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Zahraa Taha Naqee
Department of Digital Economy and Digital Technology, Technical Institute of Nineveh, Northern Technical University, Mosul, Iraq, zahraeco82@ntu.edu.iq

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RESEARCH ARTICLE

AI-Based Environmental Economic - Modeling: A Case of Germany (1994–2024)

Zahraa Taha Naqee

Department of Digital Economy and Digital Technology, Technical Institute of Nineveh, Northern Technical University, Mosul, Iraq

Abstract

This research aims to analyse the impact of economic and energy variables on carbon emissions in Germany during the period (1994–2024), within the framework of environmental economic modelling based on artificial intelligence techniques. The study is based on the hypothesis that the nature of the energy structure and the level of economic activity contribute to explaining changes in carbon dioxide emissions to varying degrees. To verify this hypothesis, an artificial neural network model was adopted to analyse the relationship between a set of independent variables represented by total energy consumption, total energy production, the proportion of renewable energy in total primary energy, GDP, and environmental taxes, and the dependent variable represented by carbon dioxide emissions. The analysis showed that total energy production and GDP are the two most influential variables in explaining changes in carbon emissions, accounting for a high percentage of the model's explanatory power. The results also showed an average effect of the renewable energy ratio. While the effect of environmental taxes was relatively limited, the effect of energy consumption appeared to be weaker than that of the other variables. The study concludes that promoting the transition to renewable energy and developing more effective environmental policies are key to reducing carbon emissions and advancing environmental sustainability.

Keywords: Artificial intelligence, Artificial neural networks, Environmental economic modeling, Carbon dioxide emissions, Renewable energy, Energy production

1. Introduction

Artificial intelligence (AI) technology has recently gained significant momentum. It is now used in many fields, including economic modelling, by employing machine learning techniques. Examples include linear regression models, random forests, and artificial neural networks. Random forests, a machine learning method based on decision models, help identify influential factors and analyse complex data. This aids understanding economic issues, especially in sustainability, forecasting, and policy development. The research problem focuses on understanding the relationship between economic variables, energy, and carbon emissions. It also evaluates how neural networks improve accuracy in predicting the environmental impact of emissions. The importance of the study lies in offering decision-makers a vision for reducing carbon emissions and supporting sustainable economic policies. This is achieved by utilising modern AI models. The research aims to advance data analysis in environmental economic modelling using artificial neural networks. This technology aligns with current AI developments. Germany is chosen for the study due to its leadership in sustainability, digital transformation, supporting infrastructure, and policies like environmental taxes and clean energy.

2. Literature review and hypothesis development

The environmental economic literature has witnessed rapid methodological development in modelling and analysis tools. Early studies focused on explaining the relationship between economic activity and environmental degradation using traditional

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E-mail address: zahraeco82@ntu.edu.iq (Z. T. Naqee).

