Received 5 January 2019
Revised 16 April 2019
Accepted 22 April 2019

Application of ANFIS, ANN and fuzzy time series models to CO_2 emission from the energy sector and global temperature increase

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Abstract

Purpose – A significant number of studies have been conducted to analyze and understand the relationship between gas emissions and global temperature using conventional statistical approaches. However, these techniques follow assumptions of probabilistic modeling, where results can be associated with large errors. Furthermore, such traditional techniques cannot be applied to imprecise data. The purpose of this paper is to avoid strict assumptions when studying the complex relationships between variables by using the three innovative, up-to-date, statistical modeling tools: adaptive neuro-fuzzy inference systems (ANFIS), artificial neural networks (ANNs) and fuzzy time series models.

Design/methodology/approach – These three approaches enabled us to effectively represent the relationship between global carbon dioxide (CO_2) emissions from the energy sector (oil, gas and coal) and the average global temperature increase. Temperature was used in this study (1900-2012). Investigations were conducted into the predictive power and performance of different fuzzy techniques against conventional methods and among the fuzzy techniques themselves.

Findings – A performance comparison of the ANFIS model against conventional techniques showed that the root means square error (RMSE) of ANFIS and conventional techniques were found to be 0.1157 and 0.1915, respectively. On the other hand, the correlation coefficients of ANN and the conventional technique were computed to be 0.93 and 0.69, respectively. Furthermore, the fuzzy-based time series analysis of CO_2 emissions and average global temperature using three fuzzy time series modeling techniques (Singh, Abbasov–Mamedova and NFTS) showed that the RMSE of fuzzy and conventional time series models were 110.51 and 1237.10, respectively.

Social implications – The paper provides more awareness about fuzzy techniques application in CO_2 emissions studies.

Originality/value – These techniques can be extended to other models to assess the impact of CO_2 emission from other sectors.

Keywords ANN, ANFIS, Global temperature, Fuzzy models, Fuzzy analysis of time series

Paper type Research paper

This paper forms part of a special section "Climate change and arid land agriculture: impact and adaptive", guest edited by Mirza Barjees Baig, Gary S. Stradquadine, Joel L. Cuello and Mahmoud El Solh.

International Journal of Climate Change Strategies and Management
Vol. 11 No. 5, 2019
pp. 622-642
Emerald Publishing Limited
1756-8692
DOI 10.1108/IJCCSM-01-2019-0001

1. Introduction

According to environmental experts, carbon dioxide (CO_2) is a major contributor to the increasing global temperature. CO_2 emissions come from various sources including the agricultural, energy, industrial and waste sectors. The share of CO_2 emissions from the energy sector accounts for 58.8 per cent of all greenhouse gas (GHG) emissions (Statistics, 2011). Regression techniques can be used to understand the past trends and predict the future trends in CO_2 emissions (Köne and Büke, 2010). CO_2 emissions from fossil fuel consumption and other sources were reported to be the highest, contributing 55 per cent of the total amount by three major countries: China, Russia and the European Union (Olivier *et al.*, 2012). Andres *et al.* (2012) discussed the emission of CO_2 from fossil fuel combustion and cement, which continues to increase year after year. Davis *et al.* (2010) estimated the CO_2 emissions from oil and gas (energy sector) for the years 2010-2060 and related it to the global temperature increase using conventional modeling tools. Their results showed a continual increase in both emission amount and temperature for the period considered in the investigation [4]. Quadrelli and Peterson (2007) also presented trends in CO_2 emissions from different sectors, regions and for various kinds of fuel, which proved the significant increase of emissions over time. Rodhe (1990) and Jenkinson *et al.* (1991) compared the gas emissions from natural gas and other energy sources and estimated the corresponding increase in the temperature. Global warming is the result of the emission of CO_2 from soil (Jenkinson *et al.*, 1991). The impact of CO_2 emission on the air quality using artificial neural network (ANN) technique has been reported by Ćirić *et al.* (2012). Similarly, (Baghban *et al.*, 2016) applied adaptive neuro-fuzzy inference systems (ANFIS) technique to predict the true vapor pressure of volatile petroleum products. ANFIS modeling was also proposed for CO_2 emission for amine solution (Ghiasi *et al.*, 2016). The concentration of carbon monoxide in the environment was also estimated using ANN and ANFIS (Noori *et al.*, 2010). (Baghban *et al.*, 2016) explored the estimation of natural gas water content using ANFIS.

The emission of CO_2 has an irreversible impact on the environment (Pearce, 1991). Cherubini *et al.* (2011) proposed a technique to evaluate the effect of CO_2 emissions on the environment from biomass combustion and suggested that emission of CO_2 from biomass has no serious impact on the atmosphere. Schneider (1989) discussed the reasons of global environment change and its impact on global temperature. According to Jackson *et al.* (2017), 90 per cent of CO_2 was emitted from fossil fuels and progression is expected in 2018.

Various conventional and non-conventional models were used to represent the relationship between CO_2 emissions, global temperature increase and other GHG emissions. Greenhouse emissions that resulted in global temperature increase were presented using probability analysis to overcome the unpredictable nature of the CO_2 emissions cycle (Meinshausen *et al.*, 2009). On the other hand, Zedeh (1965) proposed the idea of fuzzy set theory, which can be applied in uncertain circumstances and conditions where data are imprecise or fuzzy in nature. Likewise, according to, Aslam (2018, 2019) a noble closely related more comprehensive modeling tool, neutrosophic statistics, was applied to perform various studies in various areas. This method is considered as a generalization of fuzzy set theory.

Furthermore, ANFIS, another fuzzy technique, was considered to be an efficient tool to predict the environmental factors of GHG production with a high degree of accuracy and minimal error. Jang (1991) proposed the concept of an ANFIS for the first time. This technique was implemented to investigate complex systems by modeling, controlling and estimating the parameters in reference (Amid and Mesri Gundoshmian, 2017). Piotrowski *et al.* (2015) proposed ensemble adaptive-network-based fuzzy inference systems (FIS) and applied them in the prediction of river water temperature, including hilly and coastal areas in severe cold and hot weather conditions. It was concluded that the proposed model provided comparatively better results by reducing the mean square error (MSE). Bektas Ekici and Aksoy (2011) developed an ANFIS-based model to predict energy consumption and selected the best control strategy in an icy zone. Mohammadi *et al.* (2016) also applied ANFIS to select the relevant variables that had a high impact on global solar radiation forecasting. Yadav and Sahu (2017) predicted wind speed using ANFIS and ANN techniques as wind speed shows complex trends and indirectly affects global temperature increase trends. The predictions using the proposed tools provided a more accurate and reliable output when compared to conventional regression technique. Memon *et al.* (2007) proposed a life cycle impact assessment of four treatment technologies using a fuzzy inference system and concluded that the application of a natural treatment process had a less ecological effect.

