the applied model is capable of predicting potential carbon dioxide emissions in emerging economies with the greatest precision.

Key words: Carbon dioxide emissions, ANN (Artificial Neural Network), LM, Emerging economies.

1. Introduction

Reducing future emissions from the global carbon stock is a daunting task. Many researchers have used more or less different models of black boxes, fed into by economic growth, population, industrialization, and energy consumption to produce trajectories of carbon dioxide (CO₂) emissions and other carbon stocks worldwide. Currently, with the burgeoning development of an economy, CO₂ emissions increase in emerging economies in particular has become unprecedented. The search for efficient methods to forecast CO₂ emissions and propose targeted reduction measures has become a common concern. Hence, identification of the trajectories is important because climatic modelers use them to project the future climate with higher concentrations of CO₂ in the atmosphere. The argument now is on the technique to use to produce effective, efficient and accurate prediction based on non-marginal changes in the results. Several scholars have considered the econometric approach to find the connection between disaggregated form of agriculture production [1, 2]; energy consumption [3-6]; international trade [7, 8] and environmental pollution. Others as well have focused on using econometric modus operandi such as ARIMA [9-11]; extreme learning machine [12] and other optimization algorithms [13] to predict emissions. The argument of some researchers however remains that the use of econometric methods does not
generally lend themselves to these non-marginal changes [14-16].

On the other hand, several researchers have used ANNs (Artificial Neural Networks) [14, 17, 18] and have shown great potentials for conducting prediction. A typical example is a study by Nuroğlu [14] which is similar to our current study, used 15 EU countries for the period from 1964 to 2003. The model of increased severity was applied to real bilateral exports as a dependent variable, while the volatility of Exchange rates as influential factors, income, distances between the countries and population were considered as predictors. To arrive at the results of the study, a panel econometric model with fixed effect and neural network of neurons were used. The empirical results of the neural network gave 97% of the variation in exports explained by the explanatory variables compared to 84% of econometric panel model. The study also revealed a lower MSE (Mean Square Error) of 0.02 (neural network) compared to an MSE of 2.97 (econometric panel model). Nuroğlu [14] argued that, based on the results, the prediction technique of the neural network is superior to the econometric method.

There are so many instances in empirical studies that ANN has been applied to predict various kinds of variables with different explanatory variables based on country-level and cross-section of countries [15, 19-24]. A study in Turkey by Özceylan [25] predicted carbon dioxide emissions; while energy consumption was predicted by Azadeh, et al. [26] in Iran; Geem and Roper [27] energy demand in South Korea; Ekonomou [28] energy consumption in Greece and Pao [29] total energy use in Taiwan. Rezaei, et al. [30] deployed Group Method of Data handling to predict CO₂ emissions using economic activities such as total primary energy use and gross domestic product as driving factors of emissions. These research works lead to the fact that most of the predictions are done on energy with scanty work on emissions especially potential carbon dioxide emissions of emerging economies.

To predict potential carbon dioxide emissions of emerging economies as BRICS (i.e. Brazil, Russia, India, China and South Africa), the study applied distinct non-cumulative variables of agriculture production, energy consumption and international trade based on World Resources Institute [31] report. The report emphatically pointed the agricultural sector as the second leading emitter in the world, after the energy sector (i.e. emissions from power consumption and transport). The general idea is that increased agricultural production, energy consumption, and international trade lead to higher emissions. Therefore, it is necessary to use a disaggregated component of these variables to predict possible potential emissions. Thus, to ensure that emerging economies understand future emissions well so that appropriate measures can be put in place to mitigate their impact. To achieve the stated goal, the study applied ANN. Neural network is a forecasting technique that attempts to mimic the doings of neurons in the human brain. Neural network acts as the human brain by recognizing the pattern of the data fed into the system, learns from the experience and then generates results based on previous knowledge. Thus, neural network is structured in a model form which is represented by interconnected neurons. The main idea of the neural network is to capture a complex nexus between output and inputs by creating layers of derived variables or nodes. Neural network performs this function by creating or training the model and also tests the performance of the model.

