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Effect of activation function in modeling the nexus between carbon tax, CO_2 emissions, and gas-fired power plant parameters

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ABSTRACT

Huge emissions of carbon dioxide (CO_2) from the utilization of fossil fuel for power generation has significantly contributed to global warming. In view of this, technological pathways have been initiated to mitigate the effect of CO_2 emissions through capture, storage, and utilization. Besides, there is an increasing acceptance of carbon tax which is levied in the proportion of carbon emissions from the utilization of fossil fuel. In this study, the nexus between carbon tax, equivalent CO_2 emissions from the gas-fired power plant, natural gas flow rate, and air-to-fuel ratio was modeled using a perceptron neural network. The effect of various combinations of identity, hyperbolic tangent, and sigmoid activation functions at the hidden and outer layer of the neural network on the performance of the models was investigated. The various network configurations were trained using the Levenberg-Marquardt algorithm with the network errors backpropagated to enhance the performance. The optimized networks consist of three input units, 15 hidden neurons, and one output unit. The network performance in modeling the carbon tax prediction resulted in R^2 of 0.999, 0.999, 0.999, 0.998, and 0.999 for model 1, model 2, model 3, model 4, and model 5, respectively which is an indication that the calculated carbon tax was strongly correlated with the predicted values. The prediction errors of 0.019, 0.009, 0.002, 0.016, 0.002 obtained from model 1, model 2, model 3, model 4, and model 5, respectively revealed the robustness of the models in predicting the carbon tax with minimum error. Among the various configurations investigated, the perceptron neural network configured with hyperbolic tangent and sigmoid activation function at the hidden and outer layers, as well as the configuration with sigmoid activation functions at the hidden and outer layers, offer the best performance. The sensitivity analysis shows that the flow rate of the natural gas had the most significant effect on the predicted carbon tax.

Introduction

The anthropogenic activities from the utilization of fossil fuels had been reported to results in serious health implications which arise from the emissions of gaseous pollutants [1]. Over the years various measures have been employed to reduce the emissions of these poisonous pollutants [2–5]. These measures include the use of technological strategies such as the production of biofuel, synthetic fuel, the use of CO_2 capture, storage, and utilization [6,7]. Besides, policy and legislation have also played a vital role in the mitigation of emissions of CO_2 [7–9]. One of such policies is carbon tax which is a price set aside by the government for emitters to pay for each ton of CO_2 emitted [10,11]. The carbon tax can either be in the form of an emission tax which is a function of the quantity of CO_2 produces by a company or tax levied on the products or services that are CO_2-intensive. In some jurisdictions or countries, fossil fuels such as gasoline, coal, and natural gas are the main target of carbon tax [12]. As shown in Table 1, the carbon tax has been implemented in countries such as Finland, Netherlands, Norway, Sweden, Denmark, United Kingdom, and California [13]. The carbon tax rate per metric ton of CO_2 differs from country to country. Sweden has been reported to have the highest carbon tax of \$104.83/metric ton of CO_2 emitted which was implemented in 1991 [13]. The carbon tax policy has significantly encouraged the use of renewable energy and increased its share in the country's energy mix. A total of \$3.665 billion was estimated to have

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Table 1
Summary of Carbon Tax Policy in different countries [13].

Country/ Jurisdiction	Start Date	Tax Rate ($USD unless noted otherwise)	Annual Revenue	Revenue Distribution
Finland	1990	$30/metric ton CO_2 (€20)	$750 million (€500 million)	Government budget; accompanied by independent cuts in income taxes
Netherlands	1990	~$20/metric ton CO_2 in 1996	$4.819 billion[a] (€3.213 billion)	Reductions in other taxes; Climate mitigation programs
Norway	1991	$15.93 to $61.76/ metric ton CO_2 (NOK 89 to NOK 345)	$900 million (1994 estimate)	Government budget
Sweden	1991	Standard rate: $104.83/metric ton CO_2 (910 SEK) Industry rate: ~ $23.04/metric ton CO_2 (~200 SEK)	$3.665 billion (25 billion SEK)	Government budget
Denmark	1992	$16.41/metric ton CO_2 (90 DKK)	$905 million	Environmental subsidies and returned to industry
United Kingdom	2001	$0.0078/kWh for electricity; $0.0027/kWh for natural gas provided by gas utility; $0.0175/kg for liquefied petroleum gas or other gaseous hydrocarbons supplied in a liquid state; and $0.0213/kg for solid fuel	$1.191 billion (£714 million)	Reductions in other taxes
BAAQMD, California	2008	$0.045 per metric ton of CO_2e[b]	$1.1 million (expected)	Climate mitigation programs

[a] Revenue in the Netherlands is from all environmentally related taxes, of which carbon taxes are the clear majority.

been generated from the carbon tax levied. Besides Sweden, Finland also records a high carbon tax rate of $30/metric ton of CO_2 emitted which was implemented in 1990 with total annual revenue of $750 million generated. It is often difficult to quantify carbon emission reductions that are due to carbon taxes. Although carbon tax has been adjudged as being economically efficient in tackling carbon emissions, perhaps it might address a set level of emissions reduction [14]. In a situation where the emission targets desired are not met carbon tax can be implemented in such a manner that there is an automatic increase in the tax rate to meet the anticipated target [13].

The revenue generated from carbon taxes in the various countries has been employed for funding carbon emission mitigation programs as well as being used to partly fund government budgets as obtainable in Sweden and Norway. Steenkamp [15] reported a classification framework for the use of carbon tax revenue. The framework consists of four modalities namely the constrained/unconstrained, revenue-neutral/ revenue-raising, public preference, and thematic. Based on the proposed classification framework, the authors recommended its usage by policymakers to identify the best alternatives for carbon revenue in a situation when it is expedient to formulate carbon tax policies for the mitigation of carbon emissions. Yamazaki [16] investigated the employment impact of British Columbia's revenue-neutral carbon tax implemented in 2008. The study revealed that most of the industries in British Columbia benefited from the redistributed carbon tax revenues.

