Neural Computing and Applications (2021) 33:13567–13585
https://doi.org/10.1007/s00521-021-05980-1

ORIGINAL ARTICLE

Estimates of greenhouse gas emission in Turkey with grey wolf optimizer algorithm-optimized artificial neural networks

Ergun Uzlu[1]

Received: 23 November 2020 / Accepted: 25 March 2021 / Published online: 7 April 2021
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2021

Abstract
The main purpose of this study was to predict Turkey's future greenhouse gas (GHG) emissions using an artificial neural network (ANN) model trained by a grey wolf optimizer (GWO) algorithm. Gross domestic product, energy consumption, population, urbanization rate, and renewable energy production data were used as predictor variables. To probe the accuracy of the proposed model, the new ANN-GWO model's performance was compared with the performance of ANN-BP (back propagation), ANN-ABC (artificial bee colony), and ANN-TLBO (teaching–learning-based optimization) models using multiple error criteria. According to calculated error values, the ANN-GWO models predicted GHG emissions more accurately than classical ANN-BP, ANN-ABC, and ANN-TLBO models. According to the average relative error values calculated for the test set, ANN-GWO performs 32.23% better than ANN-BP, 35.29% better than ANN-ABC, and 19.33% better than ANN-TLBO. Using the ANN-GWO model, GHG emissions were forecasted out to 2030 under three different scenarios. The predictions obtained, consistent with a prior forecasting study in the literature, indicated that GHG emissions are expected to outpace official predictions (model prediction range for 2030, 956.97–1170.54 Mt CO_2 equivalent). The present study demonstrated that GHG emissions can be predicted accurately with an ANN-GWO model, and that the GWO optimization method is advantageous for predicting future GHG emissions.

Keywords Grey wolf optimizer algorithm · Teaching–learning-based optimization algorithm · Greenhouse gas emission · Neural networks

1 Introduction

Greenhouse gas (GHG) emissions into the atmosphere cause global warming and associated climate change, which threatens the Earth's ecosystems and the organisms living within them. Fossil fuel use is the most important source of increasing GHG emissions. There have been several international agreements aimed at reducing fossil fuel combustion and thus GHG emissions. The first of these agreements was the United Nations Framework Convention on Climate Change signed in 1992 under the leadership of the United Nations. Later, the Kyoto Protocol and the Paris Agreement were signed in 1997 and 2015, respectively. These agreements were intended to mitigate economically driven GHG emission-related damages, but economic concerns have led countries to not meet agreement standards.

With the aim of reducing GHG emissions and preventing further climate change, Turkey joined the Kyoto Protocol in 2009. However, this protocol was created 12 years prior to 2009, in 1997. In addition, Turkey adopted a National Climate Change Strategy and a National Action Plan on Climate Change in 2010 and 2011, respectively. Although Turkey signed the Paris Agreement in 2015, it has not yet ratified it and thus not put it into effect. Turkey committed to reduce its GHG emissions for the first time with this deal. In the Paris Agreement, Turkey is expected to reduce its GHG emissions by 21% (79% of its otherwise projected course). In addition, Turkey has committed that a total GHG emission mitigation limit of $\leq$ 929 million tons (Mt) CO_2 equivalent (eq) by 2030 [1].

CO_2, which constitutes the largest portion of GHG emissions worldwide, is a major driver of global warming,

✉ Ergun Uzlu
ergunuzlu@ktu.edu.tr

1 Faculty of Engineering, Department of Civil Engineering, Karadeniz Technical University, 61080 Trabzon, Turkey

climate change, and consequent environmental problems. According to global emission data, the total GHG emissions in the world in 2016 amounted to 46,141 Mt CO_2 eq, with the 10 highest-emitting countries generating 62.6% of the total global emissions. In 2016, 81% of Turkey's total GHG emissions were CO_2. After CO_2, the largest GHG components in Turkey in 2016 were methane (11%), nitrous oxide (6%), and hydrofluorocarbons (1%) [1]. Emission values for Turkey and the top 10 GHG-emitting countries are presented in Fig. 1. Briefly, China ranks first with a 25.8% emission rate, USA ranks second at 12.8%, and India ranks third at 6.7%. Turkey is ranked seventeenth among ranked GHG-emitting countries, contributing about 1.0% of global GHG emissions in 2016 [2].

The per capita total GHG emissions in Turkey increased from 4 tonnes CO_2 eq in 1990 to 6.4 tonnes CO_2 eq in 2018 [2]. GHG emissions per capita in Turkey are about 1/3 of the average of that of OECD (Organisation for Economic Co-operation and Development) countries and 1/2 of the average of European Union (EU) countries. In the last 150 years, Turkey's contribution to global warming has been estimated to be just 0.04% [3]. During the period of 2005–2016, Turkey had a 49% increase in per capita GHG emissions, which was quite high among the OECD countries [1]. Turkey's emissions are expected to increase further consequent to economic growth and population growth. These increasing GHG emissions will lead to increasing pollution levels in Turkey, raising further concerns about global warming and climate change.