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standard models, but these models proved limited in their ability to capture the dynamic complexity of environmental relationships. In this context, Shahbaz et al. (2018) analysed the Kuznets environmental curve hypothesis, highlighting the nonlinear relationship between economic growth and carbon emissions, which underscores the need for more flexible tools to capture this nonlinearity. In line with this, Yang et al. (2021) used an ARDL model to demonstrate a long-term dynamic balance between energy consumption and emissions. However, this framework remained limited by implicit linear assumptions. In a critical direction, Babatunde et al. (2017) pointed out. However, traditional models, despite their explanatory importance, do not adequately reflect the complex interactions in modern ecosystems, especially in light of global shocks. From a policy perspective, Adedoyin et al. (2023) explained that, through CGE models, the effectiveness of environmental policies depends fundamentally on the accuracy with which economic relationships are represented within the model, while Saqib et al. (2023) added. An integrative dimension by linking environmental technology to economic complexity, stressing that reducing emissions requires simultaneous interaction between innovation and tax policies. It also supported the findings of Sun et al. (2020) and Radoine et al. (2022). This trend proves that expanding the use of renewable energy represents a decisive factor in reducing carbon intensity, but these studies remained within the framework of relatively traditional models. As data volumes increase and environmental relationships become more complex, the need for more advanced analytical tools has emerged, with artificial neural networks marking a turning point in this field. Acheampong and Boateng (2019) have shown that ANN models outperform conventional regression methods in terms of carbon emission prediction accuracy, due to their ability to capture nonlinear relationships. Zhang et al. (2022) expanded. This approach uses machine learning algorithms, emphasising that these models provide a deeper understanding of the interconnectedness between environmental and economic variables. As Du et al. (2025) showed that integrating machine learning with standard methods enhances estimation accuracy, reflecting a trend toward hybrid models. At the applied level, Nassef et al. (2023) reported that LSTM models achieve predictive accuracy exceeding 93% in emissions time-series analysis, thereby enhancing the reliability of these tools for long-term forecasting. In the same context, Talaei et al. (2023) reported that multitasking learning models outperform single models, underscoring the importance of accounting for variable correlations within a unified framework. The focus was not limited to the technical aspect but extended to assessing the environmental impact of AI technologies themselves, as Lacoste et al. (2019) cautioned. The rise in energy consumption associated with digital infrastructure prompted Zoubi and Mishra (2024) to introduce the concept of "green AI" as a framework that balances economic efficiency and environmental sustainability. As confirmed by Nishant et al. (2020), Goralski and Tan (2020), AI can contribute to achieving the Sustainable Development Goals by improving resource efficiency, but this requires the responsible use of these technologies. At the sectoral level, Chen et al.'s (2022) study showed that artificial intelligence applications in cities contribute to reducing urban pollution through improved energy management, while Yu et al. (2024) provided empirical evidence of the ability of machine learning algorithms to explain emission determinants at the city level, reflecting the power of these models in analyzing spatial data. In the industrial sector, Lv et al. (2022) pointed out. Smart manufacturing reduces emissions intensity by improving production efficiency, while Di Vaio et al. (2020). Integrating AI into business models enhances both environmental and financial performance, which is consistent with the findings of Dwivedi et al. (2021) on the role of digitisation in reducing waste. In the construction sector, Giannelos et al. (2024) showed that machine learning models provide more accurate predictions of CO_2 emissions than conventional models, a finding also confirmed by Li et al. (2024) and Hua et al. (2025). Systematic review studies highlighted that prediction accuracy improved by up to 20%. In the transportation sector, Gurcan (2024) and Udoh et al. (2024) demonstrated that deep learning and ensemble models outperform vehicle emissions analysis, demonstrating their ability to handle complex, multidimensional data. At the macro level, Li et al. (2021) provided an in-depth analysis of the German economy using the deconstruction methodology, showing that technological innovation and energy efficiency represent the main drivers of emissions reduction, but this approach has remained more interpretive than predictive. In contrast, recent studies, such as those by Wang et al. (2024) have shown. Artificial intelligence contributes to reducing the environmental footprint and enhancing the efficiency of the energy transition at an international level, especially with the high levels of economic openness. As confirmed by the reviews by Jin et al. (2024), Zhao et al. (2023), and Yalçın (2024), machine learning models clearly outperform traditional models in terms of prediction accuracy, but they also highlight a gap in integrating these models into an integrated environmental economic framework. In the same vein, Liu (2024) and Feng et al. (2024) explained that neural networks provide superior predictive performance, while Tian et al. (2025) and Meng and Noman (2022) emphasised the importance of using multiple models to improve the reliability of results, which reflects a trend towards composite models. As Li et al. (2021) and Liu et al. (2025) showed, employing big data enhances the accuracy of environmental analysis, while Wu and Zhang (2025) emphasised that innovation in artificial intelligence can improve environmental efficiency in the long term. Despite this significant progress, the literature still suffers from a clear gap in distinguishing between traditional economic models and artificial intelligence models, with most studies focusing on either interpretive or predictive analysis in isolation. There are also limitations in studies that apply neural network models within an integrated environmental economic framework using long-term data for a specific country. Hence, the current study aims to bridge this gap by employing a neural network model to analyse the relationship between economic variables and environmental emissions in the German economy, providing an analytical framework that combines predictive accuracy and explanatory power.

Based on the theoretical framework and historical data, the hypothesis can be formulated as follows:

- The null hypothesis (H0), which expresses the lack of a significant effect of the economic factors included in the modeling (energy consumption, environmental taxes, the percentage of renewable energy supply, and gross domestic product) on carbon monoxide emissions for the period 1994–2024.
- The alternative hypothesis (H1), which asserts the existence of a significant effect of the economic factors included in the economic modeling (energy consumption, environmental taxes, the percentage of renewable energy supply, and gross domestic product) on carbon monoxide emissions for the period 1994–2024. Temporal and spatial limitations of the research: The research relied on time series data for the period (1994–2024) in Germany.

3. Methods

3.1. Data sources and variable definition

This study is based on the quantitative approach (Quantitative Approach), with an emphasis on the use of artificial neural networks (Artificial Neural Networks - ANN) to analyse economic and environmental relationships and predict carbon emissions. This approach was chosen for its ability to model complex, nonlinear relationships between variables, beyond the limits of traditional models. Before applying artificial neural networks, the traditional linear regression equation was used to clearly and accurately identify independent and dependent variables, as in Eq. (1).

$$SE = \alpha_0 + \beta_1 EC + \beta_2 EP + \beta_3 RES + \beta_4 GDP + \beta_5\, ET + \varepsilon_i \cdots \quad (1)$$

Where:

SE: Environmental Impact Index (carbon dioxide emissions)

EC: Total energy consumption

EP: Total energy production

RES: Share of renewable energy in total primary energy

GDP: Gross domestic product

ET: Environmental taxes

ε_i: Random error

This representation serves as a conceptual framework for the relationship between variables before being transformed into an artificial neural network (ANN) model, in which variables are processed within a nonlinear structure and assigned relative weights rather than linear coefficients. This design allows for capturing complex relationships between variables and improving the accuracy of analysis and prediction of the environmental impact index.