The same ANFIS model has been used to predict and represent several other temperatures, CO_2 levels, weather and climate-related parameters. Karandish *et al.* (2017) studied the influence of weather conditions on maize crops. Environmental factors such as average temperature and CO_2 and oxygen levels were calculated using an ANFIS, which was proven to perform well. Similarly, Saghafi and Arabloo (2017) proposed an account of CO_2 immersion on a microporous material emphasized some of the captivating problems of the present adsorption studies and observed that ANFIS performed better than conventional adsorption isotherms. ANFIS, multiple linear regression models and other statistical indices have also been used to model temperature data against crop yield (Cobaner *et al.*, 2014). A comparison of the forecasted values showed that the ANFIS model performed better than multiple linear regression and the other statistical indices considered in their study. Talebizadeh and Moridnejad (2011) conducted a study in Iran to predict the water level in Lake Urmia. Fluctuation levels and three important variables were investigated. Two important techniques, namely, ANFIS and ANN were applied and the performance of both approaches was evaluated where it was concluded that ANFIS outperformed ANN. Wahyuni *et al.* (2017) proposed a new approach consisting of a mixture of an adaptive neuro-fuzzy inference system and genetic algorithm (ANFIS-GA). The prevailing weather forecasting system was inconsistent in predicting rain, and farmers were not able to grow potatoes in a timely manner, and therefore, suffered production loss due to the uncertainty of rain. This hybrid technique helped farmers make a timely and accurate prediction of rain. ANFIS and ANN is applied on environmental data and results indicate ANFIS performed better than ANN with high accuracy and less error in prediction of ecological indices (Khoshnevisan *et al.*, 2013).

The modeling of complex, non-linear systems where information about the system is incomplete was discussed with fuzzy set theory and fuzzy logic in reference (Babuška, 2012). The advantage of fuzzy modeling is that it overcomes complications of traditional modeling for a system with a non-linear nature and impreciseness of knowledge. According to Azadeh *et al.* (2008), ANNs are currently applied in several disciplines comprising prediction, grouping, pattern recognition, data mining and process modeling. ANNs have also been applied to investigate the relationship between parameters influencing the manufacture of CO_2. The application of this technique made prediction, optimization and refinement proficient in the seizure process of CO_2 (Zhou *et al.*, 2010).

One weakness of conventional forecasting approaches is that they cannot predict historically fuzzy data. In this situation, fuzzy time series models are used. In conventional time series prediction, autoregressive moving average (ARMA) models are used to build the relationships between variables. ARMA models suffer several limitations. First, the relationships among non-linear variables cannot be established using ARMA models due to their linear nature. Second, the computation of the parameters of several variables is also difficult. Third, strong correlations may cause large errors. Furthermore, when the past data are in a verbal form, no conventional approach can be applied. In this situation, fuzzy time series models are efficient techniques to analyze the data (Khashei *et al.*, 2009). The basis of the fuzzy time series is fuzzy set theory, proposed in reference (Zedeh, 1965). The fuzzy time series model was proposed in reference (Song and Chissom, 1993). A complete illustration of the fuzzy technique and application was given in the prediction of the enrolment rate of university students. Moreover, fuzzy time series have been applied in various fields of life including economics, finance, information technology and environmental sciences.

Chen and Hwang (2000) proposed two factors in the time-variant fuzzy time series model to predict fuzzy data and concluded that the fuzzy time series model provided a better prediction. Song and Chissom (1993) proposed a fuzzy time series model and elaborated on some of the properties of the proposed model. Chen (1996) proposed a technique to project university enrolment by using a fuzzy time series and compared the results of the proposed model with the model developed in Reference (Song and Chissom, 1993). Chen and Hsu (2004) proved that a fuzzy time series model could predict more accurate results than competing models. Abbasov and Mamedova (2003) proposed a fuzzy time series model and applied it to demographic data to predict population. Singh (2008) proposed a fuzzy time series model, and applied it to crop prediction and proved its advantage over competing models. Martínez-López and Gay Garcia (2011) proposed a simple climate model to predict an increase in temperature as a function of CO_2 emissions and presented different scenarios for CO_2 emissions and global temperature. Jones *et al.* (1999) presented an account of the surface temperature of the past 150 years and concluded that the hottest periods of this century were during the ranges from 1925 to 1994 and 1978 to 1997.

The studies mentioned above clearly show that the fuzzy-based modeling techniques of ANFIS, ANN and fuzzy time series produce more accurate results when compared to conventional techniques in regression, correlation and time series analyzes. In spite of this, currently, there have been no studies that have analyzed the applicability of these fuzzy techniques (ANFIS, ANN and fuzzy time series models) to model global temperature increase as a function of CO_2 emission, specifically from the energy sector. In the same manner, as the aforementioned literature, CO_2 emissions from the energy sector and their impact on global temperature increase can be studied using fuzzy techniques to obtain more accurate and reliable results.

Therefore, this study aimed to evaluate the performance of three fuzzy-based modeling techniques (ANFIS, ANN and fuzzy time series models) in predicting the relationship between CO_2 emissions from the energy sector and global temperature increase. The prediction capacity and the performance of the fuzzy modeling techniques were also compared to conventional techniques and to each other. The novel contribution of this study is the comparison made between conventional modeling techniques and the proposed three non-conventional fuzzy set theory-based modeling techniques of ANFIS, ANN and fuzzy time series to predict global temperature increase as a function of CO_2 emission from the energy sector.

2. Methodology

2.1 Data collection and organization

The global temperature and CO_2 emissions data set were taken from the Earth Policy Institute for the years 1900 to 2012, with a total of 113 data points. All data points for both variables were normalized and converted into a matrix form that was acceptable to MATLAB. The collected data were divided for training (85 per cent, 96 data points) and testing (15 per cent, 17 data points). For this data set, the three CO_2 emission sources from the combustion of gas, oil and coal; were considered as inputs and the global temperature was set as an output variable. Figure 1 shows the total CO_2 emissions from the energy sector against global temperature for the years 1900-2012.

2.2 Modeling techniques

2.2.1 Adaptive neuro-fuzzy inference system. There are three main parts of the fuzzy inference system: membership functions, fuzzy set operations and inference rules. Selected inputs and outputs have a domain called the universe of discourse, which is divided into subsets that are expressed by linguistic expressions. The relationships between subsets of inputs and outputs, and also among the subclasses of inputs are illustrated by if–then–else rules and fuzzy set operators. ANFIS is a mixture of ANN and FIS. Membership functions and fuzzy rules are generated during the training process. There are two major inference systems: Mamdani and Sugeno. In the Sugeno inference system, output membership functions can be linear or constant (Jang, 1993). In the Mamdani inference system, the output membership function can be triangular or Gaussian. A Sugeno-type fuzzy inference system is computationally effective, while the Mamdani-type is based on expert knowledge. A Sugeno-type system usually uses real data. The fuzzy inference model for the current data sets were organized in temperature as shown in Figure 2 where each input had three membership functions, and there are 27 rules and 27 output membership functions that will ultimately be defuzzified to one temperature output.

2.2.2 Structure of adaptive neuro-fuzzy inference system. We explain the ANFIS structure with a simple two variable, x_1 and x_2, example. The two fuzzy if–then rules for a first order Sugeno fuzzy model are expressed as follows:

(1) *Rule 1*: If x_1 is C_1 and x_2 is D_1, then, $y_1 = c_1\,x_1 + d_1\,x_2 + m_1$; and

(2) *Rule 2*: If x_1 is C_2 and x_2 is D_2, then, $y_2 = c_2\,x_2 + d_2\,x_2 + m_2$.

Where C_i and D_i are considered as fuzzy sets; y_i is the output; and c_i, d_i and m_i are the model parameters that are calculated during the training process.

There are five layers in the ANFIS structure (Figure 2).