Realistic GHG emission projections are needed to inform planning such that measures needed to control and reduce GHG emissions can be taken. Countries are subject to financial sanctions if they exceed their declared GHG emission limits in signed international agreements. More importantly, excessive emissions cause irreversible damage to the environment. Therefore, in this study, the development of a hybrid model for CO_2 projection in Turkey consisting of artificial neural network (ANN) and grey wolf optimizer (GWO) algorithm components is reported. Population, energy consumption, gross domestic product (GDP), renewable energy production, and urbanization rate were used as input data for the model, and GHG emission level was the model's output data. Calculated estimates of Turkey's future GHG emissions under different scenarios are then provided.

2 Literature review

Methods employed for national GHG emission estimates have consisted primarily of statistical methods and soft computing techniques. Frequently used statistical methods include trend analysis, time series methods, grey models (GMs), autoregressive integrated moving averages (ARIMAs), and regression analyses. Meanwhile, ANNs represent the most commonly used soft computing technique. In addition to ANNs, metaheuristic algorithms, such as the artificial bee colony (ABC), particle swarm optimization (PSO), and harmony search (HS) algorithm, as well as evolutionary algorithms, such as gene expression programming (GEP), are other preferred soft computing techniques.

Choi and Abdullah [4] used multiple linear regression and probabilistic fuzzy linear regression techniques to predict CO_2 emissions in Malaysia, and obtained better results with the former than the latter. Pao and Tsai [5] and Lotfalipour et al. [6] used GMs and ARIMA models to forecast CO_2 emissions in Iran and China, respectively. In Pao and Tsai's [5] study, the two methods performed similarly well, whereas Lotfalipour et al. [6] obtained

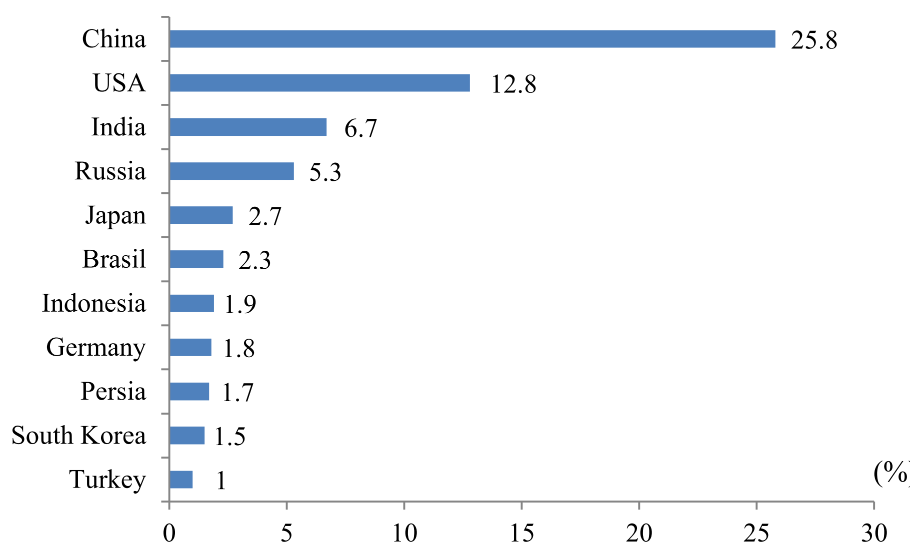


Fig. 1 Turkey and the top 10 countries that emitted most greenhouse gases in 2016 [2]

better results with a GM than with an ARIMA model. Wang and Li [7], Ding et al. [8], and Yu et al. [9] used GMs for the same purpose in China. Zhao et al. [10] and Chen et al. [11] utilized both regression and ANN modeling to forecast CO_2 emissions in the USA and China, respectively; both groups found that ANN models yielded better results than regression analyses. Zhou et al. [12] and Tian et al. [13] used ANN models to forecast the CO_2 emissions in China. Similarly, Appiah et al. [14] used the ANN technique to obtain CO_2 emission predictions in China, Brazil, India, Russia, and South Africa. To estimate CO_2 emissions in Serbia, Radojevic et al. [15] used an ANN model with renewable energy sources, GDP, gross energy consumption, and energy intensity as input parameters. Gonzalez et al. [16] proposed a genetic algorithm (GA) model for reducing the GHG emission produced by transportation in Brazil. The model gave very good results.