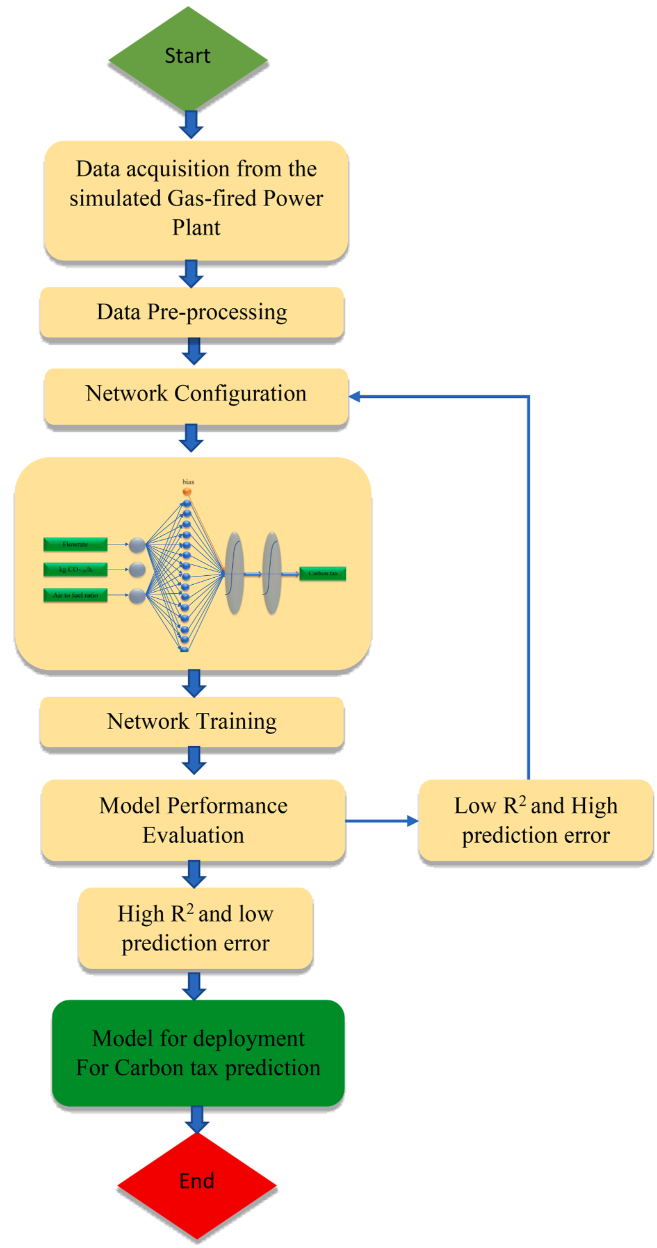

Fig. 1. Stages involved in the Modeling the Nexus between Carbon Tax, CO_2 emissions, and gas-fired power plant parameters.

However, the study shows that there was a fall in employment among the most carbon-intensive and trade-sensitive industries with the remittance of the carbon tax. Whereas the non-carbon intensive industries experience a rise in employment. Yuan et al. [17] reported the implications of revenue generated from the carbon tax. The study evaluated different carbon prices and emissions reduction goal scenarios in relation to how they significantly influence carbon reduction. There was an anticipation of an increase in revenue generated from the high carbon tax rate based on the findings. The authors confirmed that carbon tax revenue is a reliable revenue source to fund government fiscal initiatives.

The relationship between carbon tax, revenue sharing, and various parameters has been investigated. Yang et al. [18] studied the influence of carbon tax revenue sharing in the manufacturer's carbon emissions mitigation efforts. The study revealed that the abatement level promise strategy and abatement level requirement strategy maximized the manufacturer's profits with a greater consumer environmental

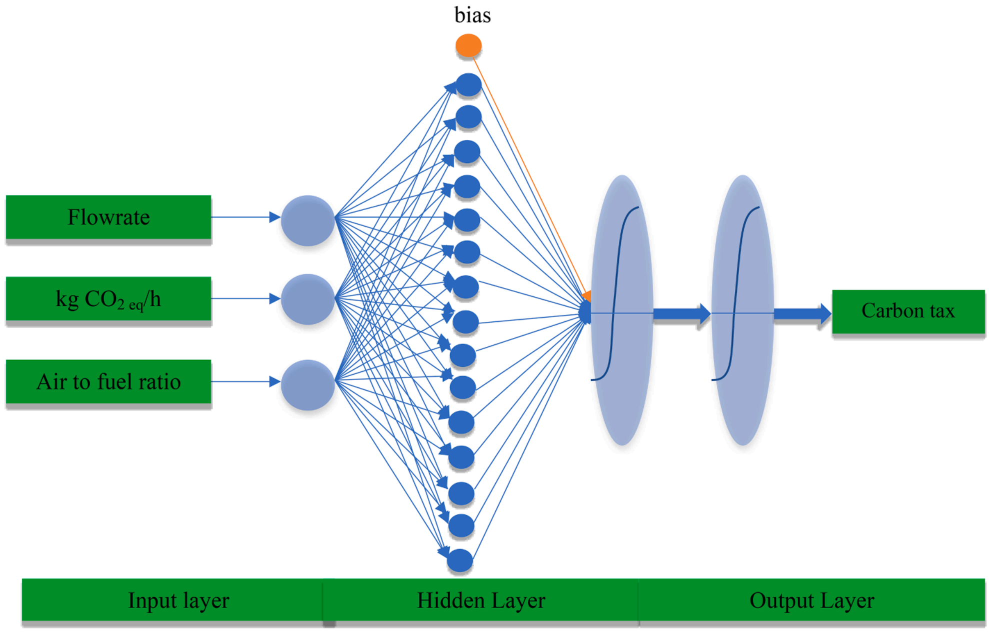

Fig. 2. The configuration of the Perceptron Neural Networks.

Table 2
Detail of the Network Information for each of the models.