3.1.1. Environmental impact index (SE)

Carbon dioxide emissions represent a measure of many aspects of environmental sustainability. They are guiding principles that should be considered goals and measures for any action taken by the German government at the national level. To achieve these policies, strategies must be developed to reduce carbon emissions from the transportation and electricity sectors, primarily through trade in final products (Li et al., 2021).

3.1.2. Total energy consumption (EC)

Primary energy consumption measures a country's total energy demand and includes consumption by the energy sector itself, losses during the transformation (e.g., from oil or gas to electricity), energy distribution, and final consumption by end users (Bel & Joseph, 2018).

3.1.3. Total energy production (EP)

Includes the total supply of energy produced in or imported into a country, minus that which is exported or stored. It represents all the energy required to supply the country's end users. Some of these energy sources are used directly, while most are converted into fuel or electricity for final consumption (iea.org/world/energy-mix,2022).

3.1.4. Renewable energy share of total primary energy (RES)

The share of renewable energy sources in total primary energy supply, which includes primary renewable energy sources equivalent to hydropower, geothermal energy, and solar energy (OECD, 2020).

3.1.5. GDP (Gross Domestic Product)

Gross domestic product (GDP) equals the sum of the gross value added of all resident institutional units engaged in production, plus any product taxes and minus any product subsidies. Gross value added is the difference between production and intermediate consumption (European Union, 2010).

3.1.6. Environmental taxes

Environmental taxes are tax revenues related to the environment. These taxes include revenues, tax bases, tax rates, and exemptions. They are applied to environmental areas, such as taxes on vehicle fuels, measured or estimated emissions into air or water, and ozone-depleting substances (OECD, 2021).

Data were collected from official sources, including the World Bank and the International Energy Agency, for the period 1994–2024. The study follows a deductive quantitative approach, where theory-based variables are tested to provide empirical evidence of their impact on environmental performance.

4. Application of artificial intelligence techniques

4.1. Neural networks

To analyse the diversity of the economic model in an unconventional way, the term cryptography is used to refer to these tools, which employ artificial intelligence and networking techniques, considered among the most brilliant tools using artificial intelligence techniques and the army of cellular work mechanisms and human data. One of its advantages compared to statistical models is that it can adapt to the data presented in the traditional analytical literature, where the classical ANOVA used to analyze data, Such as regression and analysis of variance, the relationship between the independent and dependent variables is non-linear, where algorithms for non-linear analysis are used to analyze the data to identify and remove correlations between variables, whether linear or non-linear (Nedic et al., 2014). A dataset collects information that is correlated or related. One piece of information depends on or affects another part of the same Dataset (Najem & Abdulhammed, 2025).

4.1.1. Neural network components

- Input layer: This layer refers to the data entered into the neural network and represents the data for the independent variables.

- Hidden layer: This layer lies between the input layer and the output layer, processing the input data and then using it for the output layer.

- Output Layer: Refers to the layer where data is output from the neural network after processing.

- Relative Weights: These are numerical values that control the extent to which each independent variable affects the output. Weights are used to multiply the inputs and determine their impact.

According to the model variables, the components of the neural network can be drawn as follows, according to Fig. 1:

Summation function: It is used to calculate the sum of the inputs and is expressed as the sum of the weights multiplied by the independent variables. According to Eq. (2):

$$u = \sum_{j=1}^{m} w_j x_j + b \ldots \tag{2}$$

According to the specified variables, the formula of the addition function will represent the weights multiplied by the study variables as in Eq. (3):

$$u = (w_1 \times EC) + (w_2 \times EP) + (w_3 \times RPE) + (w_4 \times GDP) + (w_5 \times ET) + b \ldots \tag{3}$$

(b) Bias is a constant added to the weighted sum.

Activation function: It is the function that transforms the nonlinear form of the assembly function (u) and its formula and formula according to Eq. (4)

$$y = \varphi\,(u + b) \ldots \tag{4}$$

The sum of the effects that occur within this function is referred to as the Induced Field, and what was mentioned above can be summarized in Fig. 2.

