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A Novel Hybrid Artificial Intelligence Approach to the Future of Global Coal Consumption Using Whale Optimization Algorithm and Adaptive Neuro-Fuzzy Inference System

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Abstract: Energy has become an integral part of our society and global economic development in the twenty-first century. Despite tremendous technological advancements, fossil fuels (coal, natural gas, and oil) continue to be the world's primary source of energy. Global energy scenarios indicate a change in coal consumption trends in the future, which in turn will have commercial, geopolitical, and environmental consequences. We investigated coal consumption up to 2030 using a new hybrid method of WOANFIS (whale optimization algorithm and adaptive neuro-fuzzy inference system). The WOANFIS method's performance was assessed by the MSE (Mean Squared Error), MAE (Mean Absolute Error), STD (error standard deviation), RMSE (Root Mean Squared Error), and coefficient of correlation (R^2) among the real dataset and the WOANFIS result. For the prediction of global coal consumption, the proposed WOANFIS had the best MAE, RMSE, and correlation coefficient (R^2) values, which were 0.00113, 0.0047, and 0.98, respectively. Lastly, future global coal consumption was predicted up to 2030 by WOANFIS. Following 150 years of coal dominance, the results demonstrate that WOANFIS is a suitable method for estimating worldwide coal consumption, which makes it possible to plan for the transition away from coal.

Keywords: whale optimization algorithm; adaptive neuro-fuzzy inference system; climate change; energy consumption

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1. Introduction

The two most important environmental problems, as confirmed by the world's scientific centers, are global warming and climate change. Carbon dioxide emissions have had the greatest effect on the greenhouse effect and air warming. Pollutants from combustion and increasing concentrations of carbon dioxide have adverse consequences, such as climate change, global warming, and rising sea levels. The energy requirement has increased due to the increase in industrial activity and life quality improvement. Different energy sources are used for electricity production, desalination, heating, and cooling. In terms of consumption, fossil fuels, among other such sources, have the greatest share. In many countries, some strategies have been ratified to limit such energy source use since they are limited and have a negative effect on the environment. On the other hand, the depletion of these resources in the near future and the possibility of rising prices have led policymakers to enact laws to control the environment [1]. It has also prepared investigators to promote the replacement of renewable sources with low-pollution sources.

In the current century, energy makes up an essential portion of the global economy in our society. Though the world has endured great technological promotions, fossil fuels (such as natural gas, coal, and oil) are the major energy source of the world. Coal has a key role in the universal energy mix, mostly because of its affordability, abundance, and great reliability at the start of the industrial revolution.

Coal is broadly distributed and the most abundant source of fossil energy in the world; in addition, it is an inexpensive and conventional source. From 2013 to 2016, the worldwide market for coal presented a three-year descending tendency in consumption of coal, which could be a probable sign of a reduction in demand for coal. Though there was a minor increase and recovery in 2017, that was anticipated to lead to other robust increases due to both demand and supply. The increasing electricity demand for power generation has resulted in the consumption of coal, demonstrating a global coal recovery. However, coal's recognition as a key carbon emissions source attracts attention. Naturally, the consumption of coal is the volume of coal energy that society consumes. While a society consumes coal to reach other societies' demands, consumption of coal is observed as a change from one production activity to another. The footprint of coal through regions and countries is defined as the embodied consumption of coal, which is calculated based on coal transfers and flows. Analyzing and measuring the footprint of coal could lead to new views for exploring transferred coal via trade, consumption of coal in a domestic country, and flows from regions to other zones. Due to its broad availability and easy transportation and storage, coal has been an important source of energy for India, China, Germany, United States, Poland, South Africa, and emerging non-OECD countries, mainly countries situated in Asia, where consumption of coal is estimated to increase by around 90% in 2040 [2]. Additionally, the quickly fluctuating prices of natural gas and oil and the unstable politico-social market have permitted coal to become an indispensable and fundamental source of fuel in the steel, power, cement, and iron industries. However, coal creation is considerably more carbon-demanding than substitutions. The complex relation among demographics, economic growth, and consumption of energy (mainly in countries that have coal-demanding industries and high dependence on fossil fuels), with the increased greenhouse gases amount in the atmosphere (mostly associated with the combustion of natural gas, oil, and coal), have elevated serious worries in the scientific community about the prospect of coal. Therefore, besides environmental studies of coal [3,4], several investigations have concentrated on the application and development of predicting methods to forecast the economic views of coal, production, future reserves' levels, consumption, and its effect on the environment. In the coal sector, lasting prediction models are of major significance since they propose information on market imbalances, investment strategies, future trade, and permit decision-makers to forecast and evaluate the potential influence of changes in government policy [1,5,6]. To manage the energy supplement effectively, it is necessary to understand the factors that affect the amount of energy required in a particular region. Due to the hazy and complicated nature of the energy demand procedure and the factors that influence it, efficient instruments for effective energy use are needed. As a result, it is necessary to identify effective instruments for precisely determining energy demands.

Non-classic methods to identify and predict associated issues with complex systems have been extended. Several methods have been introduced for predicting natural phenomena across the world; however, their accurate prediction is still challenging.