Parameters			Model 1	Model 2	Model 3	Model 4	Model 5
Input Layer	Factors	1	Flowrate	Flowrate	Flowrate	Flowrate	Flowrate
		2	Air to fuel ratio	Air to fuel ratio	Air to fuel ratio	Air to fuel ratio	Air to fuel ratio
		3	kg $CO_{2\ eq}$/h	kg $CO_{2\ eq}$/h	kg $CO_{2\ eq}$/h	kg $CO_{2\ eq}$/h	kg $CO_{2\ eq}$/h
	Number of Units[a]		116	116	116	116	116
Hidden Layer(s)	Number of Hidden Layers		1	1	1	1	1
	Number of Units in Hidden Layer 1[a]		15	15	15	15	15
	Activation Function		Hyperbolic tangent	Hyperbolic tangent	Hyperbolic tangent	Sigmoid	Sigmoid
Output Layer	Dependent Variables	1	Carbon tax	Carbon tax	Carbon tax	Carbon tax	Carbon tax
	Number of Units		1	1	1	1	1
	Rescaling Method for Scale Dependents		Standardized	Standardized	Standardized	Standardized	Standardized
	Activation Function		Identity	Hyperbolic tangent	Sigmoid	Hyperbolic tangent	Sigmoid
	Error Function		Sum of Squares	Sum of Squares	Sum of Squares	Sum of Squares	Sum of Squares

[a] Excluding the bias unit.

awareness and carbon tax. Xiang and Lawley [18] employed panel data regression and synthetic control model to study the effect of British Columbia's carbon tax on per capita residential natural gas consumption. The results from the panel data regression model showed that the carbon tax significantly diminished as a function the residential natural gas consumption. The authors established the efficacy of carbon taxes in reducing the consumption of fossil fuels with a particular interest in residential natural gas consumption. The economic impacts and political feasibility of carbon tax or emission trading policy mechanisms for greenhouse gas emissions reduction in the Mexican power sector have been investigated by Barragán-Beaud et al. [19]. The study suggested both the carbon tax and emission trading are vital in mitigating the CO_2 emissions in the Mexican power sector. Nong et al. [20] compared the impacts of a carbon tax that solely covers CO_2 emissions and non-CO_2 greenhouse gas emissions. The study revealed that the non-CO_2 emissions contributed to discrepancies in the impact from country to country, with emerging economics most influenced by this issue. In a similar study, Zhang and Zhang [21] employed a computable general equilibrium model to study the relationship between carbon tax, tourism CO_2 emissions, and economic welfare. The finding shows that carbon tax policy could have a remarkable impact on tourism-related carbon emissions and economic welfare. However, there is a dearth of study on the nexus between carbon tax, CO_2 emissions, and the various parameters in the industrial or power generating plants. This study therefore aimed at investigating the nexus between Carbon Tax, CO_2 emissions, and Gas-fired power plant parameters using a perceptron neural network. The effect of various activation functions of the hidden and outer layer on the model output is also investigated.

Process description, carbon tax calculation, and model development

Natural gas is widely used as fuel in a gas-fired power plant for electricity generation using a gas turbine [22]. For a typical electricity generation in a natural gas-fired power plant, the natural gas is mixed with a stream of air using a defined air-to-fuel ratio while the flow rate into the turbine is regulated [23]. The air–fuel mixture is combusted and expanded through the turbine thereby generating electricity through the spinning of the magnet by the generator. Compared to other power plants, the gas-fired power plant is highly thermodynamically efficient. Besides, the combustion process comes with less emission of NO_x, SO_x, and other particulate matter. However, the utilization of natural gas for electricity generation often comes with CO_2 emissions which are lower compared to using coal. In this study, the data employed were obtained from the simulation of a real-life natural gas power plant reported by Babatunde et al. [23]. A total of 57 datasets which consist of natural gas flow rate, the air-to-fuel ratio, and the equivalent CO_2 emissions was employed for training the models. The carbon tax was calculated based

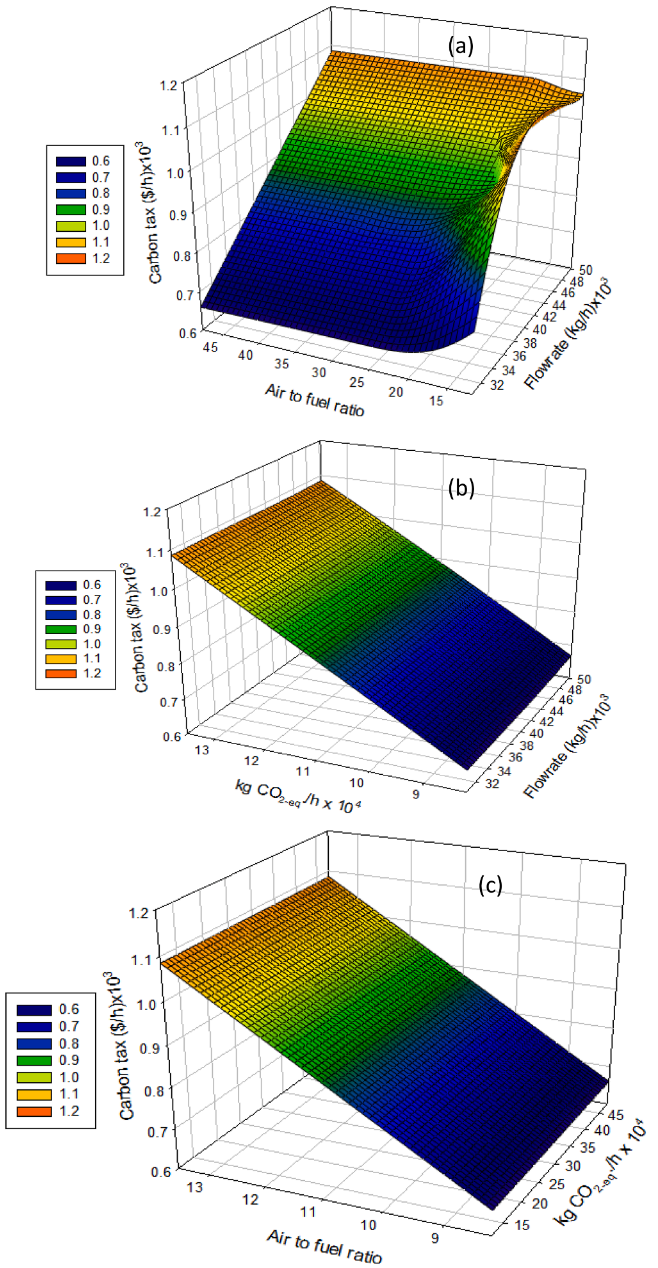

Fig. 3. The three-dimensional plots showing the interaction effect of (a) air-to-fuel ratio and fuel flow rate (b) equivalent CO_2 emission and fuel flow rate (c) air-to-fuel ratio and equivalent CO_2 emissions on the Carbon tax.