Each of these layers contains neurons, which are similar to the neurons in nerve cells; each neuron performs a mathematical operation on its inputs and then passes the result to other neurons. In the input layer, the number of neurons equals the number of independent variables (ET, GDP, RPE, EP, EC) without modification, and the data are then passed to the hidden layer, which processes them through weights and mathematical functions. Each neuron in this layer represents a mathematical operation that combines

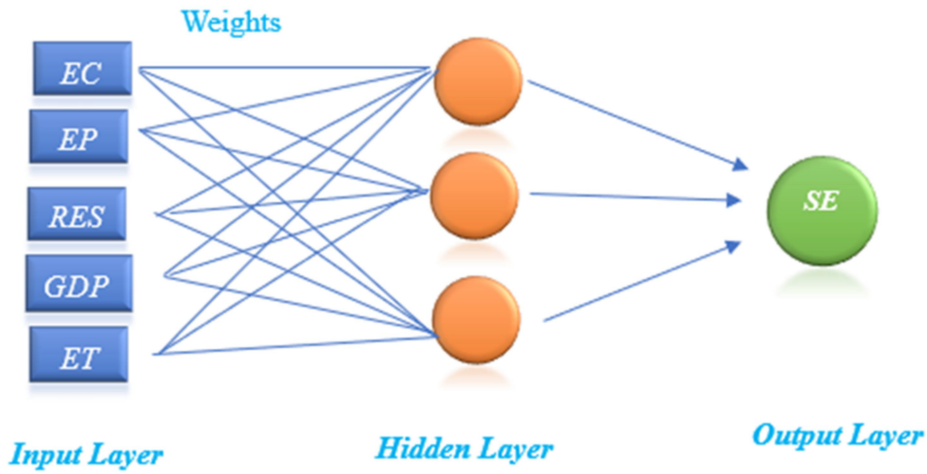

Fig. 1. ANN neuron structure.
Source: Prepared by the researcher based on the above-mentioned discussion.

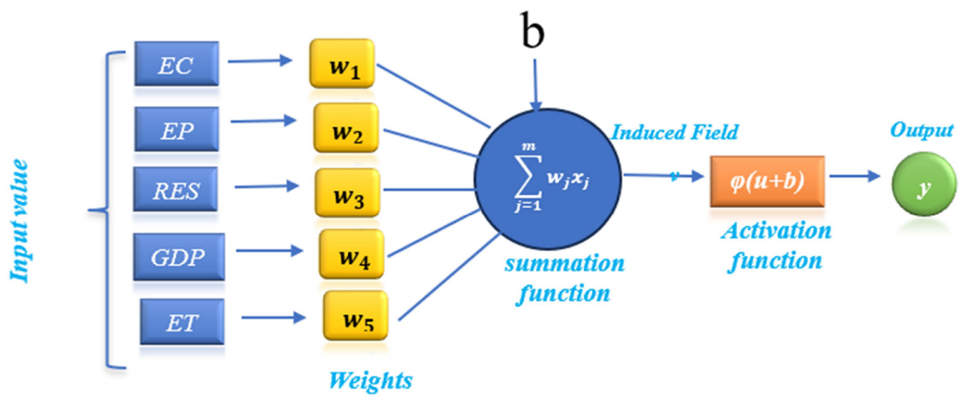

Fig. 2. Structural model of artificial neurons in mathematical form.
Source: Prepared by the researcher based on the Eqs. (2) to (4).

the variables and weights. As for the output layer, it contains one neuron that represents the expected environmental impact (carbon dioxide emissions) SE.

A neural network model was built to analyse the relationships among economic and environmental variables, with environmental emissions (SE) as the dependent variable and the other economic and environmental variables (EC, EP, RPE, GDP, ET) as independent variables. The model included an input layer with all independent variables, a single hidden layer with [the number of] neurons to estimate nonlinear relationships among variables, and a single output layer representing the target environmental variable. The ReLU activation function was used in the hidden layer, and the Linear activation function in the output layer. The model was trained using the Backpropagation algorithm, with the data split 70%:30 % for training and testing.

The model's performance was evaluated using key forecasting indicators, such as R^2 and RMSE, and the results showed strong agreement between expected and actual values, reflecting the model's ability to predict environmental emissions behaviour based on economic variables.

The added value and innovation of this study lies in the use of artificial neural networks, which enable researchers to analyse complex economic and environmental data in an interactive and direct manner. They can detect nonlinear relationships between variables that traditional models in programs such as R may be unable to, and provide accurate predictive results based on the data itself without the need for prior hypotheses or strict restrictions on their distributions. Neural networks are also highly flexible in handling raw, diverse data without the need to convert it into logarithmic formulas, allowing the original information to be preserved and fully analysed. These capabilities make neural networks a powerful tool for exploring mutual influences among variables and improving prediction accuracy, while providing a

Table 1. Case processing summary.