Intelligent methods have been globally popular since they provide simple approaches for representing and replicating a process behavior with a good performance. The potential of intelligent techniques lies in the precise modeling of linear and nonlinear processes, and they are extensively used for nonlinear processes. As a result of the revolution and developments in the artificial intelligence field, a new window has been opened for hybrid algorithms for modeling parameter optimization to enhance the efficiency and effectiveness of models [7]. For further enhancement of these capacities, the combination of ANFIS and evolutionary algorithms for effective integration of the artificial neural network (ANN) learning capability and relational structure, using the fuzzy logic's dynamic nature in decision making and the capability of parameter tuning in evolutionary methods for the improvement of model performance has been recommended [8].

Related Works

An adaptive neuro-fuzzy inference system (ANFIS) is an example of a hybrid predictive model, in which fuzzy logic and an ANN are combined to create a mapping relationship between outputs and inputs [9]. The structure of the ANFIS model is made up of five layers, each of which is made up of several nodes. Similar to ANN [10,11], each layer's inputs are gained by the previous layer's node in the ANFIS model. ANFIS has been found to have promising applications in the prediction of machining, material, and manufacturing process performance [12]. Among recent computing techniques, the adaptive neuro-fuzzy inference system (ANFIS) is recommended due to its capabilities for dealing with nonlinear modeling and complex stochastic datasets [13,14]. Numerous algorithms for optimizing the architecture and parameters of neural networks have been proposed [15]. The inspiration for those methods is often taken from nature—such as flocks of birds, ant colonies, or in our case, whales. Swarm-based algorithms for deep learning parameter optimization have been described in detail in several papers [16–18]. In the ANFIS, the dataset features are used for learning, and the system parameters are modified based on an error criterion [19,20]. The ANFIS has been successfully implemented in the prediction of renewable energy results, including in wind energy [21,22], bioenergy [23,24], and solar energy [25]. For instance, hybridized ANFIS with DE, PSO, and GA was experimented with by Hossain et al. for forecasting wind power density in the long term [26]. The effectiveness of the three hybrid models was compared in this work, and it was found that the GA and PSO hybrids of the ANFIS model had a higher performance than the DE hybrid. The ANFISPSO efficiency and effectiveness were examined for the prediction of combustion municipal solid waste's enthalpy based on its elemental compositions by Olatunji et al. [27]. The model was evaluated using statistical performance measures, and during the model testing stage, mean absolute deviation (MAD), mean absolute percentage error (MAPE), log accuracy ratio, and root mean square error were calculated. These authors also studied ANFIS-PSO's effectiveness in the prediction of elemental compositions from the biomass proximate values using a large dataset [28]. When ANFIS models are trained with evolutionary algorithms, the adaptive layer parameters of the model are improved, leading to a rapid convergence, global minimum error, and enhanced accuracy of the model at a lower output [29]. Nevertheless, there are some drawbacks to the ANFIS model when it is used in real applications, which are due to training the membership function parameters and weights between the ANFIS model's layers. Meta-heuristics were used to overcome these problems. Hence, to address this issue, the whale optimization algorithm (WOA) was employed.

This paper introduces a new hybrid approach for predicting global coal consumption. The data of the global coal consumption were investigated for analyzing and forecasting the global coal consumption using a hybrid method based on a whale optimization algorithm and an adaptive neuro-fuzzy inference system (WOANFIS). This article is structured as follows: The specification of the adaptive neuro-fuzzy inference system and the whale optimization algorithm is explained in the next section. The proposed method is provided in the third section. The model estimates and forecasts are presented in section four, and finally, the conclusions are specified in section five.

2. Materials and Methods

2.1. Adaptive Neuro-Fuzzy Inference System

Today, fuzzy inference systems are developed to describe complex systems and have become a powerful tool for modeling uncertainties in the real world in the form of mathematical relations. These systems are computational structures that establish a nonlinear mapping between input and output variables based on fuzzy set theory. In other words, these systems model the behavior of a phenomenon in the form of "if–then" rules, using expert knowledge and sampled data. The method of creating rules and selecting the parameters of membership functions is an important issue in fuzzy inference systems that requires an understanding of the phenomenon under study and experience. On the other hand, neural networks have the ability to learn from the phenomena under study and to arrange the structure of input and output pairs. Therefore, based on fuzzy set theory and also inspired by the model proposed by Takagi and Sugeno in 1985, the model of the adaptive neuro-fuzzy inference system was introduced by Jang in 1993 in an article entitled "Adaptive neuro-fuzzy inference system" [20]. In this model (ANFIS), the goal is to find the function $\hat{f}$, in a way that can be used instead of the main function f. As a result, the prediction of the output variable $\hat{y}$ for the input variable $X = (x_1, x_2, x_3, \ldots, x_n)$ should be close enough to the true value of y. A set of m with multi-input and one-output data is considered as the following relation:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}), \quad (i = 1, 2, 3, \ldots, m) \tag{1}$$

Now, the problem is to define a structure for ANFIS in order to minimize the difference between the output values and the predicted values, which can be considered as follows:

$$\min \sum_{i=1}^{m} \left[\hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) - y_i\right]^2 \tag{2}$$

In this method, the Sugeno fuzzy model is used to approximate the function f with $\hat{f}$ from m vector, including n inputs and one output (X_i, y_i) ; $(i = 1, 2, 3, \ldots, m)$.