To cope with the ANN problems of memorization and getting stuck in a local minimum, scientists have developed hybrid ANN-metaheuristic algorithm models. Uzlu et al. [17, 18] used hybrid ANN-ABC and ANN-TLBO techniques in the energy modeling area to overcome the abovementioned problems of ANN-BP. According to the obtained results, hybrid models performed better than the ANN-BP model. This is because ABC and TLBO algorithms have high discovery capability in the search space and these algorithms abandon a local optimum if they encounter the memorization problem. Similarly, Kankal and Uzlu [19] developed a hybrid ANN-TLBO model to estimate electricity consumption in Turkey. To test the accuracy of their proposed model, they compared the ANN-TLBO model results with the results obtained from the ANN-BP and ANN-ABC models. The proposed ANN-TLBO model gave better results than the ANN-BP and ANN-ABC models. They found that the ANN-TLBO showed better performance due to reasons such as the low number of control parameters in TLBO, the simpler structure of the algorithm and its convergence to the optimum solution requiring less effort. Similar hybrid methods are also used in GHG emission prediction models in different countries. For example, Li and Gao [20] used a modified ANN approach to estimate China's cement industry's carbon emissions. Specifically, they developed a model that uses an improved PSO-based back propagation (BP) model, termed IPSO-BP, to train an ANN and found that the IPSO-BP model performed better than an ANN-BP model. Sangeetha and Amudha [21] used a PSO algorithm with an ANN to project CO_2 emission levels in India employing coal, oil, natural gas, and primary energy consumption as independent variables. Hybrid models that combine metaheuristic and evolutionary algorithms have also been used in GHG prediction studies. For example, Hong et al. [22] developed a hybrid HS algorithm-GEP model to estimate the amount of CO_2 being emitted from buildings in Korea, using GDP, population, imports, exports, and floor area data as independent variables in the model, and found that the hybrid model made more accurate predictions than their GEP model. Pintea et al. [23] developed a hybrid model using the nearest neighbor technique to reduce GHG emissions produced by transportation in Romania. Their studies showed that the model was a suitable solution to reduce the amount of GHG caused by transportation.

The approaches used above have also been applied to predictions of Turkey's future GHG emissions, different regions. Say and Yücel [24] carried out regression analysis, with only total energy consumption as an independent variable, to model Turkey's CO_2 emissions up to year 2015. Aydin [25] carried out regression analysis with seven independent variables (population, GDP, alternative and nuclear energy consumption, combustible renewables, waste energy consumption, and fossil fuel consumption) to estimate Turkey's energy-related CO_2 emission values out to 2025. Şahin [26] and Köne and Buke [27] utilized trend analysis approaches to model Turkey's energy-related CO_2 emissions. Ayvaz et al. [28] and Hamzaçebi and Karakurt [29] used a GM approach to estimate energy-related CO_2 emissions in Turkey. Pabuççcu and Bayramoğlu [30] employed an ANN technique with six variables (population, GDP, energy generation, energy consumption, and energy demand for transport) to predict Turkey's GHG emissions between the years of 2020 and 2030. Sozen et al. [31] developed three different ANN models based on energy consumption, GDP, and gross national product data to model Turkey's GHG emissions, but they did not make any future GHG predictions. Özceylan [32] applied ABC and PSO algorithms to linear, exponential, and quadratic functions to estimate future CO_2 emissions values in Turkey, using GDP, number of motor vehicles, population, and energy consumption as independent variables in the model.

Regression analyses [24, 25], trend analyses [26, 27], and GMs [28, 29] are used frequently in the field of energy-related CO_2 emission modeling. However, because these statistical methods are based on precise mathematical expressions, they cannot be adapted readily to changes in GHG emission trends and the independent variables affecting GHG emissions [33]. Therefore, these methods are not well suited for GHG emission estimation. This problem has been dealt with by applying artificial intelligence methods, such as ANN and metaheuristic algorithms, that do not rely on precise mathematical expressions and have high nonlinear modeling capabilities. In addition, the ANN technique achieves more successful results, with less data, than time series and regression analyses. Two studies [30, 31], which used ANN to model Turkey's total GHG emission, were found in the literature. Although Sozen et al. [31] used ANN to develop a model of Turkey's total GHG emissions, they did not make any forward predictions. A literature review indicated that Turkey's total GHG emission has been predicted with an ANN approach only in the work of Pabuçcu and Bayramoğlu [30]. The remaining researchers have used statistical methods to make future predictions of energy-related CO_2 emissions. Previous studies clearly show that there is a need for the development of more reliable GHG emission estimation models in Turkey.

In this study, a new GWO technique based on a simple and robust metaheuristic algorithm is proposed. GWOs can be used to solve constrained or unconstrained optimization problems. Although they are relatively new, GWO algorithms have been applied in various engineering fields, including civil engineering [34], electrical engineering [35], industrial engineering [36], optical engineering [37]. A couple of previous comparative studies found that GWO algorithms performed better than advanced optimization techniques (PSO, GA, and ACO) [37, 38]. Here, the development and testing of a hybrid ANN-GWO model, which was applied to estimate Turkey's future GHG emissions out to the year 2030 under three potential scenarios, is presented. In the presented ANN-GWO models, GDP, population, energy consumption, urbanization rate, and renewable energy production were used as input data, and GHG emission values were the output data. According to a literature review, the ability of an ANN-GWO to model and predict GHG emissions has not been tested in any previously published study. Therefore, this study is an innovative and practical application for the estimation of GHG emissions in Turkey. The main features that distinguish this study from previous studies are presented below.