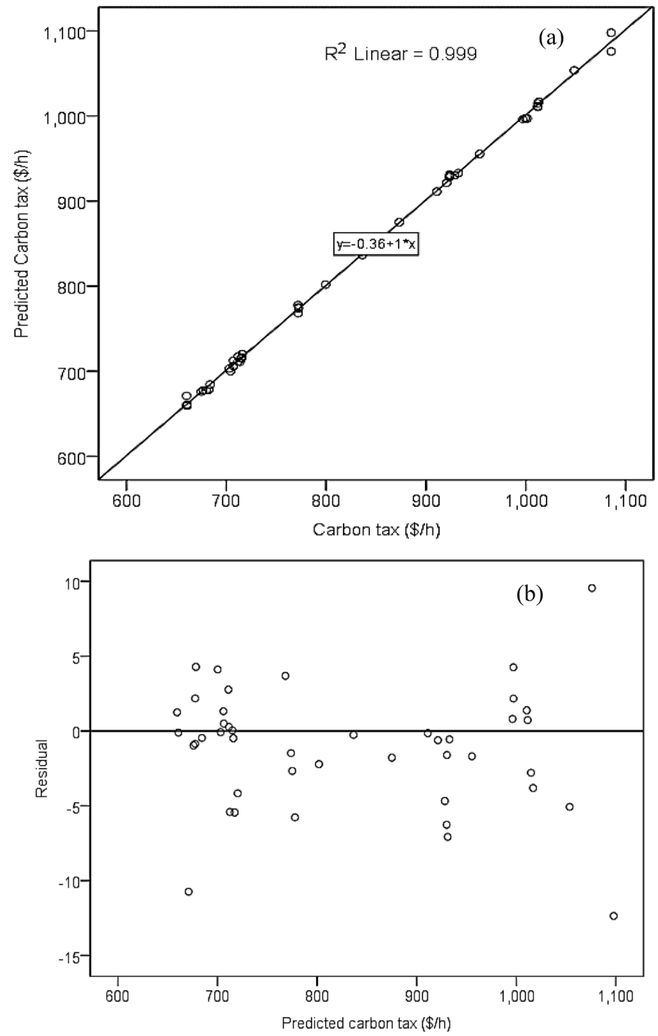

Fig. 4. (a) The parity plot of the observed and predicted carbon tax (b) the residuals of predictions using hyperbolic tangent activation function at the hidden layer and identity activation function at the output layer.

on the equivalent CO_2 emissions as reported by Babatunde et al. [23]. The detailed stages involved in the modeling are depicted in Fig. 1. These stages involve data acquisition, data preprocessing, network configuration, network training, model performance evaluation, and model deployment for the prediction of the carbon tax from the gas-fired power plant. To ensure reliability, as well as avoiding errors and outliers, the dataset was pre-processed using an Excel spreadsheet before being employed for the modeling. A perceptron neural network configuration depicted in Fig. 2 was employed for the modeling of the Nexus between Carbon Tax, CO_2 emissions, and gas-fired power plant parameters. The configuration consists of the input layer, the hidden layer, and the output layer. The details of the network information are depicted in Table 2. The input layer comprises a set of artificial neurons with each input unit (x_i) associated with a weight (w_i) along with the bias (b). The associated weights determine the extent of influence an input unit will have on the output. While the bias helps to evaluate the extent of parity between the intended values and the predictions and subsequently make up for the differences. There are total of 116 artificial neurons units in the perceptron neural network configuration. The hidden layer consists of 15 hidden neurons which are interconnects with the input layers through the various units. Each of the x_i is multiplied with the corresponding w_i and the total are summed up together with the bias as output of the hidden layer as shown in Eq. (1). The output of the hidden layer is normalized by activation function with non-linearity for proper computation by the neural network algorithms. Three combinations of the activation functions namely identity (Eq. (2)), hyperbolic tangent (Eq. (3)), and sigmoid function (Eq. (4)) were employed in this study. The choice of identity, hyperbolic tangent, and sigmoid function is to determine the effect of linearity and non-linearity on the model output.

The adequacy of the model was evaluated by comparing the differences between the observed output and the predicted output using the sum of squares error (SSE) analysis (Eq. (5)) and coefficient of determination (R^2).