To provide a simple explanation of the ANFIS process, we can consider a fuzzy inference system with two inputs, y and x, and one output, f, and the relevant if–then (leader–follower) rules can also be considered, as follows:

$$\begin{array}{ll} \text{If x is } A_1 \text{ and y is } B_1 & \text{Then } f_1 = p_1 x + q_1 y + r_1 \\ \text{If x is } A_2 \text{ and y is } B_2 & \text{Then } f_2 = p_2 x + q_2 y + r_2 \end{array} \tag{3}$$

Figure 1 shows the fuzzy reasoning procedure in such a system for a first-order Sugeno model.

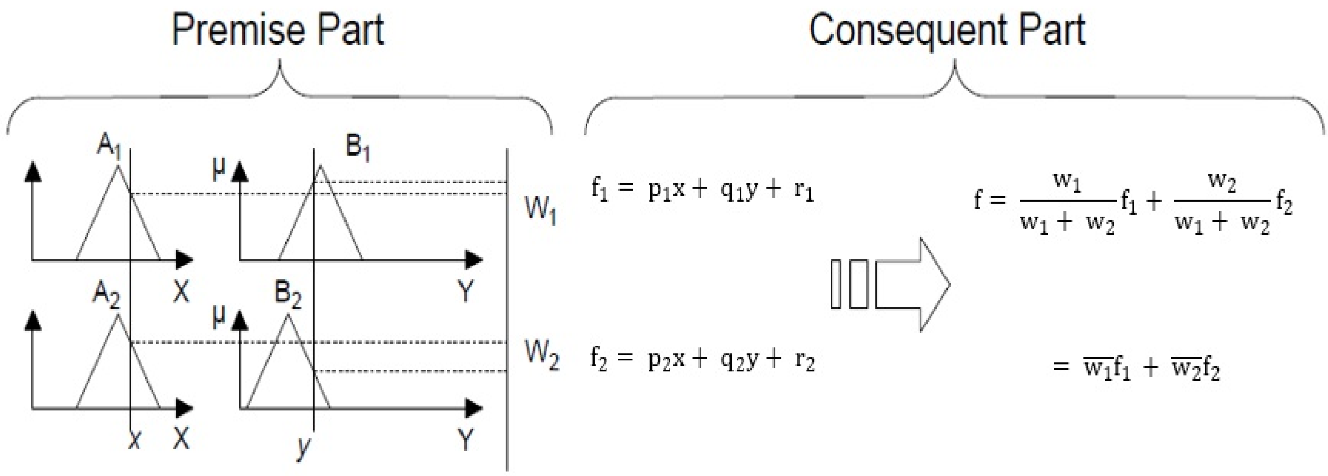


Figure 1. General ANFIS architecture of first-order Takagi–Sugeno fuzzy model.

The membership functions A and B are shown as triangular functions in Figure 1. However, other membership functions can be used for fuzzy reasoning in ANFIS. The structure of the adaptive neuro-fuzzy inference system is shown in Figure 2. This system consists of 5 layers:

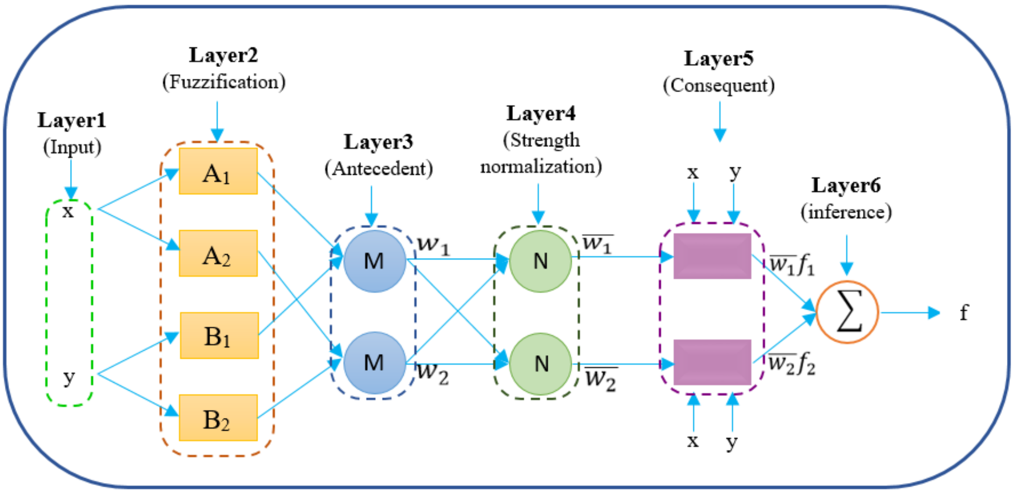


Figure 2. The structure of the adaptive neural fuzzy inference system.