- In this study, a new method is presented for ANN training. Thanks to the proposed method, the ANN avoids becoming stuck in a local minimum and encountering memorization problems. On the other hand, tuning of control parameters is a very big problem in ANN training. The proposed method facilitates selection of the optimum control parameters as the GWO has low number of control parameters.
- This work represents the first time that ANN-GWO, ANN-ABC, and ANN-TLBO techniques have been used for GHG prediction, as well as the first GHG emission projection using four different techniques.
- This study provides the first demonstration of the GWO algorithm performing better than the powerful and popular BP, ABC, and TLBO algorithms in ANN training.
- Energy consumption-related CO_2 emissions have been estimated in numerous previous studies though CO_2 is only one constituent of GHG emissions. In this study, the total GHG emission projection was obtained.
- Previous GHG emission models have been developed using two or three of the independent variables such as GDP, population, energy consumption, and urbanization rate. Most of them were developed based solely on energy consumption without consideration of many important factors affect GHG release. The present GHG prediction model is the first to incorporate the factors of population, energy consumption, GDP, renewable energy production, and urbanization rate. This consideration of more GHG emission-influencing parameters makes the presently presented model able to produce more reliable predictions than other models.
- In this study, GHG emission projections were developed out to 2030, extending beyond previously reported shorter-term estimates. In addition, the presently developed projection is more reliable than prior projections owing to its low error values and being developed based on more up-to-date data.

3 Methodology

3.1 ANN approach

In this study, it is desired to create a GHG emission prediction model using ANN. To create a good model, it is necessary to select the independent variables that have the most influence on the dependent variable. As a result of the literature review, GDP, population, energy consumption, urbanization rate, and renewable energy production were selected as the independent variables that affect GHG emissions the most. In addition, ANN's architecture and selected transfer functions are other factors that affect the success of the model. ANN architecture and transfer functions are determined as described below. There is no formula or rule to determine the number of hidden layers, number of neurons in the hidden layer, or type of activation functions to be used in an ANN. The architecture of an ANN is created completely by trial and error and based on experiences from previous studies [33]. Rumelhart et al. [39], Kankal et al. [40], and Cinar et al. [41] used a multilayer feed-forward neural network consisting of single input, output, and hidden layers in their model and obtained very good results. Based on observations made in preliminary studies and the previous studies to select the architectural features of the network (described below) a three-layer (one hidden layer) feed-forward neural network was used to model GHG emission forecasts. Trials were conducted with 5, 10, 15, and 20 neurons in the hidden layer to determine the optimal number. Hyperbolic tangent sigmoid (input layer → hidden layer) and linear (hidden layer → output layer) transfer functions were used within the network.

Although the choices made so far for the creation of the ANN model are part of the optimization, the most important part of the optimization is to determine the most suitable network weights for the ANN. At this point, algorithms come into play and determine the most suitable weights.

To emphasize the importance of ANN weights and to reveal the optimization problem clearly, the function of the weights in ANN can be explained as follows. As seen in Fig. 2, the selected network consists of three layers and there are neurons in each layer. Each neuron is connected by a weight to the neuron in the next layer. Neurons between the input and intermediate layer interact with each other to create the value of the neuron in the output layer. This value is also the output of the model. For example, to calculate the value of a neuron in the intermediate layer, the values of six neurons in the input layer are processed with six different weights and a bias value. The result is passed through a transfer function and the value of the neuron is found. This process is repeated for each neuron in the intermediate layer and finally the value in the output layer is found. This is the basic working principle of an ANN. The important thing is the weight values chosen while performing this routine process. Optimized weight values are the most important factor determining the predictive power of the network.

Initially, the weights of the ANN are randomly selected by the algorithms (BP, ABC, TLBO, or GWO) and the output of the model is calculated for the selected weights. The error value between the output of the model and the actual value is calculated through a specified objective function. If the calculated error value (objective function value) is greater than the targeted error value, the weights are redetermined by the algorithm and the operations are repeated. This process is repeated until it reaches the target function value or the maximum number of iterations. Among the weights obtained, the weights that give the smallest goal function value are determined as the most appropriate weights. Thus, the optimization process is completed. In Fig. 3, the optimization process has been explained graphically.

In this study weights of ANNs were optimized with BP, teaching–learning-based optimization (TLBO), and GWO algorithms. The BP algorithm is well known and has been described many times in the literature since being introduced in 1986 (for details, see [17] and [39]). Because they are not yet well known, descriptions of the ABC, TLBO, and GWO algorithms are provided below.