$$\vartheta = \sum_{i}^{n}(w_i x_i) + b \tag{1}$$

$$z(x) = \begin{cases} 0 for x < 0 \\ x for x \geq 0 \end{cases} \tag{2}$$

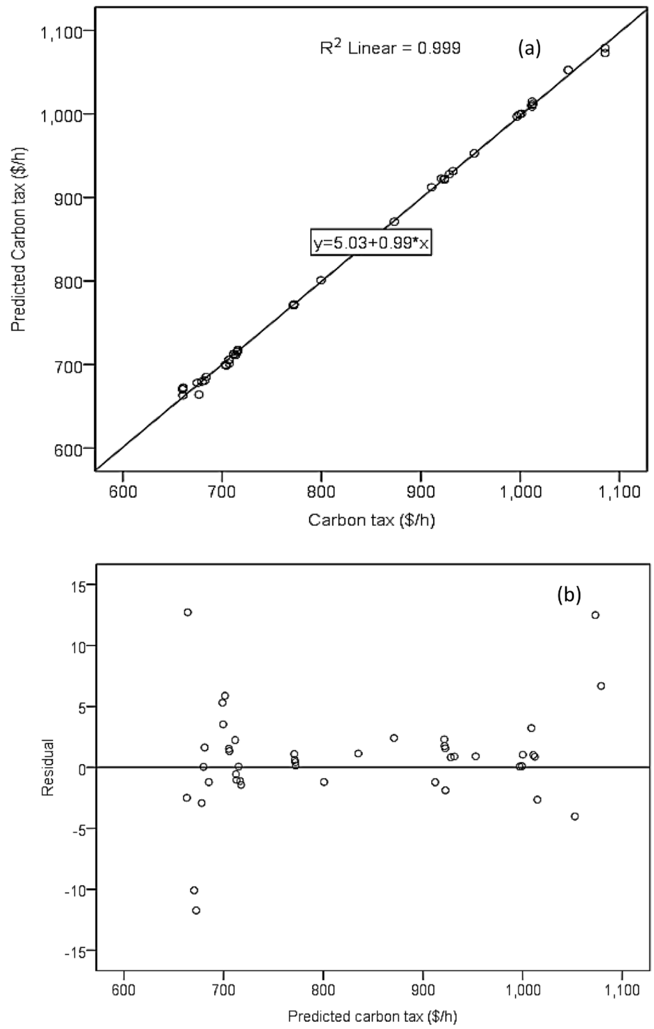

Fig. 5. (a) The parity plot of the observed and predicted carbon tax (b) the residuals of predictions using hyperbolic tangent activation function at the hidden layer and hyperbolic tangent activation at the output layer.

$$z(x) = \tanh(x) \tag{3}$$

$$z(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

where ϑ is the output from the hidden layer, w_i is the weight, x_i is the input unit, b is the bias, $z(x)$ is the transfer function.

The network was trained using the Levenberg-Marquardt algorithm with the network error backpropagated [24]. The backpropagation helps in fine-tuning the network weights as a function of the error obtained in the initial iteration [25]. The repeated back-propagation process helps to minimize network error thereby improving the output generalization. To prevent overfitting, the datasets are divided into two portions equivalent to 70% and 30% for training and testing, respectively [26]. The network configurations and the analysis were performed using the neural network tool in IBM-SPSS version 22. The stages in the model configurations involve the pre-processing of the dataset in an Excel Spreadsheet, the uploading of the dataset into the neural network platform, the setting of the network information, training the model using the uploaded datasets.

$$SSE = \sum_{i=1}^{n} \left(y_i - \ddot{y}_i \right)^2 \tag{5}$$

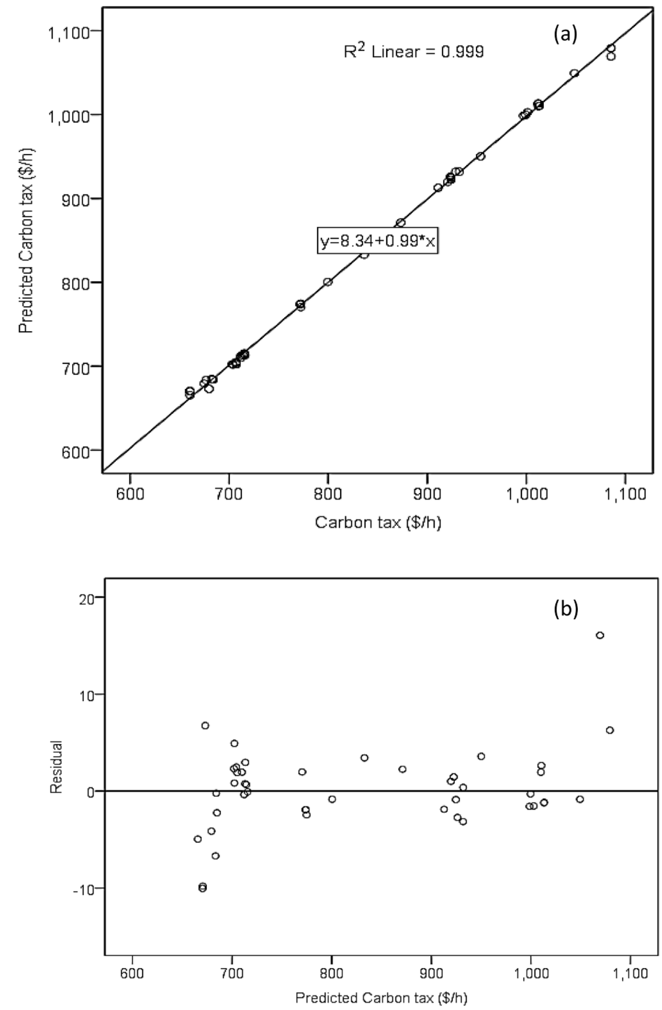

Fig. 6. (a) The parity plot of the observed and predicted carbon tax (b) the residuals of predictions using hyperbolic tangent activation function at the hidden layer and sigmoid activation at the output layer.

Results and discussion

Three-dimensional parametric analysis

The relationship between the air-to-fuel ratio, the flowrate of the natural gas, the equivalent CO_2 emissions are represented using the three-dimensional plots shown in Fig. 3. The interaction between the natural gas flow rate and the air-to-fuel ratio resulted in a carbon tax of \$1.09×10^3/h. The increase in the flow rate of the natural gas implies more consumption thereby increasing the CO_2 emissions and the carbon tax as shown in Fig. 3 (a). It can be seen that the natural gas flow rate has more impact on the CO_2 emissions compared to the air-to-fuel ratio. The influence of the natural gas flow rate on the carbon tax is further ascertained in Fig. 3 (b) through the equivalent CO_2 emission. An increase in the equivalent CO_2 emissions per kg of the natural gas utilized invariable leads to an increase in the carbon tax. According to the United States Energy Information Administration, about 0.91 lb of CO_2 is emitted per kWh electricity generation from the utilization of natural gas as fuel [27]. This amounts to 560 million metric tons of CO_2 emissions from the generation of 1,358,047 million kWh electricity using natural gas. The nature of the fuel source significantly influences the amount of CO_2 emitted per kWh at a stipulated time. The report also shows that the use of coal, natural gas, and petroleum fuels for electricity generation contributed about 99% of US CO_2 emissions from electricity. As a result of this, various states have implemented a carbon