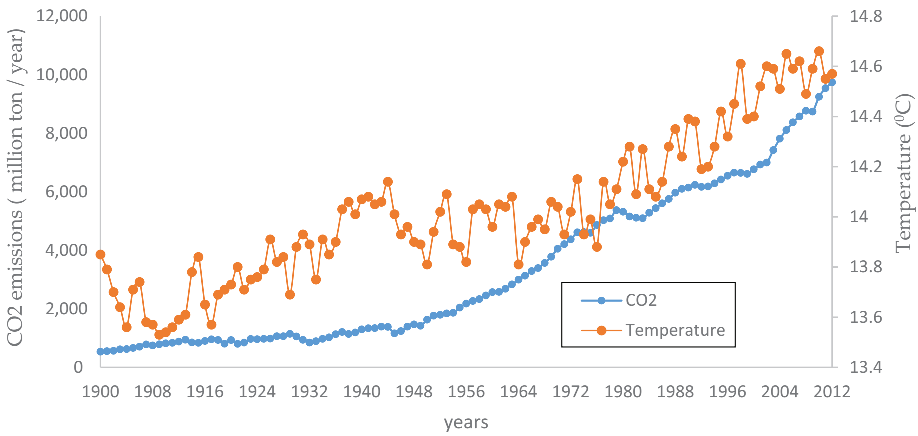

Figure 1.
Time series data of the total CO_2 emission in the energy sector (blue), and average global temperature (orange) for the period from 1900 to 2012

(1) *Layer 1*: In Layer 1, each node represents a node function:

$$O_i^1 = \mu_{A_i i}(x),\ i = 1, 2.$$

.

(2) *Layer 2*: In Layer 2, each node represents the firing strength of a rule by multiplication where a node function is:

$$O_i^2 = \mu_{C_i}(x) * \mu_{D_i}(x),\ i = 1, 2, 3.$$

(3) *Layer 3*: In Layer 3, firing strengths from the previous layer are normalized to distinguish between the firing strengths of each rule from the total firing strengths of all of the rules:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2, 3$$

(4) *Layer 4*: In Layer 4, calculate the firing strength of each rule from the total strength of all rules:

$$O_i^4 = \overline{w}_i * y_i = \overline{w}_i(c_i * x_i + d_i * x_i + m_i)$$

(5) *Layer 5*: In Layer 5, the single nodes are used to calculate the overall output:

$$O_1^5 = \sum_i \overline{w}_i * y_i = \frac{\sum w_i y_i}{\sum} w_i$$

2.2.3 Artificial neural network. An ANN was applied to calculate the relationship between CO_2 emissions and temperature. As in the case of the ANFIS, CO_2 emissions were the inputs, the global temperature was the output and the data set was divided into training (85 per cent) and testing (15 per cent) before executing the modeling. Ultimately, the correlation

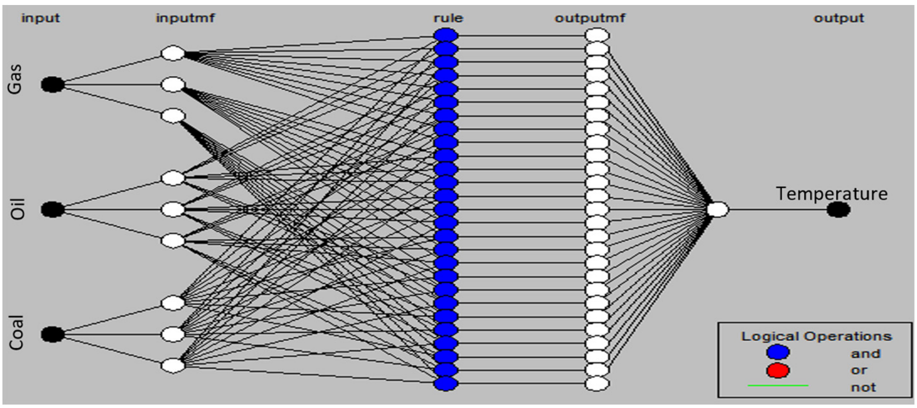

Figure 2. Structure of the ANFIS used in this work. There are three inputs; the CO_2 emissions from coal, oil and gas combustion; and one output, the global temperature

between the input and target parameters was generated for the training, testing and validation data sets.

An artificial neural network contains three layers: input, hidden and output. The input layer gets data from an outer source. Most often, the data are normalized to obtain reliable results. The hidden layer converts the input into a form that can be used by the output layer. The output layer gives the final outcome from the simulation, which depends upon the interconnection between the neurons, the composition of the three layers and the disposition of the neurons. The major structure of an ANN can be grouped into four types: single feedforward neural networks, multilayer feedforward networks, recurrent networks and mesh networks (da Silva *et al.*, 2017).

2.3 Fuzzy time series

Another important tool considered in this work was the time series modeling technique. Time series forecasting is a key factor to assess future trends and design future strategies. In time series forecasting, previous values are used to predict future values. Traditional forecasting techniques cannot be applied to a study time series containing linguistic terms. Fuzzy time series methods are easier to apply because of the following two reasons: theoretical assumptions are not required and they are capable of generating results with a smaller set of data.

As a characteristic example, let U be the universe of discourse, where $U = \{u_1, u_2, u_3, u_4, \ldots u_n\}$. A fuzzy set A_i of U can be defined via:

$$A_i = \frac{\mu_{A_i}(u_1)}{u_1} + \frac{\mu_{A_i}(u_2)}{u_2} + \frac{\mu_{A_i}(u_3)}{u_3} + \frac{\mu_{A_i}(u_4)}{u_4} + \ldots + \frac{\mu_{A_i}(u_n)}{u_n} \tag{1}$$

where μ_{Ai} is the membership function of the fuzzy set A_i and μ_{Ai}: $U \rightarrow [0, 1]$. In addition, $\mu_{Ai}(u_j)$, where $j = 1, 2,.., n$ denotes a generic element of fuzzy set SA_i, denotes the degree of belongingness of u_j to A_i; $\mu_{Ai}(u_j) \in [0, 1]$.

Time series data of CO_2 emissions and temperature were collected and converted to fuzzy time series using R software. Evaluation metrics, including the mean absolute percentage error (MAPE), MSE, the root mean square error (RMSE), the mean absolute error (MAE) and the mean percentage error (MPE), were calculated both the conventional and fuzzy series and are defined as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{\left|froecast_t - actual_t\right|}{actual_t} \tag{2}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n} (froecast_t - actual_t)^2 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (froecast_t - actual_t)^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|froecast_t - actual_t\right| \tag{5}$$

$$\mathrm{MPE} = \frac{1}{n}\sum_{t=1}^{n}100\left(\frac{(froecast_t - actual_t)}{actual_t}\right) \tag{6}$$

Our research applied fuzzy modeling techniques to assess the performance of fuzzy models related to global warming data and compared the performance of fuzzy time series and conventional time series. Fuzzy time series analysis was performed using R software (Analyze TS). Three methods of fuzzy time series were applied: first, the Singh model generated actual and fuzzy data based on time series; second, the Abbasov–Mamedova model evaluated the fuzzy data and forecasting for coming years; finally, the NFTS was used to compare the actual and fuzzy data and further forecasting was done for 25 years (2014-2037).

3. Results

3.1 Adaptive neuro-fuzzy inference system

3.2 Artificial neural network

3.3 Fuzzy time series analysis

3.3.1 Performance evaluation of time series of carbon dioxide emissions.

3.3.2 Performance evaluation of the global temperature time series.

4. Discussion

4.1 Adaptive neuro-fuzzy inference system

In the ANFIS analysis, the inputs and output variables were correlated using three input membership functions and a set of 27 rules. These membership functions and rules produced fuzzy outputs. Finally, the fuzzy outputs were defuzzified to obtain a scalar output. As discussed in the methodology section, the historical data set was divided into two parts: 85 per cent for training and the remaining 15 per cent for testing. Figure 3 shows the training data and the FIS generated outputs for the ANFIS structure shown in Section 2.2.1.