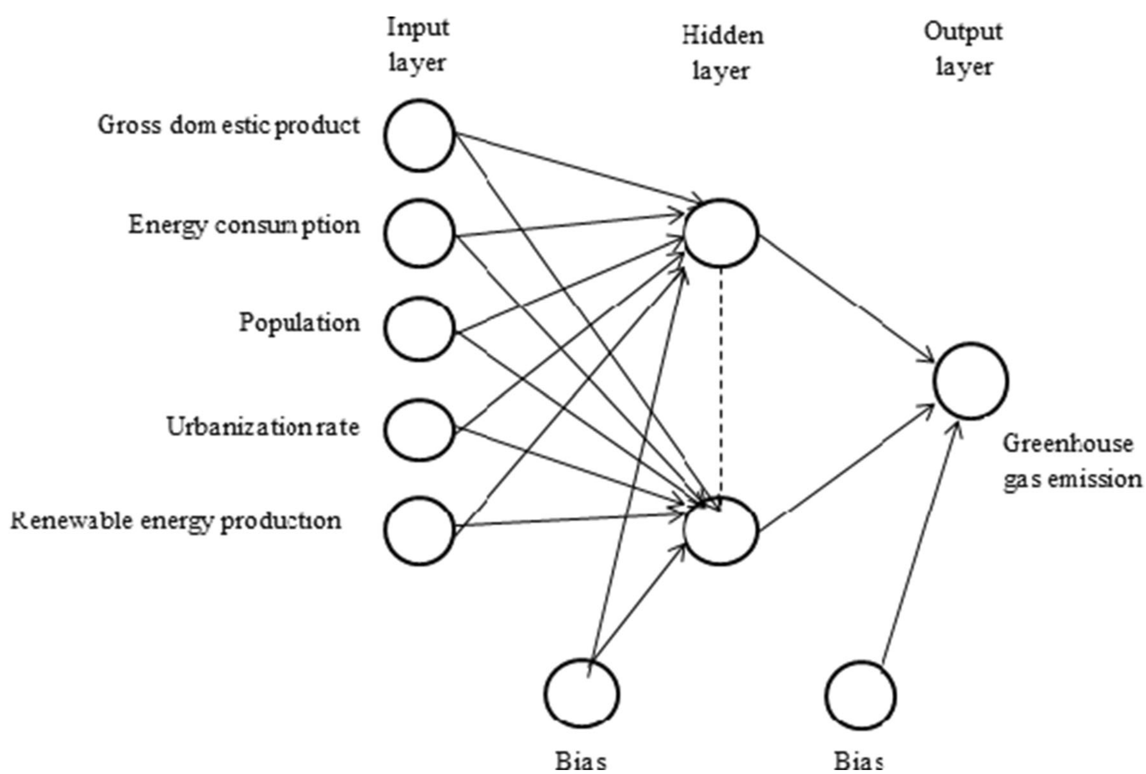


Fig. 2 Proposed ANN model for GHG prediction

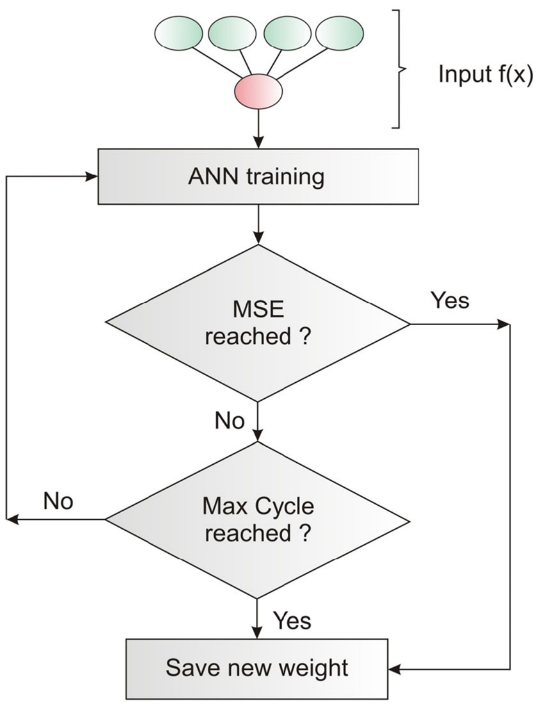


Fig. 3 The proposed ANN training scheme

3.2 ABC algorithm

ABC is a colony optimization algorithm based on the working and food searching processes of bees that was developed by Karaboga [42]. It is a powerful optimization technique that is frequently used in ANN training in many different fields and gives successful results [42–44]. For detailed descriptions of the ABC algorithm, see previous studies [17, 45–47]. The basic components of the ABC algorithm and its general operation are briefly summarized here. In the ABC algorithm, each solution corresponds to a food source, and bees try to find the locations of the most suitable food sources (highest amount of nectar) in a solution space. Conformance is the error value found for the chosen solution. As the error value of the solution gets smaller, its suitability increases. In this study, the ABC algorithm searched for the most suitable ANN weights in lieu of the most suitable food resources. The algorithm includes scout, onlooker, and employee bees. Initially, the bee population consists only of (equal numbers of) onlooker and employee bees. An employee bee is assigned for each "food source" (ANN weight in our study).

Regarding the algorithm's working principles, in the first stage, food sources are determined randomly by the algorithm. Then employee bees go to the algorithm-determined food sources and each calculates the amount of nectar present, thereby determining the suitability of the randomly chosen solutions. Employee bees share the information they gather with onlooker bees. Onlooker bees start looking for new sources near the most suitable source, based on the information from the employee bees. At this point, the onlooker bees turn into employee bees. If a better source cannot be found near a food source within the predetermined limit value, the worker bee leaves that source. Each employee bee that leaves a food source assumes the role of a scout bee. Scout bees choose new food sources randomly. The main difference between scout bees and onlooker bees is that they use external clues to find new food sources. In this way, the algorithm avoids becoming stuck in a local minimum and encountering memorization problems. The aforementioned series of events constitutes one cycle. The best solution in each cycle is recorded by the algorithm. The cycle is repeated until a predetermined number of cycles or desired error values are reached.