		N	Percent
Sample	Training	23	74.2%
	Testing	8	25%
Valid		31	100.0%
Excluded		1	
Total		32	

Source: Prepared by the researcher based on the outputs of a model. SPSS v.27.0.1 and ANN.

smoother, more flexible environment than traditional methods that require modelling and manual programming to achieve similar results.

The neural network model is implemented using a motor (MLP) in SPSS. Contrary to the assumption that the program only provides 'ready-made' results, the process involved deliberate structural design. As shown in Table 1 (Summary of Case Processing), the data were manually split into a training sample (74.2%) and a test sample (25.8%) to reduce error rates and ensure accurate predictions. The role of AI here is in the iterative learning process via a feedback algorithm, which allows the model to capture complex nonlinear relationships that standard software cannot.

5. Results

5.1. According to the sample division (Training, Validation, Testing)

In Table 2, the data were divided into three groups to ensure balanced model training and evaluation. Training set: Contains 23 cases, representing 74% of the total data, and is used to determine the weights and bias in the neural network.

The validation set includes 5 cases (16% of the data) and helps evaluate model performance when adjusting layer sizes, node counts, and activation functions. It is separate from the training and test sets.

Test suite (Testing Sample): Includes 8 cases representing 26% of the data, and is used to evaluate model performance and prediction accuracy. 31 valid cases (Valid) were used for analysis after excluding one anomaly, bringing the total sample size to 32 cases. This was done to ensure balanced model training and testing and achieve greater accuracy in results.

5.2. Neural network environment

The table below provides basic information about the neural network environment used in the analysis. The input layer shows the independent variables used; the number of units is 5. Each unit represents an independent variable, and the model uses three hidden layers using the Identity activation function, as well as the output layer represented by the dependent variable SE and the rescaling method using Standardized, the activation function for the output layer, and the error function representing the sum of the error squares to evaluate the model.

5.3. Model performance

A decrease in the sum of error squares from 0.988 in training to 0.396 in testing indicates that the model works well on new data. A relative error of 0.090 in training and 0.166 in testing reflects higher model accuracy on training data than on testing, which is expected when using neural networks (Table 3).

Table 2. Network information.

	Covariates	1	TEP
		2	TEC
		3	RES
		4	GDP
		5	ET
	Number of Units[a]		5
Input layer	Rescaling Method of Covariates		Standardized
Hidden layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1		3
	Activation Function		Hyperbolic
Output layer	Dependent Variables 1		SE
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of
a. Excluding bias unit			

Source: Prepared by the researcher based on the outputs of a model.SPSS v.27.0.1 and ANN.

Table 3. Model summary.

	Sum of Squares Error	0.988
	Relative Error	0.090
	Stopping Rule Used	1 Consecutive Step(s) with no decrease in error*
Training	Training Time	0:00:00:00
Testing	Sum of Squares Error	0.396
	Relative Error	0.166

Dependent variables: SE
a. Error computation are based on the testing sample

Source: Prepared by the researcher based on the outputs of a model.SPSS v.27.0.1 and ANN.

Table 4. Independent variable importance.

	Importance	Normalized importance
TEP	0.420	100.0%
TEC	0.57	13.5%
RES	0.135	32.1%
GDP	0.139	76.0%
ET	0.69	0.16.3%

Source: Prepared by the researcher based on the outputs of A model. SPSS v.27.0.1 and ANN.

5.4. The importance of independent variables

The Table 4 shows that total energy production (TEP) has a significant impact on the dependent variable SE, underscoring its pivotal role in determining emissions levels, especially when using conventional, polluting sources.

Gross Domestic Product (GDP) has a significant impact of up to 76%, consistent with the economic hypothesis that growth is often accompanied by increased emissions from industrial expansion and energy consumption.

In addition, the proportion of renewable energy (RES) is 32.1%; its impact is average since it represents the energy mix, but it is still below the required level.

Environmental taxes (ET) have a low, significant impact (16.3%) due to their limited effectiveness in modifying consumer and producer behaviour and in improving energy efficiency in some sectors.

Total energy consumption (TEC) has an impact 13.5%, relatively low compared to other variables.

5.5. Interpreting neural network model parameters

To support the research hypothesis, the model coefficients should be interpreted as shown in Table 5.

Table 5 shows how the variables appear within the neuron model. The results indicate that carbon (SE) emissions are indirectly affected by the three hidden-layer nodes in the model.

The results also show that the Gross Domestic Product (GDP) has a strong positive effect, as shown in nodes H(1:1) and H(1:3) with weights (0.507, 0.581). In contrast, some negative weights, such as (–0.511, –0.999), reduce the SE value. This suggests that these negative weights represent interactions in the model that reduce emissions, either through improved efficiency in economic activity or a shift towards less polluting production patterns.