The training and testing results of the ANFIS prediction are presented in Table I. Three membership functions were used for each input. Four types of input membership functions (triangular, Gaussian, trapezoidal and Gaussian Bell) and two types of output membership

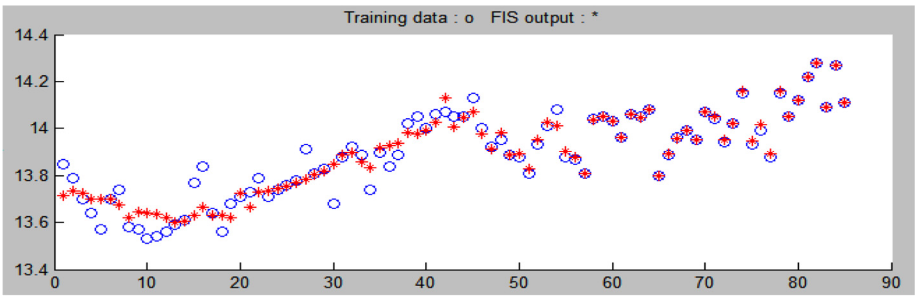

Figure 3. Structure of the training data (blue circles) versus the FIS output (red stars)

functions (linear and constant) were compared in the analysis of this model. Results of the linear output membership function show a better correlation than the constant output membership function. The performance of the Gaussian bell membership function (Gauss2mf) is better than the other three membership functions investigated in this section. Two optimization methods, grid partitioning and a hybrid method, were used to train the data. The performance of the hybrid method is found to be better than the grid partitioning method. In this study, an optimum number of 30 epochs was used. The training and testing errors associated with each method are compared and are shown in Table I. Model No. 6 shows the least training and testing errors; 0.0529 and 0.11572, respectively. Figure 4 shows the increase in temperature with increased consumption of major fossil fuels. The temperature increase as a function of CO_2 emissions from the energy sector shows an

Table I.
The ANFIS results of the various studied models

S no	MF	Output MF	Membership function	FIS optimization generation method	No of epochs	Train FIS optimization method	Training error	Testing error
1	(3,3,3)	Constant	Gaussmf	Grid partition	30	Hybrid	0.0943	0.1439
2	(3,3,3)	Constant	Gauss2mf	Grid partition	30	Hybrid	0.1060	0.8502
3	(3,3,3)	Constant	trimf	Grid partition	30	Hybrid	0.0930	0.4829
4	(3,3,3)	Constant	trapmf	Grid partition	30	Hybrid	0.1129	0.5131
5	(3,3,3)	Linear	Guassmf	Grid partition	30	Hybrid	0.0493	2.1202
6	(3,3,3)	Linear	Gauss2mf	Grid partition	30	Hybrid	0.0529	0.1157
7	(3,3,3)	Linear	trimf	Grid partition	30	Hybrid	0.0512	30.0301
8	(3,3,3)	Linear	trapmf	Grid partition	30	Hybrid	0.0628	0.1176

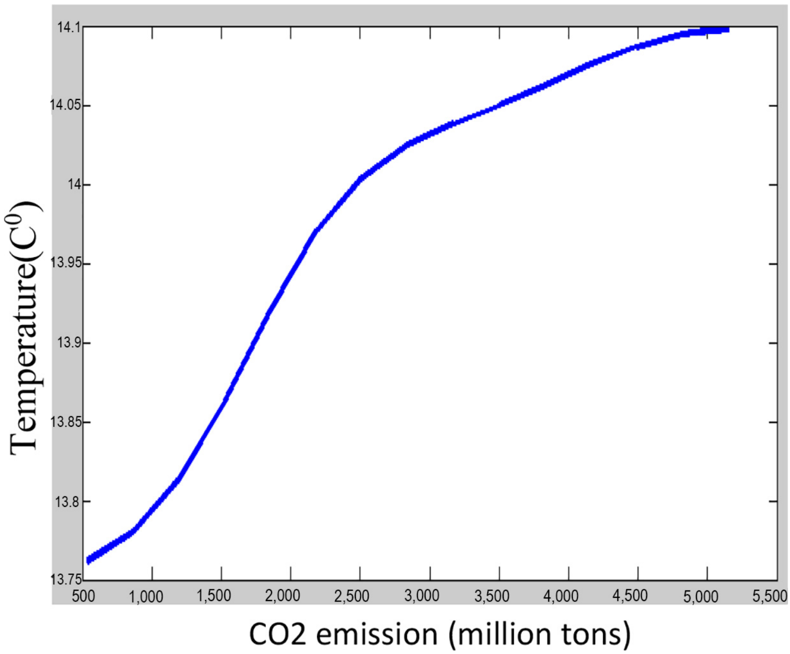

Figure 4.
CO_2 emissions (million tons) from the three combustion sources (coal, oil and gas) against global temperature increase

exponential trend with an inflection point where the trend changes direction. Figure 5, on the other hand, shows the surface response of two inputs (coal and oil) against the output (global temperature) where the combination of two inputs results in a higher global temperature increase with coal being the major contributor for the temperature increase. CO_2 emissions from coal and oil show a continuous increment with a general positive incremental effect on global temperature. Because of the nature of the model equation, intermittent fluctuations or discrepancies are observed in the surface response graph shown in Figure 5. The predictions from the ANFIS model for a given set of input and output variables are also presented using the ruler viewer where any variation or change in the input results in a corresponding change in the predicted output, as shown in Figure 6. For example, when the CO_2 emissions from Input 1 (coal), Input 2 (oil) and Input 3 (gas) are 515, 165 and 35.56 million tons/year, respectively and the corresponding value for the predicted output (global temperature) is 13.6°C. Likewise, when the CO_2 emissions from coal, oil and gas are 1,301, 1,219 and 324.4 million tons/year, respectively the predicted global temperature is 14°C. This clearly shows the prediction power of ANFIS for a combination of various sets of inputs. The three-fold increase in CO2 emission resulted in a global temperature increase of 0.7°. This prediction is quite in agreement to the average global temperature increase report by NASA's Godard Institute.

4.2 Artificial neural network

We used an ANN as another fuzzy-based modeling tool to investigate the correlation between the input and output variables. Figure 7 shows the validation performance of CO_2 emissions as the input and the global temperature as the output. Correspondingly, the overall MSE of the ANN model is 0.014172, as shown in Figure 7. On the other hand, the analysis generated by MATLAB using an ANN approach provided correlation coefficients of 0.94, 0.89, 0.95 and 0.93 for the training, validation, testing and combined

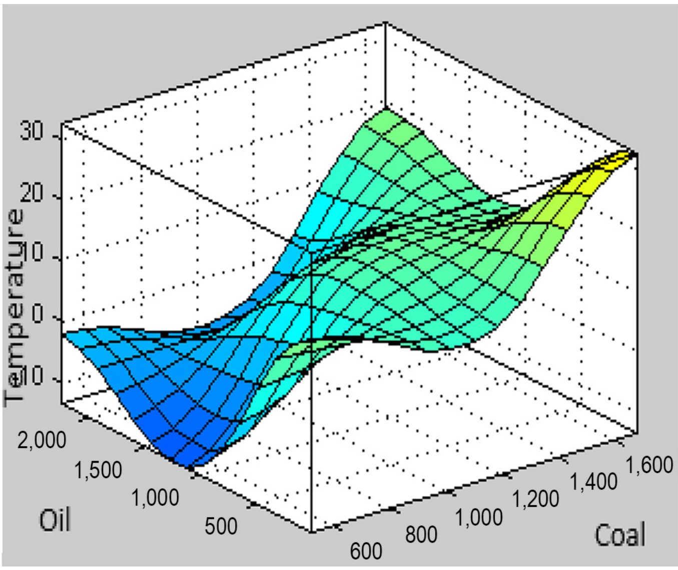

Figure 5.
Surface response graph of the global temperature versus CO_2 emissions (millions of tons) from coal and oil

overall data sets, respectively as shown in Figure 8. This fuzzy-based modeling tool also shows an acceptable prediction power that was much greater than any of the conventional modeling tools.