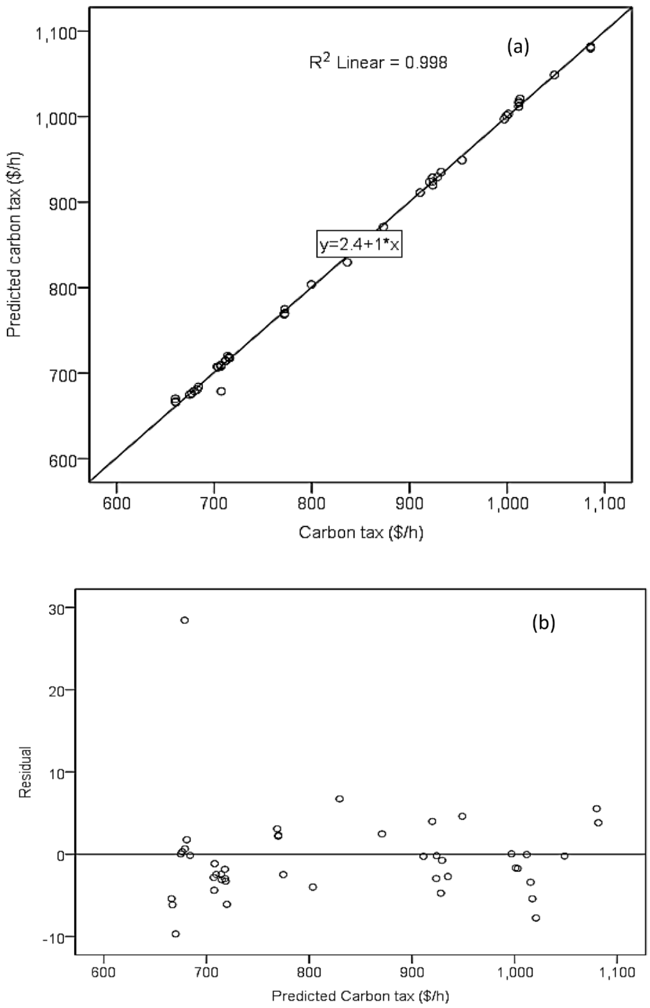

Fig. 7. (a) The parity plot of the observed and predicted carbon tax (b) the residuals of predictions using sigmoid activation function at the hidden layer and hyperbolic tangent activation at the output layer.

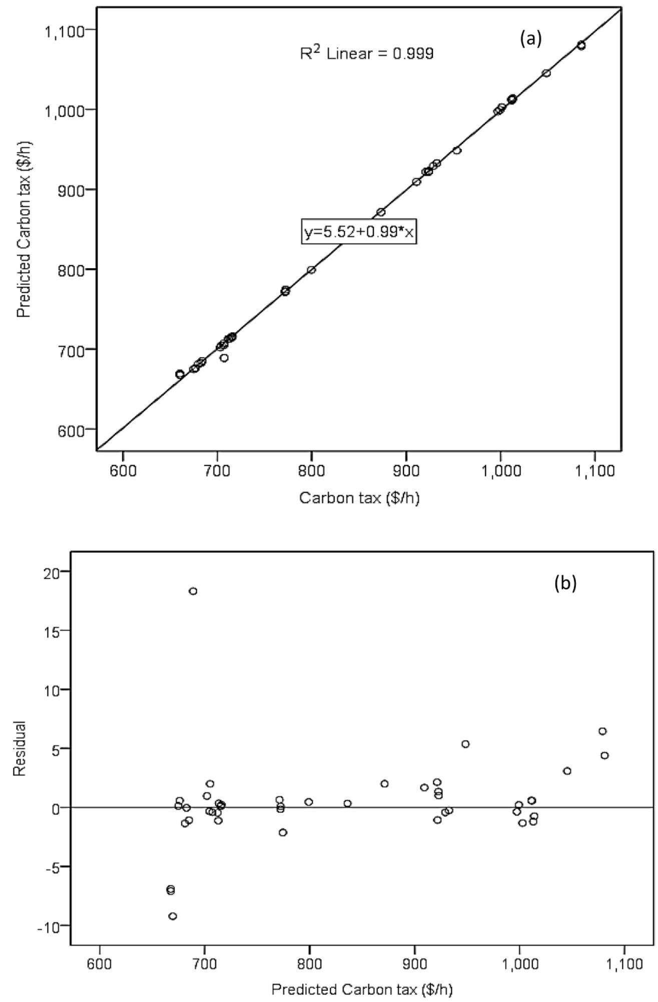

Fig. 8. (a) The parity plot of the observed and predicted carbon tax (b) the residuals of predictions using sigmoid activation function at the hidden layer and sigmoid activation at the output layer.

tax policy that is intended to reduce CO_2 emissions. Fig. 3 (c) shows the carbon tax based on the interaction between the air-to-fuel ratio and equivalent CO_2 emissions. In the interaction, it can be seen that the carbon tax increases with an increase in the air-to-fuel ratio.

Effect of activation functions on the model performance

The performance of the perceptron neural network configured using hyperbolic tangent activation function at the hidden later and identity activation function at the outer layer is depicted in Fig. 4. The regression plot showing the calculated carbon tax and the predicted carbon tax is depicted in Fig. 4 (a). With an R^2 of 0.999, the calculated carbon tax is strongly correlated with the predicted values. This shows that there is high synergy between the hyperbolic tangent activation function used at the hidden later and the identity activation function used at the outer layer. As shown in Fig. 4 (b), the residuals of the predicted values are mostly between ± \$5/h of carbon tax resulting in a prediction of error 0.019 based on the SSE. This is an indication of the strong robustness of the perceptron neural network configurations having hyperbolic tangent activation function used at the hidden later and identity activation function used at the outer layer. The combined hyperbolic tangent and identity activation function has been employed in the neural network configuration used for modeling the performance and emissions assessment of a single-cylinder diesel engine [28]. The neural network model had a high accuracy prediction of the emissions assessments in all the engine loads.