Total energy consumption (TEC) showed a positive effect at node H(1:1), with a value of 0.430, consistent with the known relationship between increased energy consumption and higher emission levels.

In contrast, renewable energy supply and energy production showed relatively weak, often negative, effects, suggesting that increased reliance on renewables may help reduce emissions over time.

Environmental taxes (ET) also showed a mixed effect, with a positive value at node H(1:1) of (0.190), while a negative value at node H(1:3) of (–0.333). This variation reflects the complex nature of the impact of environmental policies on producers' and consumers' behaviour. As shown in the following Fig. 3.

In general, the model's hidden nodes indicate that the relationship between economic and environmental variables is complex and nonlinear, with some variables increasing emissions while others reduce them. These results support the study's alternative hypothesis, which assumes a dynamic, nonlinear relationship between economic and environmental variables.

5.6. Neural network structure

Fig. 4 shows the structural structure of the neural network that was used to analyze the dynamic relationship between economic and environmental variables. The figure shows the input layer that includes the independent variables plus their associated weights. Gray arrows represent positive weights, while blue arrows represent negative weights. The thickness and strength of the arrow also indicate the degree to which the variable affects the dependent variable. The circles in the middle represent nodes in hidden layers that process nonlinear relationships

Table 5. Parameter estimates.

		Predicted			
		Hidden layer 1		Input layer	
Predictor		H(1:1)	H(1:2)	H(1:3)	SE
Input layer	(Bias)	–0.265	0.334	0.443	
	TEP	–0.008	–0.479	–0.363	
	TEC	0.430	0.14	0.303	
	RES	–029	–0.181	–0.024	
	GDP	0.581	0.007	0.507	
	ET	0.190	0.061	–0.333	
Hidden layer 1	(Bias)				0.370
	H(1:1)				–0.511
	H(1:2)				–1.037
	H(1:3)				–0.999

Source: Prepared by the researcher based on the outputs of a model.SPSS v.27.0.1 and ANN.

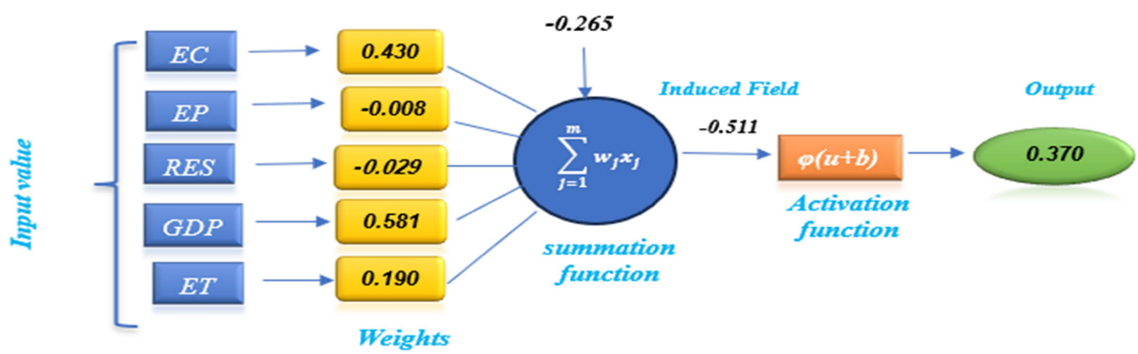

Fig. 3. The structural diagram of the neural network, including synaptic weights and estimated bias values.
Source: Prepared by the researcher based on the outputs of a model. SPSS v.27.0.1 and ANN.