In this article, Noori *et al.* (2010) investigated ANN and concluded that it showed less uncertainty as compared to competing model. It projected the best trend in CO_2 absorption level. Adaptive neuro network with other models was used by Kim *et al.* (2019) to evaluate climate indices. Prediction of CO_2 from petroleum consumption and its impact on global warming is studied using ANN (Chiroma *et al.*, 2015).

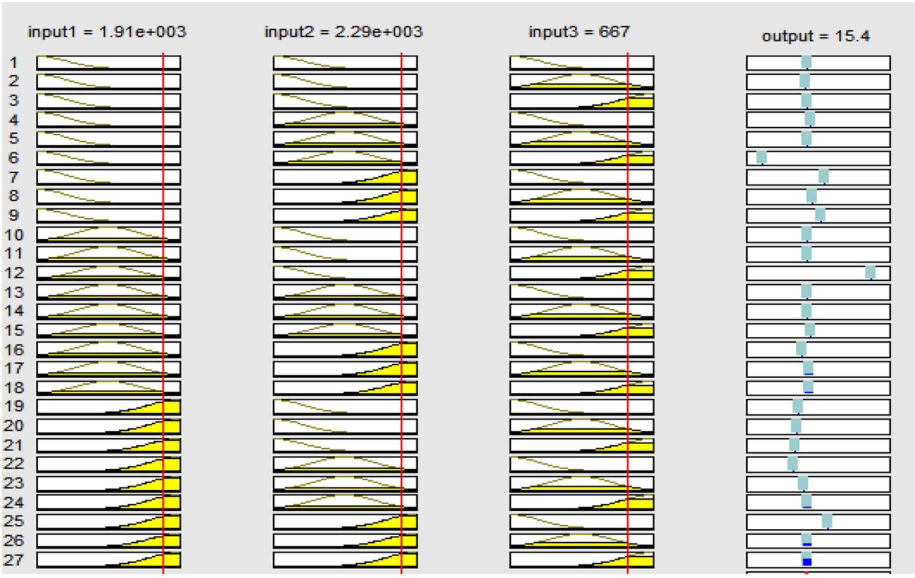

Figure 6.
ANFIS response graph showing the relationship between emission of CO_2 from the combustion of coal (Input 1), oil (Input 2) and gas (Input 3) versus global temperature increase (output) for the selected input and output conditions

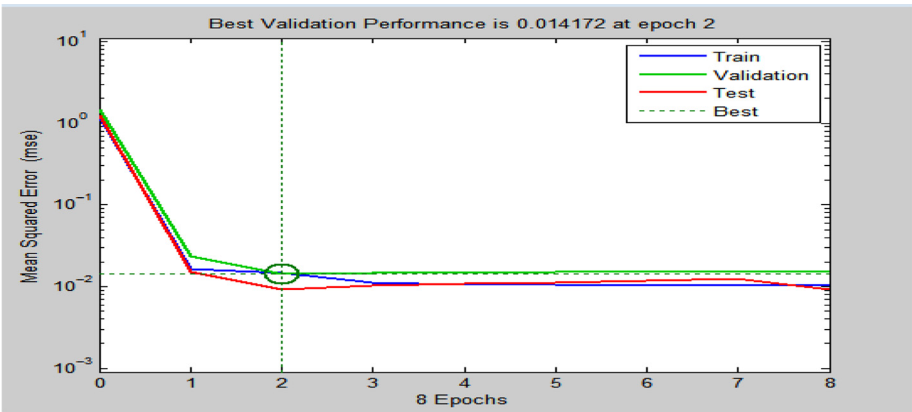

Figure 7.
Validation performance of the correlation between CO_2 emissions and temperature in the ANN model

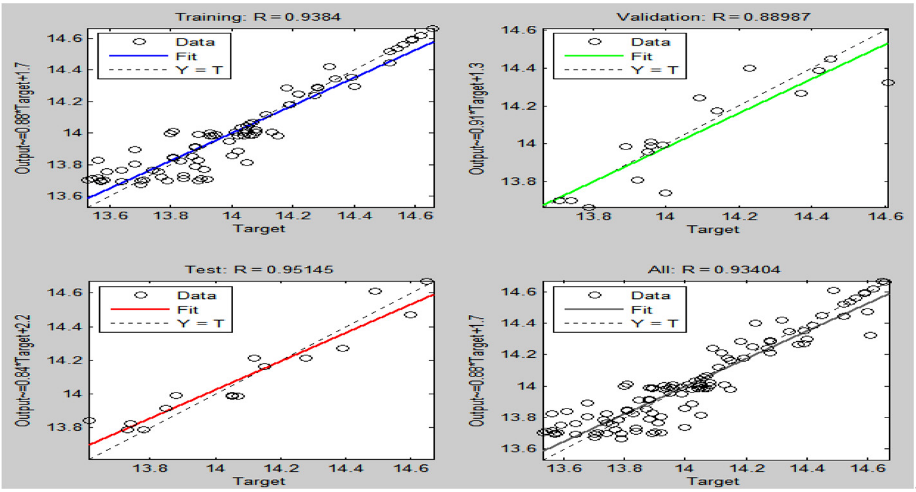

Figure 8.
Correlation coefficient between the global temperature and CO_2 emissions in the ANN model for the training, validation and testing data sets

4.3 Fuzzy time series analysis

4.3.1 Performance evaluation of time series of carbon dioxide emissions. Another important tool considered in this work was the time series modeling technique as discussed in Section 2.3. The performance tests measure both the conventional and fuzzy environments for CO_2 emissions. Results show that the fuzzy time series provided better results when compared to the conventional methods, as shown in Table II. The residual mean square error (RMSE) for the CO_2 emissions tested using conventional methods is 237.19, whereas the fuzzy prediction gives an RMSE of 110.510. Likewise, MAE and MPE for the fuzzy-based time series model are less than the corresponding errors from the conventional analysis. This clearly shows the applicability of fuzzy theory and the fuzzy time series models for historical data analysis applications; they have a superior performance and prediction power when compared to any of the existing conventional techniques. Figure 9 shows the CO_2 emissions when using the fuzzy Singh model and Figure 10 shows the time series modeling results of CO_2 emissions using the Abbasov–Mamedova model. The Abbasov–Mamedova model was used to project the CO_2 emissions trend for the next 25 years, unlike the Singh model, which cannot be used for future model prediction. Likewise, Figure 11 shows the projection of CO_2 emissions for the next 25 years using the NFTS fuzzy time series model. The projection of CO_2 emissions from the energy sector shows a very sloppy incremental trend from the years 2000 to 2037, which is much more rapid when compared to the CO_2 emissions from 1900 to 1960, where the increment is slow and from 1960 to 2000 where the trend is exponential. A comparative study of the Singh, Abbasov–Mamedova and NFTS models shows that the performance of NFTS is better than its competitors (Table II). The RMSEs of the NFTS, Abbasov–