The first layer (input and output layer of membership functions): In this layer, y and x are input variables to the node, and A, i, and B are the names of the linguistic variables corresponding to this node. Each node in this layer is an adaptive node representing a membership function and is used as a memory unit. In this node, the parameters of the membership functions are known as the trainable parameters of the leading section [30].

$$O_{1,i} = \mu_{A_i}(x) \ \text{ for } i = 1,2 \quad O_{1,i} = \mu_{B_{i-2}}(y) \ \text{ for } i = 3,4 \tag{4}$$

Equation (4) shows the output of the first layer with node i ($O_{1,i}$), where i is the degree of membership of the fuzzy set. In the system-learning phase, the parameters of the membership functions are updated with the average of the back propagation algorithm. Additionally, the propagation rate of each rule in the whole system is determined by the propagation coefficient, which is a combination of input variables at different linguistic levels, which is obtained by multiplying the average membership value [31].

The second layer (rules layer): Nodes in this layer, Π, are known as rule nodes, whose output is the result of the algebraic multiplication of node inputs. In this layer, the degree of arousal power of each rule is obtained by using the criterion of each input belonging to the relevant membership functions. Equation (5) shows the output of this layer.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{5}$$

The fourth layer (nonfuzzy layer): This layer is the place in which input variables are combined based on their propagation capacity. Each node, i, in this layer is an adaptive node, and the output of each node is the result of the normalized arousal power multiplied by a linear function of the input variables and is determined by the following function. Equation (6) shows the output of this layer.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{6}$$

Fifth layer: The only node of this layer is a fixed node indicated by Σ. In this node, the final output is calculated as the sum of the input values, so that $\overline{w_i} f_i$ is the output of node i in the fourth layer. Equation (7) shows the output of this layer.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

2.2. Whale Optimization Algorithm

The whale optimization algorithm (WOA) was first proposed by Seyed Ali Mir Jalili in 2016 [32]. This algorithm is inspired by the social behavior of humpback whales. The whale algorithm starts with a set of random solutions. In each iteration, search agents update their positions using three operators, called bait siege, bubble-net hunting technique, and extraction phase and bait search (exploration phase). In bait siege, humpback whales identify the bait and surround it. The whale algorithm assumes that the best solution is the bait. After the best search agent has been identified, other search agents will update their positions based on the best search agent. This behavior is shown in Equations (8) and (9):

$$\vec{D} = \left| \vec{C} \cdot \vec{X}^* (t) - \vec{X}(t) \right| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}^* (t) - \vec{A} \cdot \vec{D} \tag{9}$$

In Equations (8) and (9), t is the current iteration, $\vec{C}, \vec{A}$ are coefficient vectors, $\vec{X}^*$ is the position vector of the best solution obtained at the moment, and $\vec{X}$ is the position vector. It should be noted that if there is a better solution, $\vec{X}^*$ should be updated in each iteration [32,33]. Vectors $\vec{C}, \vec{A}$ are calculated in relations (10) and (11):

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{10}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{11}$$

where $\vec{a}$ decreases linearly from 2 to zero during the iterations and $\vec{r}$ is the random vector between zero and 1.

In the bubble-net hunting technique (extraction phase), the humpback whale swims around the bait in a contracting circle, concurrently following a spiral path. To model this simultaneous behavior, it is assumed that the whale selects either the contraction siege mechanism or the spiral model, for which there is a 50% probability that the position of the whales will be updated during optimization. The mathematical model of this phase is defined as relation (12):

$$\vec{X}(t+1) = \begin{cases} \vec{X}^* (t) - \vec{A} \cdot \vec{D} & \text{if } p < 0.5 \\ \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^* (t) & \text{if } p \geq 0.5 \end{cases} \tag{12}$$

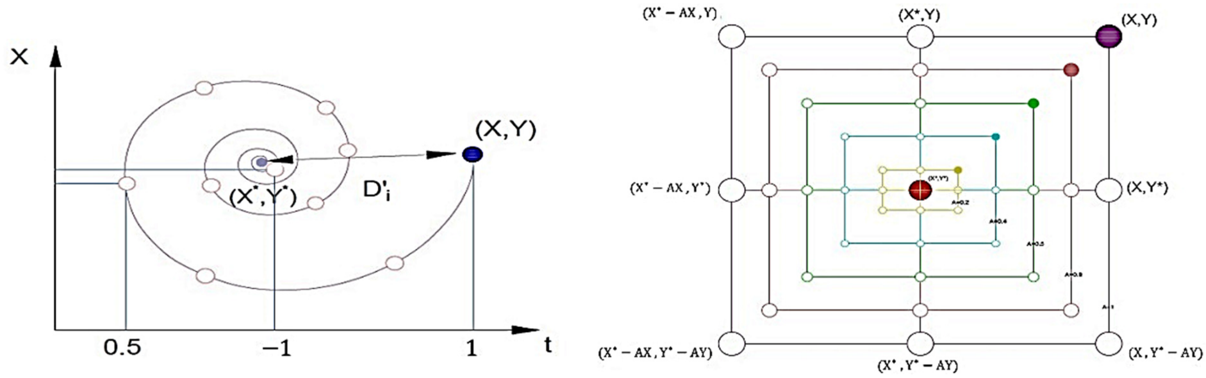
$\vec{D}$ is obtained from Equation (8) and refers to the distance from i whale to the bait (the best solution ever obtained), b is a constant defining the logarithmic spiral shape, L is a random number between −1 and +1, and p is a random number between 0 and 1.