The use of neural network comes with some advantages compared to conventional econometric techniques as put forward by some researchers. Firstly, ANN works well with any arbitrarily function provided the model has enough hidden units. Secondly, ANN can be applied without specifying any model and therefore, the desired model is based on dataset presented. This becomes highly useful when there is no theoretical backing to the data use. Thirdly, ANN is inherently non-linear, making it extra
practical and precise when modeling much more complex data patterns, as opposed to various traditional linear procedures, such as ARIMA methods. In fact, as smoothing algorithms, it is believed that ANN performs much better in prediction analysis than other linear methods. Fourthly, ANN can be applied irrespectively of whether the input data are erroneous, incomplete or incoherent. This makes the technique highly acceptable universally as the best method for predictions based on its ability to provide accurate results with inadequate input variables in the presence of a linear or non-linear relationship.

Different learning algorithms have been used in predictions using a neural network such as backward-propagation, GD (Gradient Descent) and Boyden, fletcher, goldfarb and shanno. Subsequent study findings of Mukherjee and Routroy [32] suggest these techniques to be cumbersome and slow in its process. However, learning algorithms such as LM (Levenberg-Marquardt) possess some advantages when it comes time period in training process, provision of diverse error measures and capacity to handle different neurons as alluded by Mukherjee and Routroy [32]. Additionally, the LM algorithm has better convergence properties than the GD algorithm [33]. Therefore, suitability of implementing LM algorithm for modeling and predicting potential CO₂ emissions with non-cumulative components of agriculture, energy consumption and international trade which is seldom explored is in the right direction. LM was applied on the basis of the empirical results of Refs. [32, 34, 35], which showed that the LM algorithm outperformed GD and that of Boyden, fletcher, goldfarb and shannon algorithm.

Next in line is the validation process which is considered important since it helps to avoid an excess of adjustment (i.e. overfitting) in the model. This avoidance normally happens when the dataset actually fits well in the ANN training process. One of the key step parameters that get adjusted in the course of validation is the epoch which is also the learning step in data training. Saleh, et al. [17] applied SVM (Support Vector Machine) model using trial and error approach to monitor carbon dioxide emissions of the Alcohol industry based on its energy consumption through the combustion of coal and electrical energy sources. Findings indicate that the use of Root Mean Square Error produced a small error which makes the model more accurate in terms of predictions. Saleh, et al. [36] also undertook a similar study in Indonesia sugar industry using a back-propagation neural network model with trial and error approach. The study was based on the recent trend of emissions in Indonesia which was reported to emanate from sugar industry in their operation process through fuel used in boilers as well as the electricity use, natural gas and solar energy used. These variables were used to predict the expenditure relating to carbon dioxide emissions.

Authors current study sought to open up global debate on the effect of these sectors (i.e. agriculture, energy and trade) on an environment of emerging economies so that prudent decisions can be taken to meet the associated challenges squarely. Significantly, the study will serve as an information tool for future economic policies, strategies and planning, while trying to mitigate climate impacts and ensure environmental sustainability.

2. Literature Review

Earth’s climate is changing and there is scientific evidence in this regard. The average temperature of the planet has increased by 0.8 °C during the last century and currently above 14.8 °C [37]. Pollutants such as carbon dioxide, nitrous oxide and methane are the main cause of the greenhouse effect or global warming. These pollutants are caused by several factors, the key one being deforestation caused by the intensification of agricultural activities, industrial developments and the use of hydrocarbon deposit as sources of energy. According to FAO [38], greenhouse gas emissions from agriculture, fisheries, and forestry have doubled in the last 50 years and are
expected to increase by up to 30% by 2050. The carbon footprint of agriculture, which comes from livestock, food production, fisheries and forestry, ranks fifth in the world as carbon emitters. The FAO [38] report further revealed that food and livestock emissions increased by 0.658 (or 14%) from 4.7 billion tons of carbon dioxide equivalent in 2001 to over and above 5.3 billion tons in 2011. The report postulates that this increase in emissions mostly comes from developing countries such as the BRICS due to agricultural output expansion to meet high demand.

The expansion of agricultural production contributes to economic development; this economic progress, in turn, has an impact on the environment through pollution emissions. Khashman, et al. [39] examined the non-linear association between agronomic factors and emissions in Turkey from 1968 to 2010 using neural networks. The study applied the ANN model due to the non-linear relationship between environmental emissions and factors at the origin (i.e., real income, real square income, energy consumption and agriculture). The experimental results revealed the successful approximation of a minimum MSE and a correct maximum estimation rate. Therefore, the study encourages the use of a similar model in the non-linear correlation scenario, whether temporary series or panel.