Table II.
Performance measures of CO_2 emissions in the conventional and fuzzy models

Accuracy metrics (CO_2)	RMSE	MAE	MAPE	MPE
Fuzzy (NFTS)	110.51	80.252	3.57	2.52
Fuzzy (Singh)	114.34	102.345	4.28	3.82
Fuzzy (Abbasov–Mamedova)	116.48	98.234	4.58	3.92
Conventional	237.19	182.96	6.39	4.67

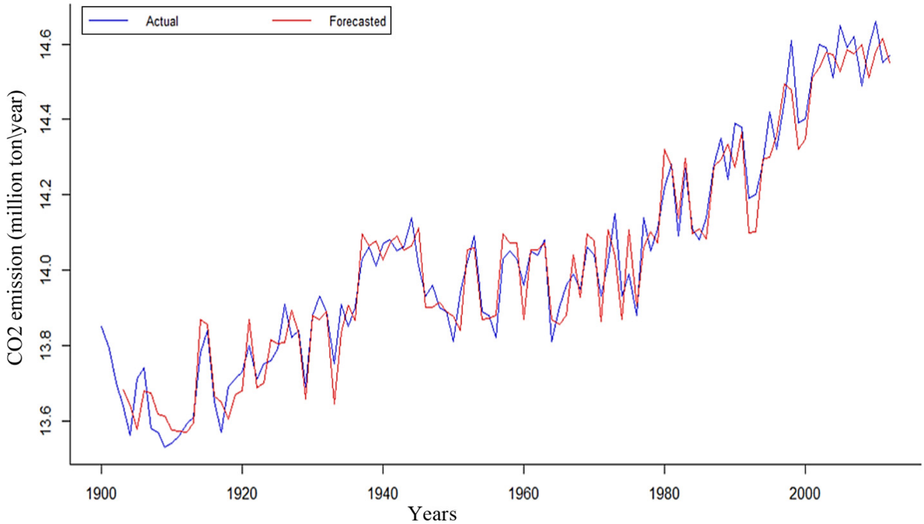

Figure 9.
Prediction of CO_2 emissions using the Singh model

Mamedova and Singh models are 110.51, 125.50 and 137.32, respectively. Similarly, the MAPEs of the same three modeling techniques are 3.59, 12.49 and 18.78, respectively. The calculated RMSE and MAPE values show that the NFTS method has better accuracy when compared to the other two fuzzy time series methods. Furthermore, the performances of nine other fuzzy time series modeling techniques were analyzed. These techniques can be clustered into two groups: fuzzy time series and extended fuzzy time series models. Figure 12 shows the prediction of CO_2 emissions using the fuzzy time series models including the ChenHsu, Chen, Singh and Heuristic and a second set of extended models such as the ChenHsu10, Chen9, Singh9, Heuristic9 and ChenHsu14. It is observed that the first set

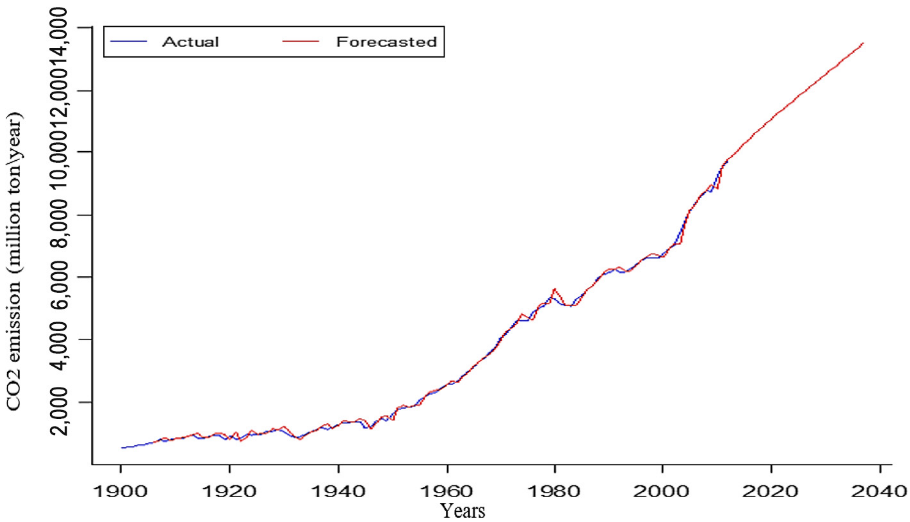

Figure 10.
Forecasting CO_2 emissions by using the fuzzy Abbasov–Mamedova model up until the year 2040

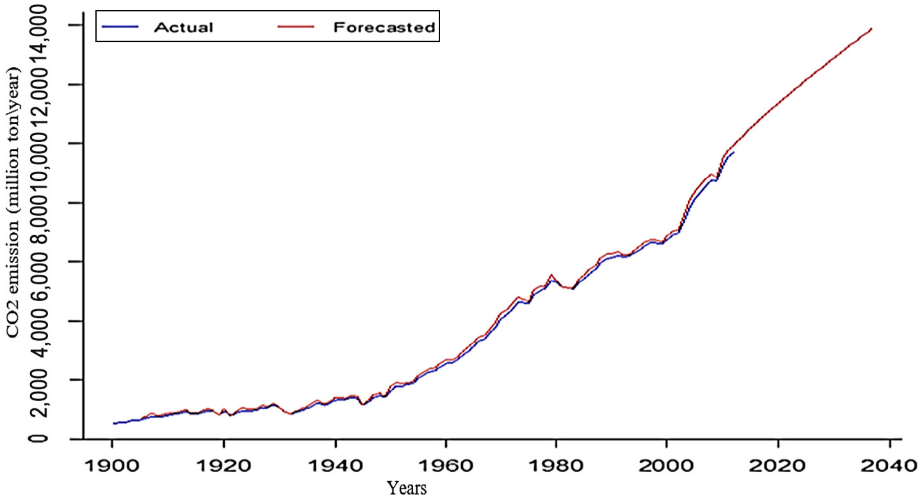

Figure 11.
Prediction of CO_2 emissions using the NFTS model

of fuzzy time series models are less robust and efficient in predicting CO_2 emissions than their extended counterparts. Figure 13 shows the comparison between the fuzzy-based models and the actual CO_2 emissions using data from all emission sources for the period (1900-2012).