3.3 TLBO algorithm

Rao et al.'s [48] TLBO algorithm employs a population-based technique to model the teaching and learning processes of teachers and students. Individuals in the population improve themselves and try to obtain the ideal individual (global solution) for solving a problem. The algorithm is composed of alternating teacher and learner phases. In the teacher phase, the teacher is supposed to be the best-informed person in the population. All other students in the population can be updated after interacting with the teacher. If a student's objective function improves after this interaction, then the student, thus modified, is exchanged with an incoming student. Otherwise, the original student is maintained. The goal of the teaching phase is to raise student performance levels to match that of the teacher [19, 49]. In the learner phase, successfully modified students are compared with one another to identify where the knowledge of each can be improved. Following the final iteration, one student is chosen as the best solution [48].

The TLBO algorithm's control parameters are the number of students (population count), and the criterion for stopping (maximum number of iterations). No algorithm-specific control parameters are required; as a counterexample, genetic algorithms (GAs) also require a mutation ratio and crossover ratio [48]. Thus, application of the TLBO algorithm to an optimization problem is very simple, making it preferred by many researchers. The TLBO algorithm has been described in detail together with its implementation by Rao et al. [50] and Uzlu et al. [18, 46].

3.4 GWO algorithm

Most evolutionary and metaheuristic algorithms are probabilistic, and they require general control parameters such as population size and iteration number in the optimization process of a problem. Some also require additional specific control parameters. For example, while GAs use mutation rate, crossover rate, and selection operators to solve an optimization problem, the ABC algorithm uses its own specific control parameters (i.e., employed bee, onlooker bee, and scout bee). Although the efficient operation of optimization algorithms depends on the correct use of control parameters, it is very difficult to determine suitable control parameter values, which are generally determined based on trial and error and based on previous experience. The lack of a recommended method for otherwise selecting these values is a major optimization challenge in itself that is inherent in using metaheuristic and evolutionary algorithms. Hence, the use of optimization algorithms with fewer control parameters is preferable.

It is very difficult to determine the optimum values for control parameters in the ABC and BP algorithms because both of them contain too many control parameters. Because there is no exact method to solve this situation, it should be repeated over and over to determine the most suitable values. However, tuning the control parameters is easier in the TLBO and GWO algorithms. It is sufficient to determine the population size and the number of iterations as control parameters in these two algorithms. In addition, the main purpose of an optimization problem is to find the optimum solution with minimum function evaluations [51]. Excessive effort wasted to find the optimum solution, too many function evaluations, and complex calculations reduce the speed and performance of algorithms such as BP, ABC, GA, and TLBO. In addition, these algorithms have a more complex structure than GWO. This is another factor that negatively affects the working speed of algorithms. In addition, GWO has high prediction power in cases where there is no clue regarding the search field. In other words, it can find the global optimum in a shorter time. The algorithm's high prediction power stems from employing the hunting principle of wolf packs as its working principle.

The GWO algorithm, developed by Mirjalili et al. [37] in 2014, is an artificial intelligence algorithm designed to have only two control parameters: population size and number of iterations. This characteristic simplifies the use of the GWO algorithm and shortens the optimization process. The facts that the GWO algorithm has a high progression of fitness speed, does not stick to local optima, does not search in abandoned areas, uses the random search feature more efficiently when faced with the problem of memorization, or when it cannot obtain a better result from the source, make GWO superior to other algorithms. In addition, the GWO has a simple numerical structure that facilitates GWO coding and allows easier implementation and faster generation of results than can be had with other metaheuristic algorithms, such as BP, ABC, TLBO, and GA algorithms.

GWO algorithm development was inspired by the natural foraging behavior of wild grey wolves and their leadership hierarchy [52]. The solutions are positions of the wolves' prey. As shown in Fig. 4, there are four types of wolves in the GWO to simulate the leadership hierarchy: alpha (α), beta (β), delta (δ), and omega (ω) [37]. The wolf called alpha leads the herd and makes important decisions. Beta, who is second in the herd hierarchy, is alpha's helper and assists in decision-making processes and herd activities. The lowest rank in the herd hierarchy is omega. Although they may seem insignificant in the herd, they are critically important elements of the herd. In the absence of omega, violence and confusion arise in the herd. Wolves that are not alpha, beta, or omega, have the delta rank, which is intermediate between the beta and omega ranks in the hierarchical order.

In the GWO algorithm, alpha, beta, and delta represent the first, second, and third best solutions, respectively. The remaining candidate solutions are ranked as omega. The solutions are ANN weights for this study. Hunting (optimization) is driven by alpha, beta, and delta. During optimization, the wolves update their hierarchical positions in accordance with Eq. 1 [38].

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \tag{1}$$

In Eq. 1, t represents the current iteration; $\vec{X}(t)$ and $\vec{X}(t+1)$ indicate a wolf's current and new location, respectively. $\vec{X}_p(t)$ indicates the location of the prey. $\vec{A}$ and $\vec{C}$ are coefficient vectors calculated as follows:

$$\vec{A} = 2\,.\vec{a}.\vec{r}_1 - \vec{a}, \tag{2}$$

$$\vec{C} = 2.\vec{r}_2, \tag{3}$$

In Eq. 2, the components of the vector $\vec{a}$ decrease linearly from 2 to zero during optimization, while $\vec{r}_1$ and $\vec{r}_2$ are random vectors in the interval [0, 1]. Each wolf can change its position to a random place around the prey based on Eq. 3 [37].