Vector $\vec{A}$, with random values between −1 and +1, is used to bring the search agent closer to the reference whale. The spiral movement and shrinking encircling mechanism are presented in Figure 3 [32].

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_{rand} \cdot \vec{X} \right| \tag{13}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \tag{14}$$

where $\vec{X}_{rand}$ is a selected random position vector (the whale is randomly chosen from the current population, and vector $\vec{A}$, with random values greater than 1 or less than −1, is used to force the search agent to move away from the reference whale.



(**a**) (**b**)

Figure 3. (**a**) Spiral updating position and (**b**) shrinking encircling mechanism.

3. Proposed Method

Each optimization algorithm has many strengths and weaknesses in various problems. The purpose of creating hybrid algorithms is to use the strengths of combined algorithms to better solve various optimization problems. The design and training of adaptive neuro-fuzzy systems (ANFIS) are usually carried out using classical approaches, such as gradient descent and back-propagation. In fact, the structure of ANFIS is based on a fuzzy inference system in which the parameters of the hypothesis section and the result of fuzzy if–then rules are set by a neural network model. Since the neural network learning algorithm is dependent on using optimization methods on the basis of slopes, it is possible to trap the final response of the learning algorithm and consequently set the parameters at local optimal points. Therefore, the use of search methods or meta-exploration optimization to reduce the above problem can be investigated. The developed model of the ANFIS system in this research, a meta-exploration algorithm, is a fuzzy inference system of the Sugeno type in which the parameters of the shape of the membership functions and the result part of its fuzzy rules are adjusted and optimized by the whale algorithm. The hybrid model works in a similar manner to ANFIS, except that meta-exploration algorithms are a random search method and the possibility of trapping the response (values of the setting parameters) in the optimal local points is less when it is used. In the hybrid model, the process of optimizing the parameters is based on the use of a set of input–output data. [34,35].

The recommended approach to predict global coal consumption is introduced in this section. The model consists of a hybridization between the WOA and ANFIS, named WOANFIS, where the WOA is used to determine the parameters of the ANFIS. In the model, there are five layers, as in two conventional ANFISs. Input variables represent the nodes in layer 1. In layer 2, the nodes are the membership functions of the input variables. The nodes in layer 3 represent the fuzzy logic rules. The resultant fraction of the Takagi–Sugeno–Kang model is used by the nodes of layer 4. The coal consumption is the output of layer 5. Using the WOA in the learning phase, the best value of the weights is determined between layers 4 and 5, and the membership function is also trained based on the input variable. To start the introduced method, the dataset is normalized and divided into two groups. The update of parameters in ANFIS is carried out according to the WOA algorithm, which discovers various areas of the searching space that have numerous local minima, after which the searching domain is reduced to the region containing the global solution. The parameters are updated in the training stage using the error information between the actual output and the equivalent forecasted values. Here, the WOA begins by generating a population, X, the randomly positioned population. For every whale, the size of X is considered N and dimension D, representing the number of ANFIS parameters. After computing the objective function for a solution within the population X, the update of parameters is performed according to the minimum of three fitness functions. Accordingly, the best solution is the one with the minimum objective function value. The phases implemented formerly are still reiterated to ultimately satisfy the stop conditions, followed by passing the best solution to the ANFIS model. The completion of the training stage occurs when the stop conditions are satisfied (the uppermost number of iterations and errors is lower than the small value). Thereafter, the construction of ANFIS is performed according to the parameters obtained from the best solution. In the test stage, the output (global coal consumption) is predicted by applying the testing dataset to the introduced approach according to input parameters, thereby evaluating the model performance. Figure 4 shows the flowchart of the introduced approach. [36,37].