4.3.2 Performance evaluation of the global temperature time series. Global temperature was also predicted using various fuzzy time series models in the same manner as the CO_2

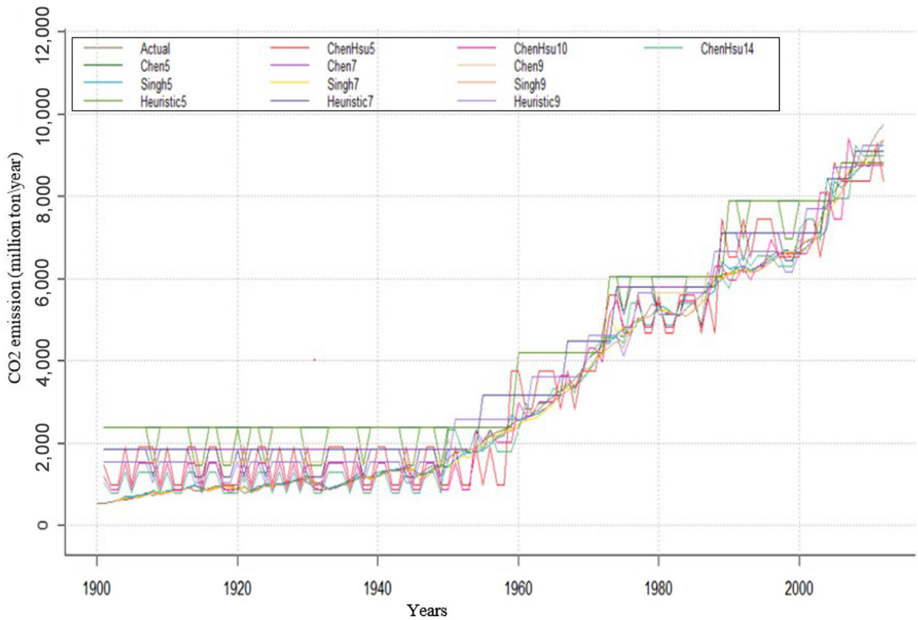

Figure 12.
Comparison of CO_2 emissions of using various fuzzy time series models

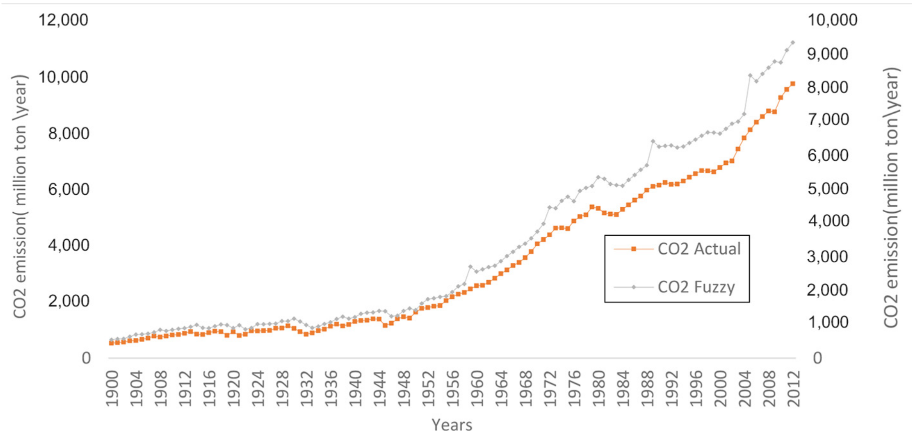

Figure 13. Emissions of CO_2: actual data (orange) versus fuzzy result (grey)

emissions predictions reported in the previous section. Figure 14 shows the global temperature trend using the Singh fuzzy time series model, Figure 15 shows the fuzzy time series model (NFTS) to predict global temperature for the next 25 years.

Figure 16 shows the fuzzy time series results using the Abbasov–Mamedova model. A comparative study of the Singh, Abbasov–Mamedova and NFTS models shows that the NFTS model performs better than the competing models in predicting global temperature (Table III). The RMSEs of the NFTS, Singh and Abbasov–Mamedova models are 0.0048, 0.57 and 0.48, respectively. Similarly, the MAPEs of the same three modeling techniques are 0.0237, 0.029 and 0.054, respectively. Both the calculated RMSEs and MAPEs show that the

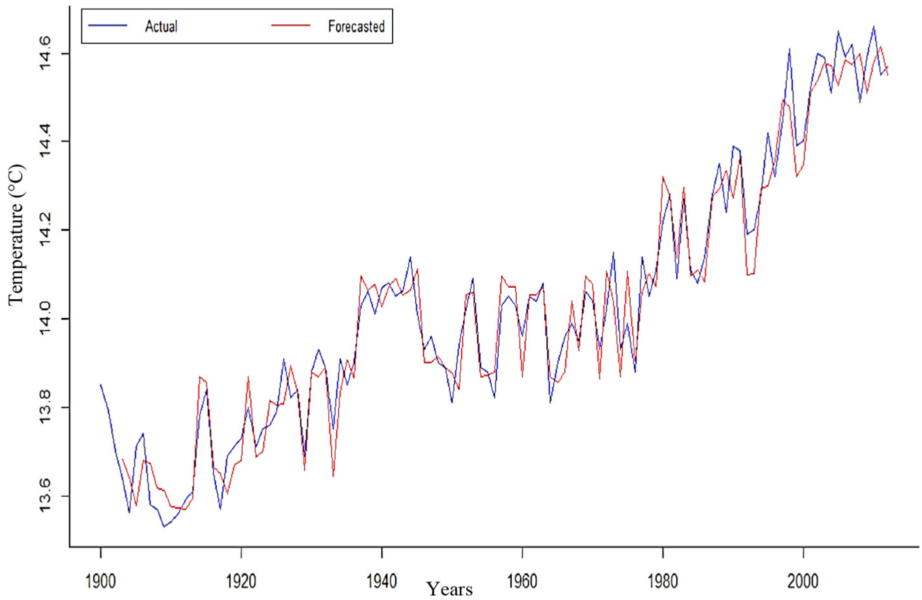

Figure 14. Fuzzy time series forecasting of global temperature using the Singh model

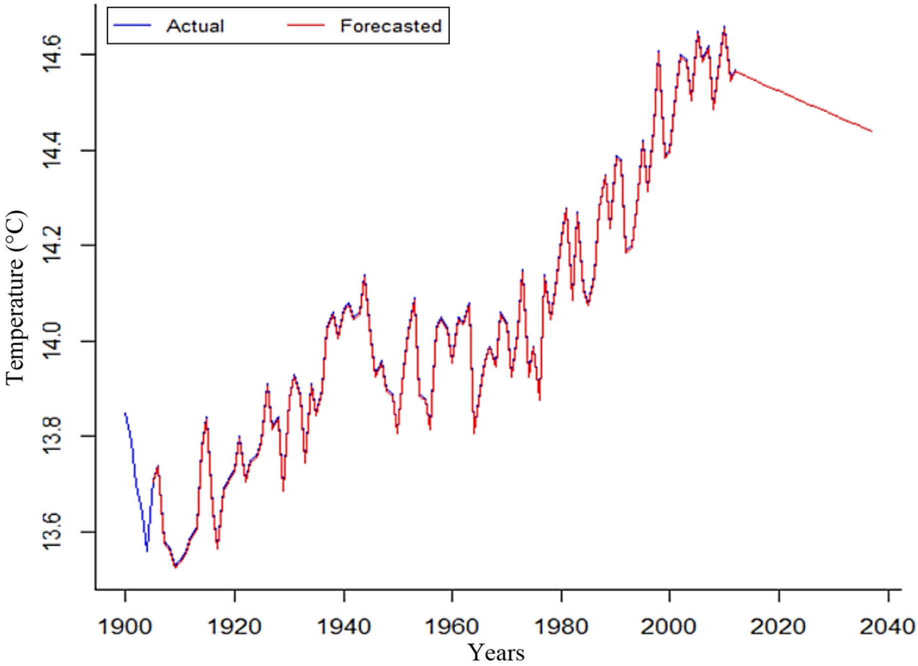

Figure 15.
Global temperature prediction using the NFTS fuzzy time series model

NFTS method has better accuracy when compared to the other two fuzzy time series methods in predicting global temperature. The projection of global temperature shows a slightly decreasing or constant trend from the years 2000 to 2037, unlike the trend in the years 1960-2000 where the temperature increased exponentially. Figure 17 shows the global temperature prediction using various fuzzy time series models including the ChenHsu, Chen, Singh and Heuristic, and a second set of extended models such as the ChenHsu10, Chen9,