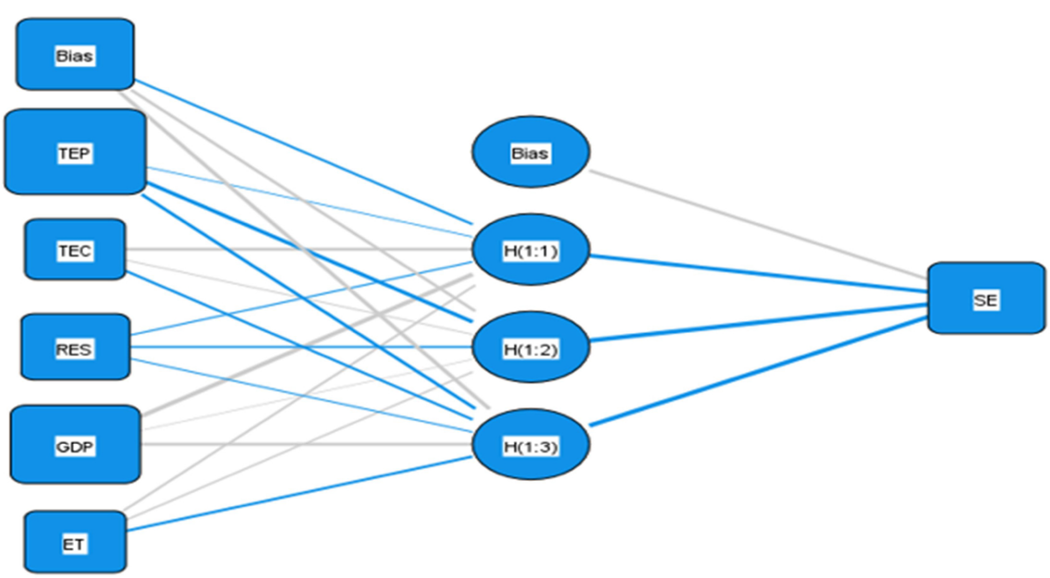

Fig. 4. Neural network structure.
Source: Prepared by the researcher based on the outputs of a model. SPSS v.27.0.1 and ANN.

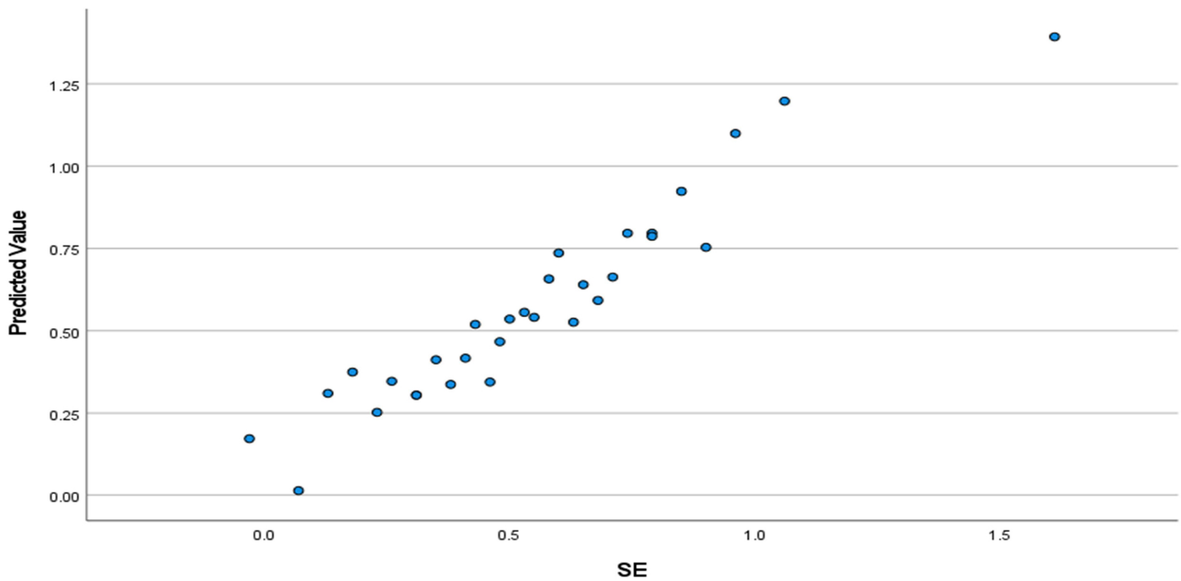

Fig. 5. Accuracy of the prediction.
Source: Prepared by the researcher based on the outputs of a model. SPSS v.27.0.1 and ANN.

between variables. This structure highlights the impact of variables such as energy production, GDP, and energy consumption on increasing emissions, while renewable energy and environmental taxes appear to contribute to varying degrees to reducing these emissions.

5.7. Model prediction accuracy

Fig. 5 shows the prediction accuracy of the model. The points in the figure appear close to each other, which indicates a high degree of agreement between the actual values and the predicted values of the dependent variable SE. This convergence reflects the model's high predictive ability, which supports the reliability of using artificial neural networks to represent the relationship between economic and environmental variables. These results also confirm the possibility of using this model for future analysis and forecasting purposes in the field of environmental and energy policies.

6. Discussion

The results of the artificial neural network model reveal the complex nature of the relationship between economic and environmental variables. The model's performance indicators showed strong predictive accuracy, indicating its ability to capture nonlinear relationships among the studied variables. The low error values and the high degree of convergence between the predicted and actual values indicate that the neural network model provides an appropriate representation of the interaction between economic activity and energy variables on the one hand, and carbon emissions on the other.

The results show that total energy production is the most influential factor in determining carbon emissions, with relative importance indicators ranking it first among the independent variables. This reflects the central role of the energy sector in shaping emissions, especially given that economic systems rely heavily on traditional energy sources. This result confirms that expanding energy production without changing the structure of its sources may lead to continued environmental pressures associated with rising emissions.