Qasrawi and Awad [40] applied multiple layers feed-forward with backpropagation neural networks to predict the solar cells power output in different parts of Palestine. The whole idea was to predict future power output of solar cell based on the real power output of the previous values. A similar procedure was used by Yan, et al. [41] to prognose solar radiation. The prediction of solar radiation should allow management to make decisions regarding the reserve of renewable energy sources. Sun, W., and Sun, J. [12] used the hybrid model form of principal component analysis to reduce the dimensionality of driving factors, hence, to forecast carbon dioxide emissions of China spanning from 1978 to 2014, using regularized extreme learning machine.

A recent study by Ye, et al. [16] used GRNN (General Regression Neural Network) to forecast CO₂ emissions with driving factors such as building’s structural attributes, relevant socioeconomic conditions, the micro-climate and the regional climate. GRNN put together various developmental scenarios in urban areas of 294 office buildings all over China. The reason is that economic progress and improving standards of building structures could have significant impacts on future CO₂ emissions. Results revealed that building’s structural attributes had the most impact on CO₂ emissions, followed by the relevant socioeconomic conditions, the micro-climate, and finally the regional climate.

The same technique was adopted by Antanasijević, et al. [23] to predict energy use as well as the intensity of carbon footprint related to energy consumption. However, the difference between the two studies is that Antanasijević, et al.’s [23] study compared GRNN to MLR (Multiple Linear Regression) to find the best prediction method using data from 26 European countries for the period of 2004 to 2012. The results exposed cost function (i.e. MAPE) of GRNN to provide more accurate results related to greenhouse carbon stock of energy consumption intensity compared to that of MLR. On the other hand, the results of the same cost function produced similar results of energy use. Yuan, et al. [42] as well, used a Bayesian approach to predict energy demand of 30 provinces in China from 1995 to 2012 using high/low growth scenarios. Empirical results of the study discovered that at the national level, energy demand is expected to grow in the future. Additionally, at a provincial level, the study also found energy demand to rise at the central and eastern parts of China in both scenarios. Corresponding to the high scenario is the findings with regards to western corridors of the country that proliferation of energy is expected in the coming years.
Table 1  Data and variable definition.

<table>
<thead>
<tr>
<th>Abbr.</th>
<th>Variable name</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO₂ eq</td>
<td>Carbon dioxide emissions</td>
<td>Kt CO₂e</td>
</tr>
<tr>
<td>GDP</td>
<td>Gross domestic product per capita</td>
<td>Gross domestic product per capita (current US$)</td>
</tr>
<tr>
<td>CRP</td>
<td>Crop production index</td>
<td>Crop production index (2004-2006=100)</td>
</tr>
<tr>
<td>LVP</td>
<td>Livestock production index</td>
<td>Livestock production index (2004-2006=100)</td>
</tr>
<tr>
<td>NRE</td>
<td>Fossil fuel energy consumption</td>
<td>Kg of oil equivalent</td>
</tr>
<tr>
<td>REN</td>
<td>Renewable energy consumption</td>
<td>Kg of oil equivalent</td>
</tr>
<tr>
<td>IMP</td>
<td>Imports of goods and services</td>
<td>Current US$</td>
</tr>
<tr>
<td>EXP</td>
<td>Exports of goods and services</td>
<td>Current US$</td>
</tr>
</tbody>
</table>

3. Material and Methods

3.1 Data Collection and Variable Definitions

To predict the potential carbon dioxide emission of emerging economies, the study data were obtained from World Development Indicators and FAOSTAT database covering sample period of 42 years from 1971 to 2013. Authors predicted the potential carbon dioxide emissions of selected emerging economies namely: China, Brazil, India and South Africa using ANN. The data used for the specified period were based on data availability. Table 1 provides data used and their descriptions. Both crop production index and livestock production index were measured for their production for each year relative to the base period 2004-2006.