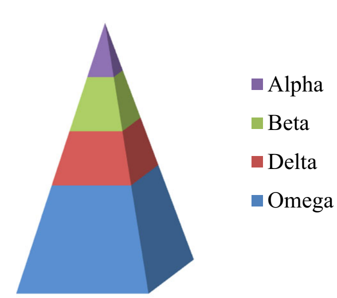


Fig. 4 Social hierarchy of grey wolves

Like other herd-based algorithms, the GWO algorithm uses an initial population before starting optimization. Initially, the wolves' hunting ground positions are random. With the initialization of the GWO algorithm, the wolves move toward prey whose positions are determined randomly in the solution space. An example of possible positions of a grey wolf relative to a prey is presented in Fig. 5. Figure 5 shows how a wolf ($X(t)$) updates the position around a prey ($X(p)$). Depending on the distance between the wolf and its prey, a wolf can update its position using Eq. 1. The solutions obtained are ranked from best to worst according to prey quality. The top three best solutions are considered alpha, beta, and delta, respectively. The other wolves in the population are then considered omega and repositioned with respect to alpha, beta, and delta [37, 38]. The proposed mathematical expression for repositioning omega wolves is presented in Eq. 7. The positions of alpha, beta, delta, and omega wolves are shown in Fig. 6. There is one omega wolf in Fig. 6, but there can be more. As seen in Fig. 6, the closest wolf to the hunt is alpha while the farthest wolf is omega. Therefore, the alpha wolf is the closest candidate to the optimum solution.

$$\vec{X}_1 = \vec{X}_a - \vec{A}_1 . \left| \vec{C}_1 . \vec{X}_a - \vec{X} \right| \quad (4)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 . \left| \vec{C}_1 . \vec{X}_\beta - \vec{X} \right| \quad (5)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 . \left| \vec{C}_1 . \vec{X}_\delta - \vec{X} \right| \quad (6)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (7)$$

In the above equations, $\vec{A}_1$, $\vec{A}_2$, $\vec{A}_3$, $\vec{C}_1$, $\vec{C}_2$, and $\vec{C}_3$ are random vectors, while t indicates the number of iterations; $\vec{X}_a$, $\vec{X}_\beta$, and $\vec{X}_\delta$ indicate the positions of alpha, beta, and delta respectively. $\vec{X}$ represents the position of the current solution and $\vec{X}(t+1)$ represents the new position of the current solution [37, 38].

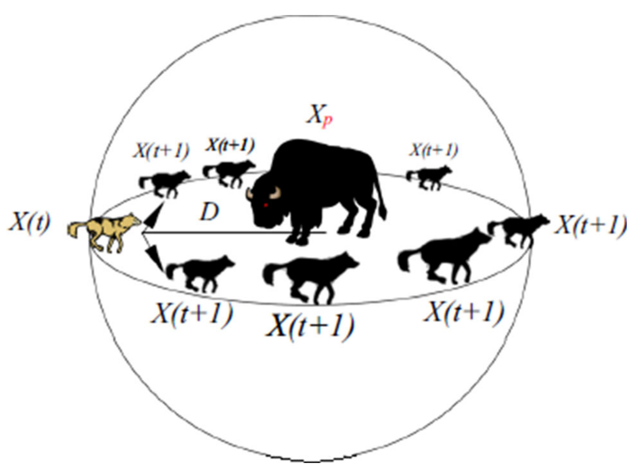


Fig. 5 An example of possible positions of a grey wolf for a prey [53]

$\vec{A}$ and $\vec{C}$ vectors enable wolves in the algorithm to imitate the behavior of real wolves in nature. In nature, wolves do not attack their prey while the prey is moving rapidly. They either start searching for another prey or act after their prey has slowed down [38]. In the GWO algorithm, the wolves imitate this behavior based on the coefficient vector. When $\left|\vec{A}\right|$ is < 1, the wolves must attack their prey (i.e., find new solutions in the neighborhood of a given solution); when this value is > 1, the wolves turn to other prey (i.e., better solutions). The vector $\vec{A}$ allows the GWO algorithm to search all points in the solution space [34].

Unlike the vector $\vec{A}$, $\vec{C}$ is a coefficient that does not change linearly and takes random values in the range [0, 2]. In this way, the vector $\vec{C}$ provides random values to find new prey when a problem such as being stuck in a local minimum or memorization is encountered $\left(\left|\vec{C}\right| > 1\right)$ just as wolves in nature will look for new prey rather than risk themselves and waste energy on a highly challenging/likely-to-fail hunt.

A detailed flowchart of GWO algorithm is presented in Fig. 7. In addition, the general steps of the GWO algorithm are as follows:

- Start a random wolf population based on the upper and lower limits of the variables.
- Calculate the corresponding objective function value for each wolf.
- Select the top three best wolves and save them as alpha, beta, and delta.
- Update the positions of the rest of the population (omega wolves) using Eq. 7.
- Update α, A, and C parameters.
- Return to the position of α as the best converged value.

3.5 ANN training with the BP, ABC, TLBO, or GWO algorithm

Traditionally, ANN training has been carried out with a BP gradient-descent algorithm. Although a BP algorithm gives very good results in ANN training, it has several limitations and drawbacks, as mentioned above (difficult to choose learning and momentum coefficients, long training period, a potential to get stuck in a local minimum, and memorization), which have been addressed with metaheuristic algorithms.