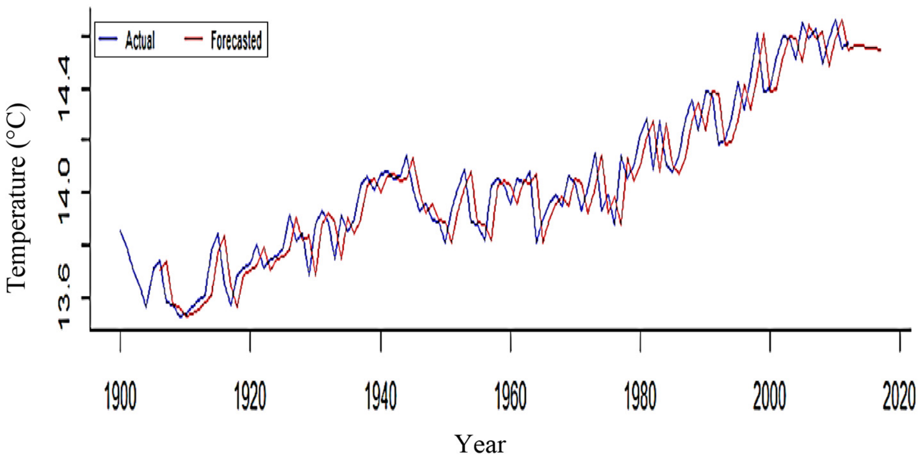

Figure 16.
Global temperature prediction using the Abbasov–Mamedova fuzzy time series model

Singh9, Heuristic9 and ChenHsu14. It is observed that the first set of fuzzy time series models are less robust and less efficient in predicting global temperature when compared to the extended models. Figure 18 shows the comparison between the fuzzy-based model and actual average global temperature trend using the global temperature data for the period 1900-2012. The model performance indicators for both the conventional and fuzzy modeling environments in predicting global temperature trends are shown in Table III. The RMSE for the global temperature analysis using conventional methods is 0.14, whereas the fuzzy prediction RMSE is 0.0048. Likewise, MAE and MPE for the fuzzy-based time series models are found to be less than the corresponding errors from the conventional analysis. This clearly shows the applicability of fuzzy theory and the fuzzy time series models for different historical data analysis applications; they have superior performance and prediction power compared to any of the existing conventional techniques.

5. Conclusions

In this article, the relationship between CO_2 emissions from the energy sector and global temperature increase was investigated and was observed to be very complex; hence, instead of using conventional correlation and regression modeling techniques, the fuzzy-based

Table III. Comparison of the performance indicators of a temperature time series for the conventional and fuzzy methods

Accuracy metrics (temperature)	RMSE	MAE	MAPE	MSE
Fuzzy (NFTS)	0.0048	0.0045	0.0323	0.0112
Fuzzy (Singh)	0.0075	0.0092	0.568	0.0135
Fuzzy (Abbasov–Mamedova)	0.0064	0.0081	0.0467	0.01131
Conventional	0.1400	0.1185	0.6194	0.01960

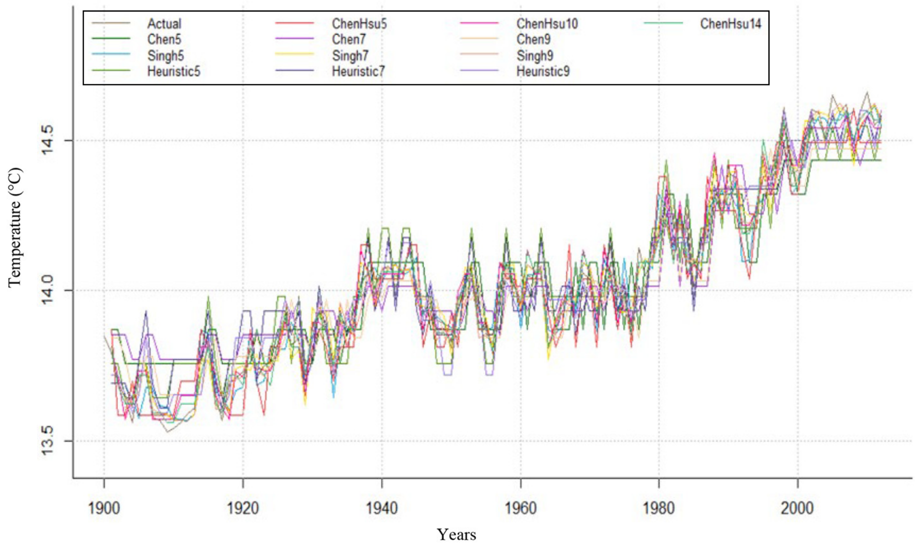

Figure 17. Prediction of global temperature increase using various fuzzy time series models

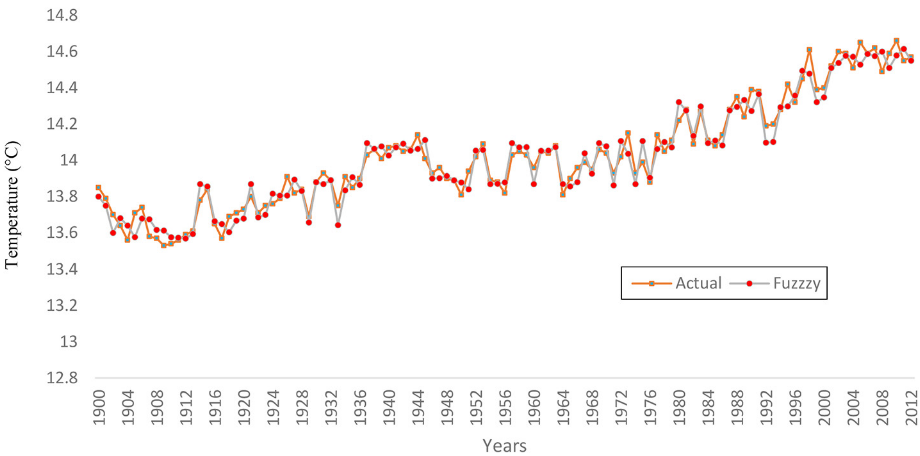

Figure 18. Comparison of actual data (orange) and fuzzy time series (grey) for the prediction of global temperature

modeling techniques of ANFIS, ANN and fuzzy time series were applied. The performance of the ANFIS and ANN models was analyzed using the RMSE and correlation coefficient (R^2)/MSE, respectively. Finally, the performance of the fuzzy time series analysis was investigated using MAPE, RMSE, MAE and MSE. A comparative study between the conventional and fuzzy time series models was also carried out using these four metrics. It was concluded that the performance of the fuzzy time series was significantly better than any of the conventional techniques. Generally, a total of nine fuzzy time series models, five of which were extended models, were compared and the ChenHsu10, Chen9, Heuristic9, Singh9 and ChenHsu14 models were observed to provide better predictions for both the global temperature and CO_2 emissions. These modeling tools can be used to predict CO_2 emissions and future temperature trends with better accuracy. However, it was also observed that the prediction power of the time series model was not as good as the ANFIS and ANN models. The same modeling tools can be used for the analysis of the relationship between any pair of variables. The complicated interactions between the many inputs and output variables from large historical data can efficiently be modeled following the same approaches. The model prediction can be extended for multiple variables or inputs by modifying the method shown in this work accordingly.

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