In this study, the inputs to the ANN model were factors considered as the key contributors to emissions in emerging economies. To test for data fit and predictive accuracy of the model using training and validation test respectively, the study applied fully connected two-layer feed-forward neural network with hyperbolic tangent activation function which is a sigmoidal activation function that comes with hidden neurons as well as linear output neurons. The study network was trained with the LM training algorithm. The whole idea of training the model is to improve the performance of the neural network and that the application of LM training algorithm is based on the fact that it requires the use of more memory but with less operating time. This is to ensure that the error between the actual output and expected output is minimized. The process will continue based on the number of iterations (i.e. Epoch) up to the point whereby the difference between actual output and target output becomes insignificant. That is, the training of the series comes to end when generalization discontinues which is proved by an upsurge of MSE of the model. The lower the values of MSE, the better the model in terms of fitness and predictive accuracy. That is when the MSE value is zero indicates no error between the actual output values and the target value. On the other hand, Regression value of 1 indicates that the relationship between the output and target values is close while value of 0 indicates the relationship is random.

3.2 Study Design

In authors’ present study, there are seven variables employed as input variables and therefore, giving the input layer seven nodes. Hidden layer neurons, on the other hand, were determined based on Fletcher and Goss [43] formula. The formula proposes that any number of nodes between the ranges from five to eleven would provide a neural network architecture that represents the model. Fig. 1 provides the framework of the study design followed by the predicting process as Fig. 2. The structure of the framework depicted in Fig. 1 postulates the introduction of data as input variables in the network. This is followed by the use of hyperbolic tangent sigmoid activation function in the hidden layer expressed as Eq. (3). LM sometimes referred to as damped least-squares is then used to solve non-linear
least squares problems in the training process. The LM techniques blend the precipitous descent modus operandi and the Gauss-Newton algorithm using the first order derivative of total error. Although, there are several techniques that can be used as cost function such as MAPE, RMSE and MAE to evaluate the performance of the prediction. However, the study applied MSE to perform this function. The adoption of MSE as the cost function of the study is based on its analytical tractability. The results of the network also produce the regression value (R) and the number of epoch. The regression value provides the variation percentage of the explanatory variables to the dependent variables in the model while the number of epoch indicates at what point the difference between actual output and target output would become inconsequential.

3.3 The Predicting Process

ANN is not considered as a function but rather an entire process which involves various stages indicated as Fig. 2.

The process starts with the selection of the variables as authors’ data set. This is then followed by transforming or normalizing the data set into their natural logarithms. The objective of model selection is to construct a model with acceptable levels of model bias and variance. Therefore, it is necessary to split the data into three subdivisions: training, validation and test sets. To improve generalization, the study trained the network using an early stopping technique. This technique makes it possible to observe the error during the formation of the network in the validation set. What happens is that the training and validation set error decreases at the initial stage of training. However, the situation changes when the network begins to adapt due to the increase in the error in the validation set. When the error of the validation set increases during a predetermined number of iterations, the training must be stopped and the weights and biases resulting from a minimum error of the validation set are accepted. The training set is used to determine the network weights and biases. Weights show how strong a signal from one node affects the other node, while bias influences the strength of the effects of inputs on the output. So, the net effect of an explanatory variable or input on the output is calculated as the product of the input and weight, including the impact of the bias. The outcome of the validation set is predicted by using these weights and biases calculated in the training set. Then, the network architecture (i.e. as Fig. 4)—a combination of weights, biases and the number of hidden neurons—that gives the smallest validation set error is chosen and the network’s performance is evaluated by using the test set. Following the division of the dataset into three partitions, an advanced two-layer network was created. In general, it is recognized that applying too many hidden layers may result in over-adjustment of the data, resulting in low model bias and high model variance. However, the network with 10 hidden neurons gives quite satisfactory results.

Fig. 1 Framework of the study design.
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Data Set
NRE, REN, GDP, IMP, CRP, EXP, LVP, CO2eq

Data Normalization

Cross Validation

Testing Data

Table 1

Training Data

MSE

R

Fig. 2 Procedure used for prediction based on ANN.

Fig. 3 Diagram of the multilayer network.

3.4 Model Estimation

ANN is considered as thought out as a network of neurons organized into layers. The layers consist of explanatory variables (i.e. inputs), hidden layers (i.e. intermediate layers) and the predicting layer (i.e. outputs) as depicted in Fig. 3.