The performance of the perceptron neural network configured with hyperbolic tangent function at both the hidden layer and the outer layer is depicted with the regression and residual plots depicted in Fig. 5 (a) and (b), respectively. Similar to the perceptron neural network configurations with hyperbolic tangent activation function at the hidden layer and identity activation function at the output layer, using hyperbolic tangent function at both the hidden layer and the outer layer of the neural network also resulted in a robust prediction with R^2 of 0.999. The high R^2 is an indication that both the calculated carbon tax and the predicted carbon tax are in strong agreement. However, using hyperbolic tangent activation function at the hidden and output layers resulted in a lower predicted error of 0.009 which revealed an improved performance. The disparity between the calculated and the predicted carbon tax as indicated by the residual plots in Fig. 5 (b) is within ± \$5/h. The use of hyperbolic tangent activation function in the neural network configuration for the prediction of the carbon price has been reported by Liu and Shen [29]. The performance of the perceptron neural network configured with hyperbolic tangent activation function and sigmoid activation functions at the hidden and outer layers, respectively depicted in Fig. 6. The regression plot in Fig. 6 (a) shows that the calculated carbon tax and the predicted values are in close agreement as indicated by R^2 of 0.999. This implies that there is synergy in the use of hyperbolic tangent activation function and sigmoid activation functions in hidden and outer layers, respectively. This synergy

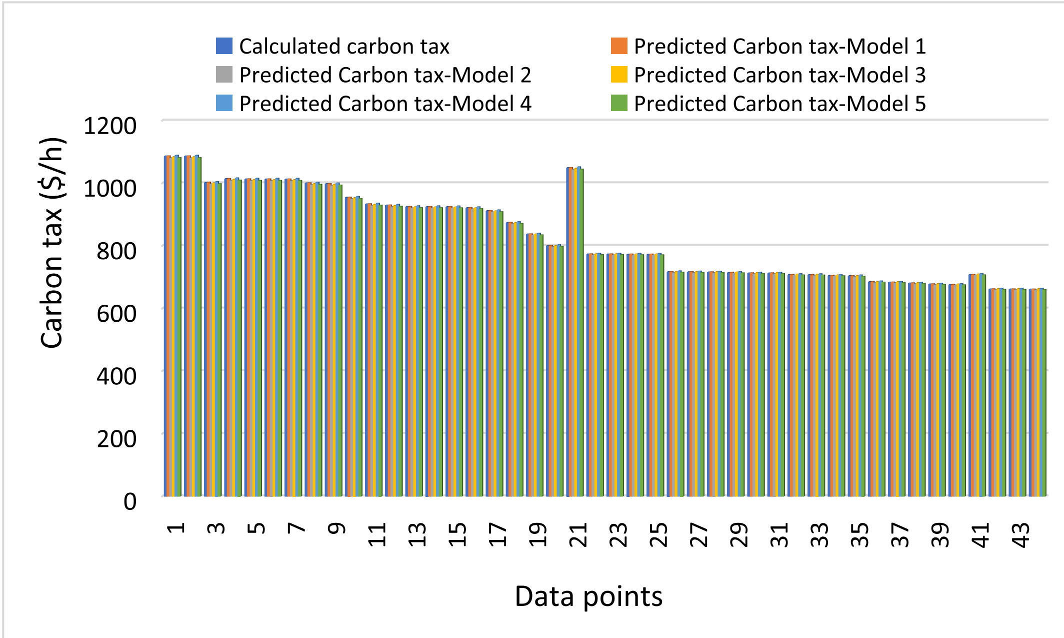

Fig. 9. Comparison of the various models used for the prediction of the carbon tax from the gas-fired power plant.

Table 3
Performance analysis of the effect of activation functions on the various model used.

Model	Network layer	Activation Function	SSE	R^2
1	Hidden layer	Hyperbolic tangent	0.019	0.999
	Output layer	Identity		
2	Hidden layer	Hyperbolic tangent	0.009	0.999
	Output layer	Hyperbolic tangent		
3	Hidden layer	Hyperbolic tangent	0.002	0.999
	Output layer	Sigmoid		
4	Hidden layer	Sigmoid	0.016	0.998
	Output layer	Hyperbolic tangent		
5	Hidden layer	Sigmoid	0.002	0.999
	Output layer	Sigmoid		

further resulted in a lower prediction error of 0.002 as indicated by the SEE and the residual shown in Fig. 6 (b). The use of hyperbolic tangent activation function and sigmoid activation functions offer better prediction compared to the two previous configurations. Neural network configuration with sigmoid as the activation function at the outer layer has been reported to be robust in predicting carbon emission intensity [30]. The model was found to be efficient in predicting the carbon emission intensity for Australia, Brazil, China, India, and the USA with R^2 of 0.80, 0.91, 0.95, 0.99, and 0.87, respectively. Zagrebina et al. [31] employed a recurrent neural network configured with hyperbolic and sigmoid activation functions for the prediction of energy consumption. A robust prediction of the energy consumption was obtained with a relative error of 2.10%.

Fig. 7 depicted the regression plot of the observed and predicted carbon tax and the residuals of predictions using the sigmoid activation

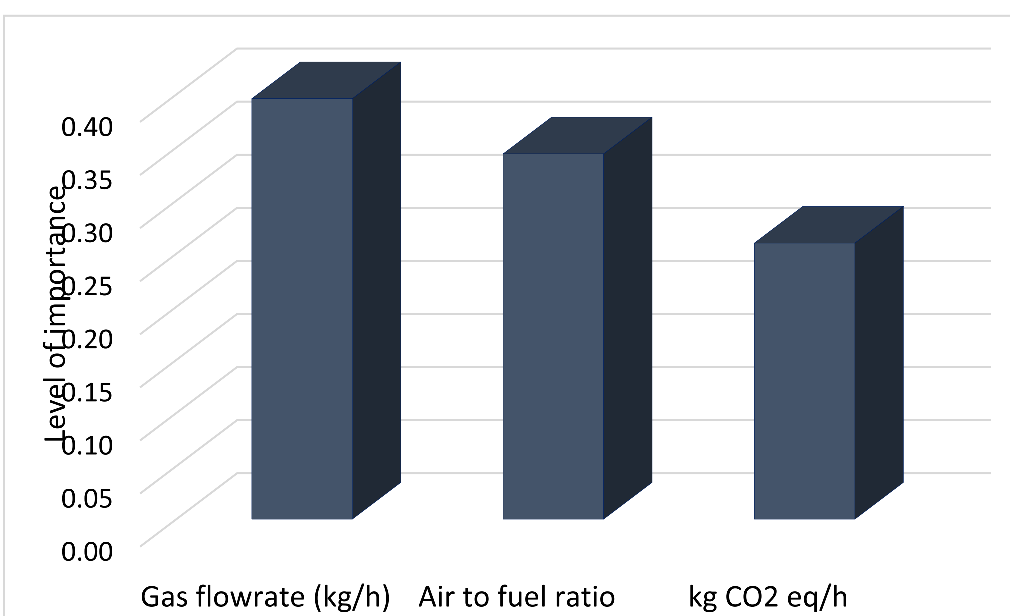

Fig. 10. Level of importance analysis of the various parameters.