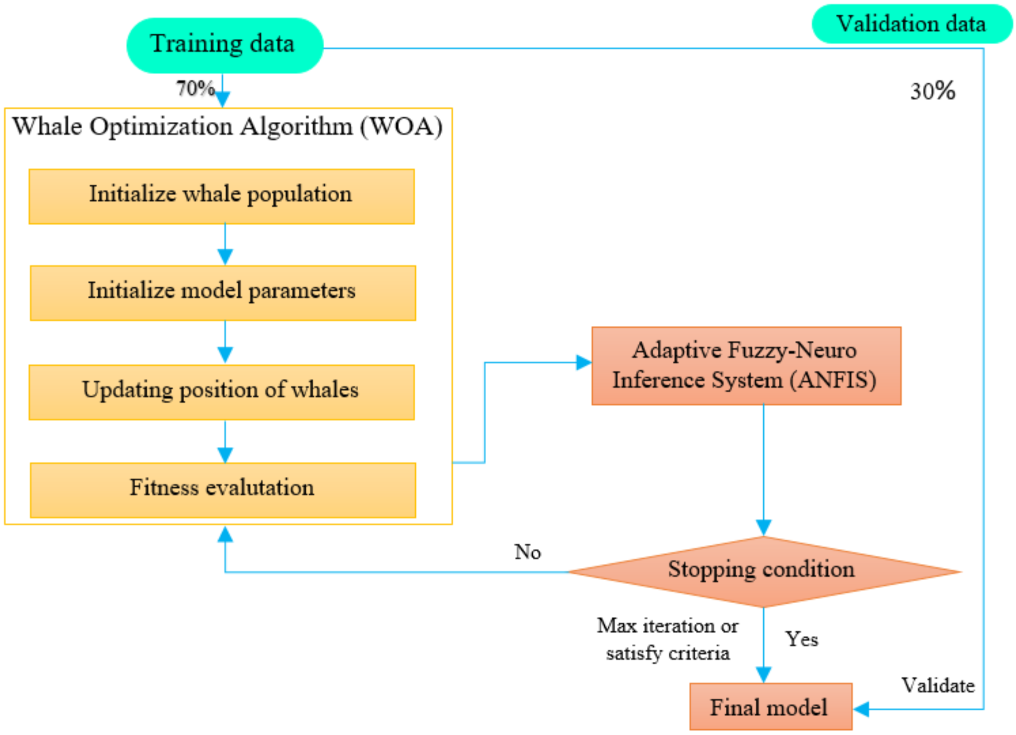


Figure 4. Flowchart of the WOANFIS.

4. Experiments

In this paper, a novel method for predicting global coal consumption is presented. Data on world population, gross domestic product (GDP), global coal consumption, primary energy consumption, and Northwest Europe coal prices were collected during the years 1987–2019 [38,39]. Population, gross primary energy consumption, domestic product (GDP), and Northwest Europe coal prices were the WOANFIS input parameters, and the global coal consumption was the output parameter. The data relating to these parameters were classified as testing data and training data. For training, 70% of data were employed, and 30% of data were used for testing and validation.

Data normalization in the first phase is required for estimating global coal consumption. Using Equation (15), data were normalized.

$$D_N = (D_R - D_{min})/(D_{max} - D_{min}) \tag{15}$$

where D_N represents the normalized data and D_R represents the original data value. The D_{min} and D_{max} values for each variable were selected for the years between 1987 and 2019 and are shown in Table 1.

Table 1. Minimum and maximum values of research variables for normalization.

Variable	Minimum	Maximum
World population (millions)	5012	7673
GDP (billion USD)	17,200	87,697
Coal consumption (million tons oil equivalent)	2162	3867
Primary energy consumption (million tons oil equivalent)	7581.30	14,072.87
Northwest Europe coal price (USD)	28.79	147.67

Mean Absolute Error (MAE), Mean Squared Error (MSE), Error standard deviation (STD), Root Mean Squared Error (RMSE), and the correlation coefficient (R^2) between the actual dataset and the WOANFIS output were used for evaluating the WOANFIS's performance [1,5]. Equations (16)–(20) represent these errors.

$$\text{MSE} = \frac{1}{33}\sum_{i=1}^{33}(\text{Target}_i - \text{output}_i)^2 \tag{16}$$

$$\text{RMSE} = \sqrt{\frac{1}{33}\sum\nolimits_{i=1}^{33}(\text{Target}_i - \text{output}_i)^2} \tag{17}$$

$$\text{MAE} = \sqrt{\frac{1}{33}\sum\nolimits_{i=1}^{33}|\text{Target}_i - \text{output}_i|} \tag{18}$$

$$\text{STD Error} = \sqrt{\frac{1}{33}\sum_{i=1}^{33}(\text{Target}_i - \text{output}_i)^2} \tag{19}$$

$$R^2 = \left(\frac{\sum(\text{Target}_i - \overline{\text{Target}}) \times (\text{output}_i - \overline{\text{output}})}{\sqrt{\sum(\text{Target}_i - \overline{\text{Target}})^2 \times \sum(\text{output}_i - \overline{\text{output}})^2}}\right)^2 \tag{20}$$

As mentioned previously, the dataset was randomly divided into two groups: the training and testing dataset. The training dataset represented about 70% of the total collected data, and the remaining dataset (30%) was used for testing. Figures 5 and 6 and Table 2 indicate the performance of the WOANFIS method against training and testing data. Figures 5 and 6 show the MSE of trained and tested data for WOANFIS's performance. The distribution of errors was regarded as a normal distribution with an approximately wide variance. The average RMSEs of the WOANFIS training and testing data were found to be 0.00008 and 0.00479. In these figures, the target and the output values are compared, and the model error value was calculated for the data. These results show an acceptable development for the newly proposed method.

Table 2. Modeling performance criteria.