The coefficients or weights of the predictors are selected using the learning algorithm. The relationship between the variables both inputs and outputs can, therefore, be expressed as:

\[
X'_{it} = \begin{bmatrix}
\text{CRP}, X_1 \\
\text{LVP}, X_2 \\
\text{IMP}, X_3 \\
\text{EXP}, X_4 \\
\text{NRE}, X_5 \\
\text{REN}, X_6 \\
\text{GDP}, X_7
\end{bmatrix}, Y'_{it} = \text{CO2eq} \quad (1)
\]

The study applied cost function such as MSE expressed as Eq. (2) to check the validity of the model predictions.

\[
MSE = \sum_{i=1}^{n} \frac{\left(\text{Actual} - \text{Predicted}\right)^2}{n} \quad (2)
\]

where \( n \) is the number of data points. The Pearson correlation (R) is to measure the relationship between predicting variables and the response variable, hence, expressed as:

\[
R = \sqrt{\frac{\sum XY - \frac{\sum X \sum Y}{N}}{\sqrt{\left(\frac{\sum X^2}{N}\right)\left(\frac{\sum Y^2}{N}\right)}}}
\]

The study used a simple neural network which provides an efficient method for the model training expressed in linear form as:

\[
\ln \text{CO2eq}_t = \alpha + \lambda_1 \text{CRP}_t + \lambda_2 \text{LVP}_t + \lambda_3 \text{IMP}_t + \lambda_4 \text{EXP}_t + \lambda_5 \text{NRE}_t + \lambda_6 \text{REN}_t + \lambda_7 \text{GDP}_t + \epsilon_t \quad (3)
\]

where \( \ln\text{CRP}, \ln\text{LVP}, \ln\text{IMP}, \ln\text{EXP}, \ln\text{NRE}, \ln\text{REN} \) and \( \ln\text{GDP} \) were used to predict the potential carbon dioxide emissions through the implementation of the hyperbolic tangent function (TanH) which is a sigmoidal activation function. The sigmoidal activation function is meant to squash the large and small values in order to maintain near-linearity in mid-range. The study predicts the potential carbon dioxide emissions of emerging economies by fully adopting multi-layer perceptron model with seven neurons as an input layer, one hidden layer with three nodes and ten neurons and lastly, the main output layer with one neuron. Hyperbolic tangent activation function applied is a standardized value between -1 and 1 expressed as:

\[
g(s) = -1 + \frac{2}{1 + e^{-s}} \quad (4)
\]

where \( g \) is the activation function of the network and \( s \) is the linear combination of the study variables. Hence, the output from one layer is input into the next
layer. The output of the derived variables \((H)\) is then expressed as:

\[
H = g \left( \phi_H + \sum_{i=m}^{p} W_i H X_i \right)
\]  

(5)

where \(\phi_H\) is the bias that controls the contribution of the derived variable \(H\). \(W_i\) represents weights of the node whiles \(X_i\) is the predicting variables and \(g\) is the activation function (i.e. hyperbolic tangent function). The estimated biases of each hidden derived variables \([H(1:1), H(1:2)\) and \(H(1:3)\)] are expressed as:

\[
H(1:1) = \text{TanH}(0.5* (-0.067 + -0.083* : CRP + 0.165* : LVP + 0.051* : IMP + 0.241* : EXP + 0.090* : NRE + -0.392* : REN + 0.340* : GDP))
\]

\[
H(1:2) = \text{TanH}(0.5* (-0.317 + -0.392* : CRP + -0.190* : LVP + -0.246* : \text{IMP} + 0.490* : EXP + -0.174* : NRE + -0.114* : REN + -0.171* : GDP))
\]

\[
H(1:3) = \text{TanH}(0.5* (-0.359 + -0.081* : CRP + 0.673* : LVP + 0.031*: \text{IMP} + -0.190* : EXP + -0.827*: NRE + -0.300* : REN + 0.463*: GDP))
\]

Details of the estimated biases or parameters of each hidden derived variable as well as the output layer can be found as Table A1 (Appendix). The predicted CO2eq (\(\text{Pr}ed\text{CO2eq}\)) of the complete neural network of the study is expressed as follows:

\[
\text{Pr}ed\text{CO2eq} = -0.162 + 0.373* : H(1:1) + -0.429*: H(1:2) + -0.828*: H(1:3)
\]

3.5 The Topology of the Neural Network

Fig. 4 provides the architectural design of the neural network model in the study. ANN organizes the neurons into layers. Predicting variables (i.e. GDP, CRP, LVP, NRE, REN, IMP, and EXP) form the input layer. The intermediate layer is called the hidden layer and CO2eq is the output variable of the output layer. Neural network uses learning algorithms to select the weights/coefficients of the explanatory variables that minimize the cost function. A typical example of the cost function is MSE.