function at the hidden layer and hyperbolic tangent activation functions at the output layer of the perceptron neural network. As shown in Fig. 7 (a), the calculated carbon tax is strongly correlated with the predicted values by the neural network model. This is evidence from the R^2 of 0.999 which indicates that the model can be generalized over 99% of the dataset with minimum prediction errors of 0.016. Fig. 7 (b) depicts that the residuals which show the disparity between the calculated and the predicted carbon tax is within ± $5/h. The use of a feedforward neural network model configured with hyperbolic tangent activation function at the outer layer has been employed for the prediction of building energy consumption in selected campuses located in the USA and China has been reported by Li et al. [31]. In comparison to other existing models, the model was reported to display superior performance in predicting the building energy consumption terms with high accuracy and convergence speed. Fig. 8 depicts the regression plot of the observed and predicted carbon tax and the residuals of predictions using the sigmoid activation function at the hidden layer and sigmoid activation at the output layer of the perceptron neural network used for modeling the prediction of the carbon using the gas-plant parameters. As shown in Fig. 8 (a), the calculated carbon tax and the predicted values are strongly correlated as indicated by the R^2 of 0.999. This implies that the datasets obtained from the simulated gas-fired power plant are well trained the neural network configuration. This can further be ascertained from the prediction error of 0.002. As indicated in Fig. 8 (b), the residuals between the calculated and the predicted carbon tax is in the range of ± $5/h. The performance of the model as indicated by the accurate prediction of the carbon tax can be attributed to the well-trained model that learned the relationship between the input parameters and the output. The performance of the neural network model configured with sigmoid activation function at the hidden layer and sigmoid activation at the output layer is comparable with that reported in the literature. The modeling of energy consumption of air conditioning system using feedforward neural network configured with sigmoid activation function at the hidden and the outer layer has been reported Chaudhuri et al. [32]. The neural network model was reported to accurately model the prediction of the building energy consumption with a prediction error of 4.97. This implies that the relationship between the input and the output model was a well model by using the neural network model. The prediction of cooling energy consumption in a building has been modeled using a neural network configured with sigmoid activation in both the hidden and output layers has been reported by Deb et al. [33]. The study revealed that the trained neural network was able to robustly predict the energy consumption in the building.

The comparison of the five models configured using the different combinations of the activation function is depicted in Fig. 9. The performance analysis of the five models summarized in Table 3 shows that the configured neural network with different combinations of the activation functions was employed to model the relationship between the air-to-fuel ratio, natural gas flowrate, the equivalent CO_2 emissions, and the carbon tax. The R^2 of 0.999, 0.999, 0.999, 0.998, and 0.999 obtained for model 1, model 2, model 3, model 4, and model 5, respectively indicates that the calculated carbon tax was strongly correlated with the predicted values. The prediction errors of 0.019, 0.009, 0.002, 0.016, 0.002 obtained from model 1, model 2, model 3, model 4, and model 5, respectively revealed the robustness of the models in predicting the carbon tax with minimum error. Model 3 which is a neural network configured with hyperbolic tangent and sigmoid activation functions at the input and outer layers as well as model 5 which is a neural network configured with sigmoid activation function at both hidden and output layers can be adjudged to have the best performance since they have the least predictive errors. The level of importance analysis shown in Fig. 10 revealed that all the input parameters significantly influence the predicted carbon tax. The gas flow rate with the highest level of importance of 0.4 displayed the most significant influence on the predicted carbon tax.

Conclusion

In this study, the nexus between carbon tax, natural flow rate, air-to-fuel flow rate, and CO_2 emissions in the gas-fired power plant has been modeled using a perceptron neural network. The effect of employing various configurations of activation functions at the hidden and outer layers of the neural network to enhance its performance was also evaluated. The optimized network which consists of three input nodes, 20 neurons at the hidden layer, and one output unit had a robust performance in modeling the relationship between the input parameters and the output. The network models configured with the various activation functions displayed robust performance in predicting the carbon tax based on the well-trained relationship between the input parameters and the output. The model configured with hyperbolic tangent and sigmoid activation function at the hidden and outer layers as well as the configuration with sigmoid activation functions at the hidden and outer layers offer the best performance with minimum prediction errors of 0.002. The R^2 of 0.999 for both models revealed that the calculated carbon tax and the predicted value are strongly correlated. The sensitivity analysis shows that the flow rate of the natural gas had the most significant effect on the predicted carbon tax. This study has established that there exists a relationship between the input parameters and the output of the datasets used in this study. Hence, given a dataset of the various parameters investigated, algorithms of the best model can be deployed to predict carbon tax which can be employed for a variety of CO_2 emissions mitigation programs. Besides being used for the prediction of carbon tax based on the parameters in a gas-fired power plant, the best-configured perceptron neural network algorithms can be extended as a tool for carbon tax prediction in other power generating plants such as coal-fired power plants, diesel-fired plants, and so on.

CRediT authorship contribution statement

Ozavize Freida Ayodele: Conceptualization, Methodology. **Bamidele Victor Ayodele:** Data curation, Investigation, Software, Writing - original draft. **Siti Indati Mustapa:** Visualization, Writing - review & editing. **Yudi Fernando:** Writing - review & editing.

Declaration of Competing Interest

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

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