Network Process	MSE	RMSE	MAE	STD Error	Mean Error	R
Training	6.5577×10^{-11}	8.098×10^{-6}	1.63×10^{-8}	8.2316×10^{-6}	6.3215×10^{-8}	0.9991
Testing	2.3028×10^{-5}	0.0047987	1.13×10^{-6}	0.004478	−0.0023408	0.9850

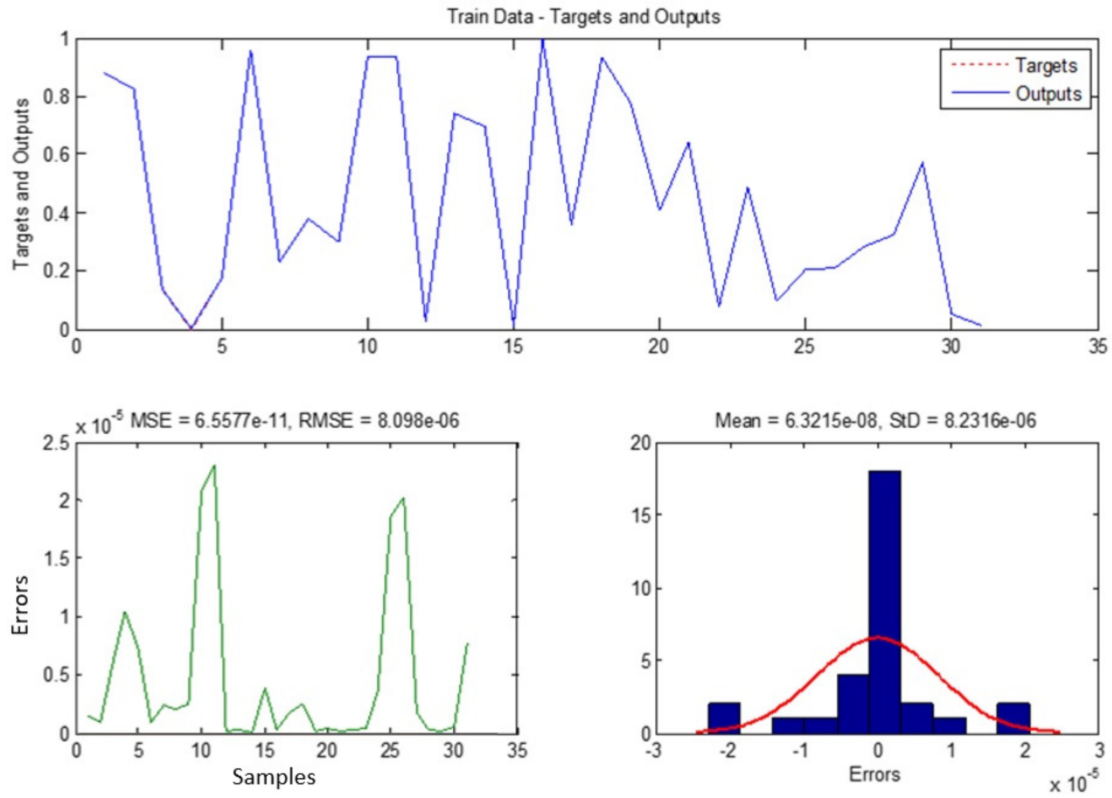


Figure 5. Model performance criteria for training data.

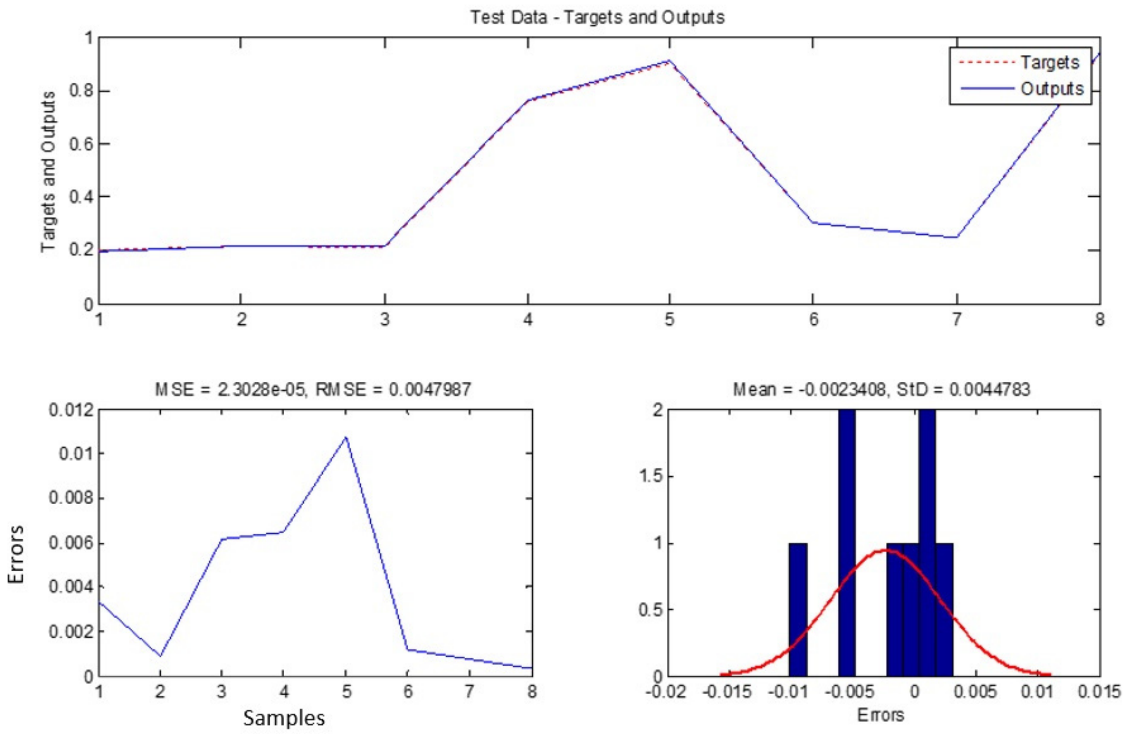


Figure 6. Optimized WOANFIS output and model performance criteria for test data.