4. Results

This section dealt with the results of the neural network model. The results provide the prediction of the potential carbon dioxide emissions of emerging economies. Table 2 provides the results of the average squared error (i.e. MSE) which is the difference between actual output values and the target value of the model while the correlation between the output and target values of the model is determined using the regression value (R). To perform the training function, the study applied a numerical optimization method called LM (MSE). Training results of the network are shown in Fig. 5. As the figure shows, when the number of epochs increases the errors of all three sets decline. At the beginning of training, the decrease in squared error is very sharp, but then it decreases at a lesser pace. To analyze the accuracy of the prediction, we calculated and graphed the performance. Results of MSE value for all the test are close to zero which means no error between the actual output value and target value while regression value for all the tests when round it up equal to 1 is a clear indication that the relationship between the output and target values is close. Analyzing the results obtained, we observe the best prediction results which are highlighted by the smallest MSE value and the highest value of the calculated correlation coefficient (R), were recorded in Table 2.

In our neural network, training is stopped after 11 epochs, because at that point the error for validation set starts increasing. If the model is constructed successfully, the test set and validation set error should show similar characteristics which are proven in Table 2. The errors on the training, validation and test sets are the first means to obtain some information
Prediction of Potential Carbon Dioxide Emissions of Selected Emerging Economies Using Artificial Neural Network

![Architecture design of the neural network.](image1)

**Table 2** Performance measures and outcome of the neural network (summary report).

<table>
<thead>
<tr>
<th>Test</th>
<th>Sample</th>
<th>MSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training data scoring</td>
<td>120</td>
<td>0.0003268</td>
<td>0.99987</td>
</tr>
<tr>
<td>Validation data scoring</td>
<td>26</td>
<td>0.0003345</td>
<td>0.99976</td>
</tr>
<tr>
<td>Testing</td>
<td>26</td>
<td>0.0014624</td>
<td>0.9995</td>
</tr>
<tr>
<td>All</td>
<td></td>
<td>0.99979</td>
<td></td>
</tr>
</tbody>
</table>

![Best Validation Performance is 0.0003345 at epoch 11](image2)

Fig. 4 Architecture design of the neural network.

Fig. 5 Performance graph of the neural network.

Table 2 shows the performance measures and outcome of the neural network. The MSE (Mean Squared Error) and R (coefficient of determination) values are provided for training, validation, and testing data. The results indicate high performance with validation performance of 0.0003345 at epoch 11.

In Fig. 5, the performance graph illustrates the mean squared error (MSE) over epochs for training, validation, and testing data. The best validation performance of 0.0003345 at epoch 11 is shown.

In Fig. 6, the network outputs are plotted against the targets. With the value of R-squared, it is possible to conclude that the neural network model can explain 99.9% of the variation in CO2eq emissions with the given seven (7) inputs. The best linear fit is displayed by a dashed line. The perfect fit, which requires network outputs equal to targets, is shown by the solid line. Here, it is very difficult to differentiate the best fit from the actual data.
linear fit line from the perfect fit line because the fit is very good. Fig. 6 shows that both outputs produced by the neural network and targets prove that our model is reliable. Fig. 7 depicts error histogram with 20 Bins, which expresses the regressions between the network targets and network outputs.

Fig. 8 provides neural network predicting variables and their importance in terms of contribution to the outcome variable. Fig. 7 provides details of the predictors in terms of their importance from the most important to the least important. Results indicate nonrenewable energy use as the most important
Fig. 8  Predictors importance to potential carbon dioxide emissions.

contributor to emissions followed by livestock production with renewable energy consumption as the least important variable.

Details of the importance of the variables can be found in Table A2 (Appendix). Table A2 provides the value of contribution of each predictor to emissions of emerging economies, as well as their percentage of contribution and ranking. Fig. A1 (Appendix) on the other hand, provides a picture of the predicted and actual values of the network.