The results also showed that GDP has a relatively strong impact on emissions, consistent with the traditional relationship between economic growth and increased productive activity and energy consumption. However, some weights within hidden nodes were negative, suggesting indirect effects of economic growth that could, in some cases, reduce emissions. This reflects the complex nature of the relationship between economic growth and the environment, as growth can simultaneously increase emissions from industrial expansion and reduce them through improved technological efficiency or a shift towards more sustainable production patterns.

Energy consumption has shown a positive impact at some nodes in the neural network, reflecting the close link between increased energy demand and rising emissions, especially in economies that rely heavily on traditional energy sources. This finding suggests that energy consumption patterns are an important factor in explaining changes in carbon emissions.

In contrast, renewable energy supplies have had a relatively small impact on emissions, though it is still lower than that of some other variables. This suggests that increasing reliance on renewable energy can help reduce emissions, but its limited contribution to the energy mix may limit its current ability to have a greater impact on pollution levels.

The results also showed that environmental taxes have a varying effect within the model, appearing with positive weights in some nodes and negative weights in others. This variation indicates that the impact of environmental policies may not always be direct, but rather depends on the nature of their implementation and the extent of their response across different economic sectors. Therefore, the effectiveness of environmental taxes in reducing emissions may be affected by compliance levels and the institutional mechanisms supporting their implementation.

In general, the model's results indicate that the relationship between economic and environmental variables is highly complex and intertwined, with energy, economic activity, and environmental policies interacting nonlinearly to determine carbon emissions. This result underscores the importance of using neural network models to analyse such relationships, given their ability to capture complex patterns that may not be apparent in traditional models.

Therefore, the results support the study's alternative hypothesis, which posits that energy-related, economic activity, and environmental policy variables influence emission levels through non-linear relationships.

7. Conclusion

The study examines the relationship between economic variables and environmental emissions in Germany using an artificial neural network model. The model weights showed that total energy production and GDP most influenced carbon dioxide emissions, accounting for 76%. Renewable energy contributed 32.1% to reducing emissions, while environmental taxes had a limited impact at 16.3%. These empirical results suggest that conventional energy policies remain the primary determinant of emissions levels. The expansion of renewable energy, however, is an effective way to reduce emissions. Thus, the study's conclusions emerge directly from the model's outputs. They provide a clear, quantitative explanation of the factors affecting environmental performance, consistent with the goal of analysing these determinants using artificial intelligence.

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Conflict of interest

The author declares that they have no conflict of interest.

Ethical approval

The project was approved by the local ethics committee at the university of Baghdad.. The study does not include any humans or animals.

Authors' contribution

The author confirms that she is the sole contributor to this work and has approved the final version of this research for submission.

Data availability

The data used to support the results of this study are available and accessible on the World Bank website https://www.worldbank.org/.

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Appendices

Neural network model input data for the period 1994–2024.

Year	SE	TEC	TEP	RES	GDP	ET
1994	1.61	0.58	187	0.07	–0.03	0.81
1995	1.06	0.66	169	0.18	0.13	0.74
1996	0.96	1.06	164	–0.03	0.07	0.63
1997	0.85	0.9	152	0.13	0.18	0.5
1998	0.79	0.85	145	0.23	0.23	0.46
1999	0.79	0.61	145	0.26	0.26	0.65
2000	0.9	0.66	143	0.3	0.3	0.71
2001	0.74	0.96	144	0.33	0.33	0.96
2002	0.71	0.74	136	0.35	0.35	0.9
2003	0.6	0.74	137	0.38	0.38	1.61
2004	0.58	0.81	136	0.41	0.41	1.06
2005	0.68	0.74	135	0.43	0.43	0.85
2006	0.65	1.61	135	0.46	0.46	0.77
2007	0.63	0.55	136	0.48	0.48	0.6
2008	0.55	0.61	138	0.5	0.5	0.55
2009	0.5	0.44	138	0.53	0.53	0.68
2010	0.53	0.53	141	0.55	0.55	0.53
2011	0.43	0.44	139	0.58	0.58	0.58
2012	0.48	0.48	136	0.6	0.6	0.48
2013	0.18	0.5	129	0.63	0.63	0.43
2014	0.41	0.33	132	0.65	0.65	0.41
2015	0.26	0.35	125	0.71	0.68	0.38
2016	0.38	0.38	126	0.68	0.71	0.35
2017	0.46	0.41	124	0.74	0.74	–0.03
2018	0.31	0.3	121	0.77	0.77	0.3
2019	0.31	0.24	120	0.81	0.81	0.26
2020	0.35	0.14	115	1.61	0.85	0.18
2021	0.23	0.18	115	0.85	0.9	0.33
2022	0.13	–0.03	112	1.06	0.96	0.07
2023	0.07	0.24	104	0.9	1.61	0.23
2024	–0.03	0.07	97	0.96	1.06	0.13