Figure 7 and Table 3 show the performance of the WOANFIS method for the modeling and the testing data.

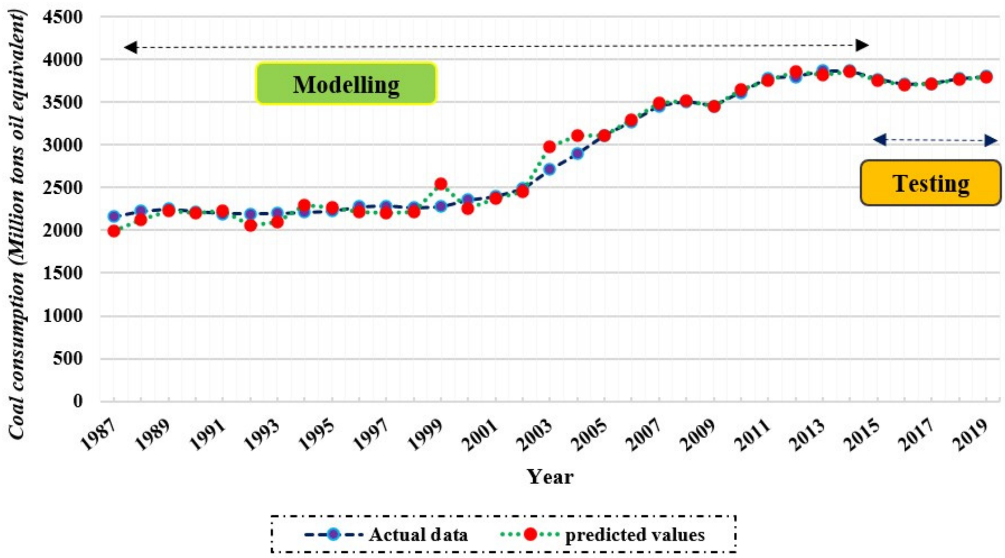


Figure 7. Comparing actual data and predicted values with WOANFIS.

Table 3. WOANFIS operation.

Years	Actual Data	WOANFIS—Output Predicted	Relative Error (%)
2015	3769	3745	0.6367
2016	3710	3702	0.2156
2017	3718	3716	0.0645
2018	3772	3759	0.3472
2019	3798	3788	0.2765
Average	-	-	0.3081

Using the WOANFIS method, which was determined above, the global coal consumption predictions were forecasted up to 2030. Table 4 indicates a comparison between forecasts published by the British Petroleum Company, BP, and the WOANFIS method.

Table 4. A comparison of projections of global coal consumption [Mtoe] for the years (2020–2030).

Years	2020	2025	2030
WOANFIS method	3894.80	4065.80	4071.09
BP (2019)	3896.84	4066.99	4072.32

5. Conclusions

A hybrid WOANFIS based on the adaptive neuro-fuzzy inference system and whale optimization algorithm is proposed in this study for enhancing the global coal consumption in terms of performance up to 2030, when it is regarded as an optimization problem. By determining parameter values that offer the minimum error rate in the fitness function, the parameter values needed for ANFIS in the testing and training processes can be found. It is possible to evaluate the performance of the WOANFIS method using the MAE, MSE, STD, RMSE, and correlation coefficient (R^2) between the output of the WOANFIS and the actual dataset. The global coal consumption was evaluated by successfully applying this method. For the prediction of global coal consumption, the proposed WOANFIS had the best values for the MAE, RMSE, and correlation coefficient (R^2), which were 0.00113, 0.0047, and 0.98, respectively.

It is worth noting that according to the findings of the present research, there is an agreement with the estimated values of consumption obtained by BP. We proposed a global coal consumption prediction method in the present paper, and WOANFIS was advantageous in comparison with other mathematical programming models as it presents a simple and easy way of modeling nonlinear and linear dependencies between variables only from data obtained here.

Global coal consumption prediction can also be investigated using new metaheuristics or neural networks, such as harmony search, simulated annealing, etc. It is possible to compare the results of different methods with the WOANFIS method. More surveys should be carried out with a focus on the comparison of approaches presented in this work with other available approaches. In addition, the electro-magnetism mechanism algorithm, krill herd optimization algorithm, and other intelligent optimization methods can also be used for predicting the global coal consumption. The results obtained for the application of different approaches can be compared with WOANFIS. The promising results of the proposed model indicate that it can be applied to other fields, such as biogas production and solar radiation, in future work.

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