5. Conclusions

Mitigating carbon dioxide emissions is a challenge for future global warming reduction. ANN technique was used to predict emerging economies potential carbon dioxide emissions. One of the key relative advantages of the neural network model is that the ANN can be applied regardless of whether the input data are erroneous, incomplete or inconsistent. This makes the technique a universally accepted solution as the best prediction method based on its ability to provide accurate results with inadequate input variables in the presence of a linear or non-linear relationship. This partly explains its success in authors’ study. Different variables, dependent and independent, have been used by researchers in prediction using an ANN. Authors’ study constructed a neural network by using the explanatory such as crop production, livestock production, trade exports, trade imports, renewable energy sources, nonrenewable energy use and economic growth to predict potential carbon dioxide emissions as the dependent variable.

The study applied classical nonlinear least squares algorithm such as LM, to predict potential emissions. The main idea is to ensure that emerging economies have a clear understanding of expected future emissions so that appropriate measures can be implemented to mitigate its impact. Analyzing the performance graphs, authors found that the best training performance is achieved at the epoch 11 when the value of the MSE is 0.0003345 which indicates that the model errors are less than 0.05. The error histogram shows that most of the errors are situated within a narrow range of values, from -0.07196 to 0.08152, while the regressions between the network targets and network outputs highlight the fact that the
correlation coefficient (R) for the whole dataset is very close to 1, with both training and validation = 99.9%. This means that variation in potential carbon dioxide emissions can be explained with these explanatory variables. This result validates the trained ANN results and the effect is that the model is reliable in terms of fitness and predictive accuracy. It can be concluded that the applied model is capable of predicting carbon dioxide emissions in emerging economies with great precision. In addition, the accurate prediction of CO₂ equivalent emission shows that the selected input variables are the most influential factors in the production of potential carbon dioxide emissions. Hence, predicting variables as NRE (Non-renewable Energy Use); LVP (Livestock Production); CRP (Crop Production); IMP (Trade Imports); EXP (Trade Exports); economic growth (GDP) and REN (Renewable Energy Use) can be used to predict the outcome of potential carbon dioxide emissions (CO₂eq). Emerging economies should, therefore, tackle the variables that have a high positive impact on the environment especially the first three variables as non-renewable energy sources, livestock production and crop production that contribute as much as 40.9%; 14.7% and 12.6% respectively to emissions disclosed as Table A2 (Appendix). Future studies can as well as look at the relationship between the predicting variables and environmental pollution using econometric model approach for comparative analysis.

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Author Contributions

All authors contributed equally to the preparation of the manuscript.

Conflicts of Interest

No conflict of interest to be declared.

References

Prediction of Potential Carbon Dioxide Emissions of Selected Emerging Economies Using Artificial Neural Network


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Appendix

Fig. A1  Predicted vs. actual values.
## Table A1  Parameter estimate of the neural network.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
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<td>Hidden layer</td>
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<tr>
<td>GDP</td>
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</tr>
<tr>
<td>CRP</td>
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<tr>
<td>LVP</td>
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<tr>
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<tr>
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<td>EXP</td>
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<tr>
<td>H (1:1)</td>
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</tr>
<tr>
<td>CRP</td>
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<tr>
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<tr>
<td>REN</td>
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<tr>
<td>IMP</td>
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<tr>
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<tr>
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<td>NRE</td>
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<tr>
<td>H (1:3)</td>
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<td>CO2 eq</td>
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</tr>
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<tr>
<td>H (1:2)</td>
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<tr>
<td>H (1:3)</td>
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<td>Intercept</td>
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## Table A2  Importance of predicting variables.

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<th>Percentage</th>
<th>Normalizes importance</th>
<th>Ranking</th>
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<tr>
<td>GDP</td>
<td>0.078</td>
<td>7.8</td>
<td>19.1%</td>
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<td>CRP</td>
<td>0.126</td>
<td>12.6</td>
<td>30.9%</td>
<td>3rd</td>
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<td>LVP</td>
<td>0.147</td>
<td>14.7</td>
<td>36.0%</td>
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<tr>
<td>NRE</td>
<td>0.409</td>
<td>40.9</td>
<td>100.0%</td>
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<tr>
<td>REN</td>
<td>0.067</td>
<td>6.7</td>
<td>16.4%</td>
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<tr>
<td>IMP</td>
<td>0.088</td>
<td>8.8</td>
<td>21.5%</td>
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<tr>
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<td>8.5</td>
<td>20.8%</td>
<td>5th</td>
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</tbody>
</table>