In this study, BP, ABC, TLBO, and GWO algorithms were applied to neural networks for training processes to

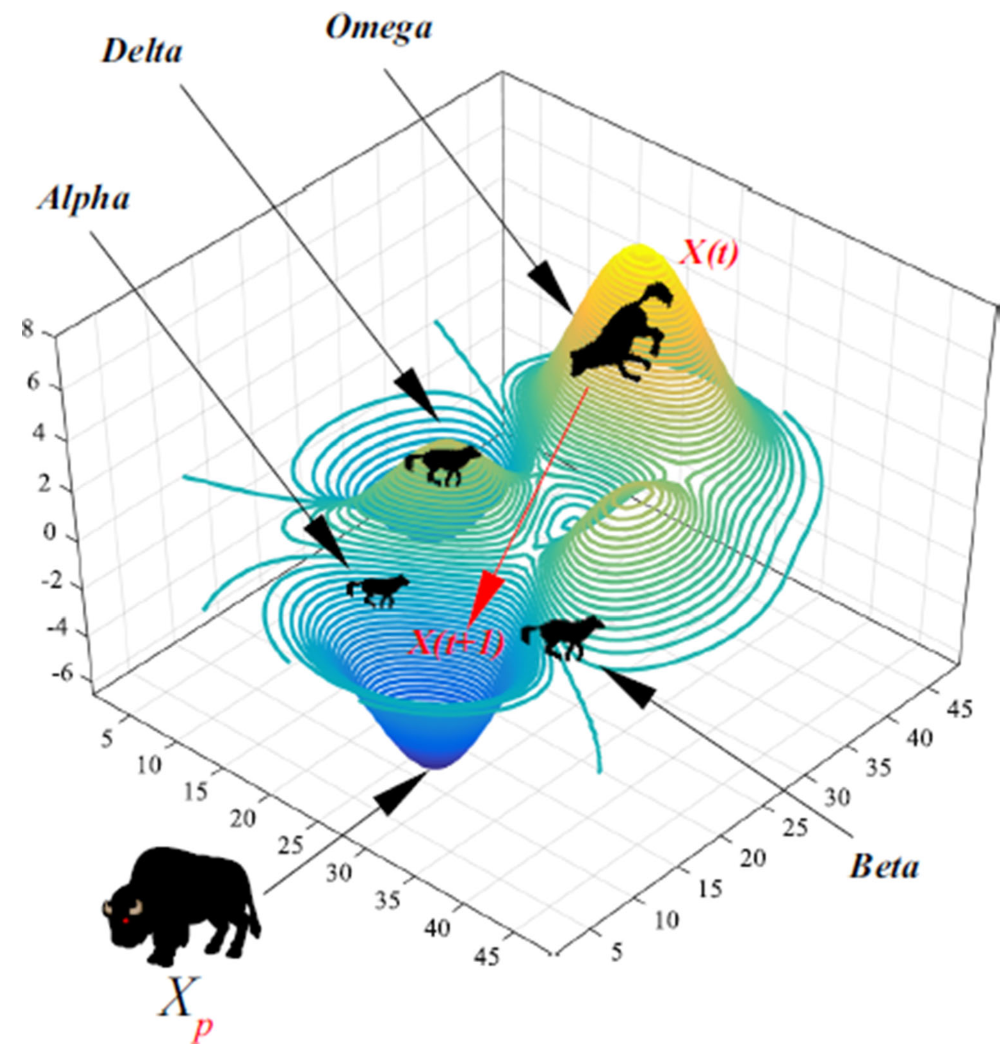


Fig. 6 Positions of alpha, beta, delta, and omega in the GWO algorithm [53]

obtain optimal weights and biases that would minimize the error function in competitive time. Weights and biases were consistently updated until the error of an objective function was reduced to an acceptable value. The objective function to be minimized by the BP, ABC, TLBO, and GWO algorithms was the mean square error (MSE) function, calculated following Eq. 8:

$$\mathrm{MSE} = \frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)^2, \tag{8}$$

where o_k is the output value obtained by the neural network, y_k is the exact output value, and n is the number of patterns.

To assess the performance of trained ANNs, average relative error (RE) [17], root-mean-square error (RMSE) [18], and mean absolute error (MAE) [19] values were calculated. These error values measure how close the predicted energy consumption path (y_k) lies to the true energy consumption path (o_k). The best model results were evaluated in terms of correlation coefficients (R values) [33], U-statistic values [33], and Nash–Sutcliffe efficiency (NSE) value [54]. RE, RMSE, MAE, U-statistic, R, and NSE values were calculated according to following equations:

$$\text{average RE} = \frac{\sum_{i=1}^{n}\left(\frac{y_k - o_k}{y_k}\right)}{n} \times 100, \tag{9}$$

$$\mathrm{RMSE} = \left[\frac{1}{n}\sum_{i=1}^{n}(y_k - o_k)^2\right]^{1/2}, \tag{10}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|(y_k - o_k)|, \tag{11}$$

$$U = \frac{\mathrm{RMSE}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(o_k)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_k)^2}}, \tag{12}$$

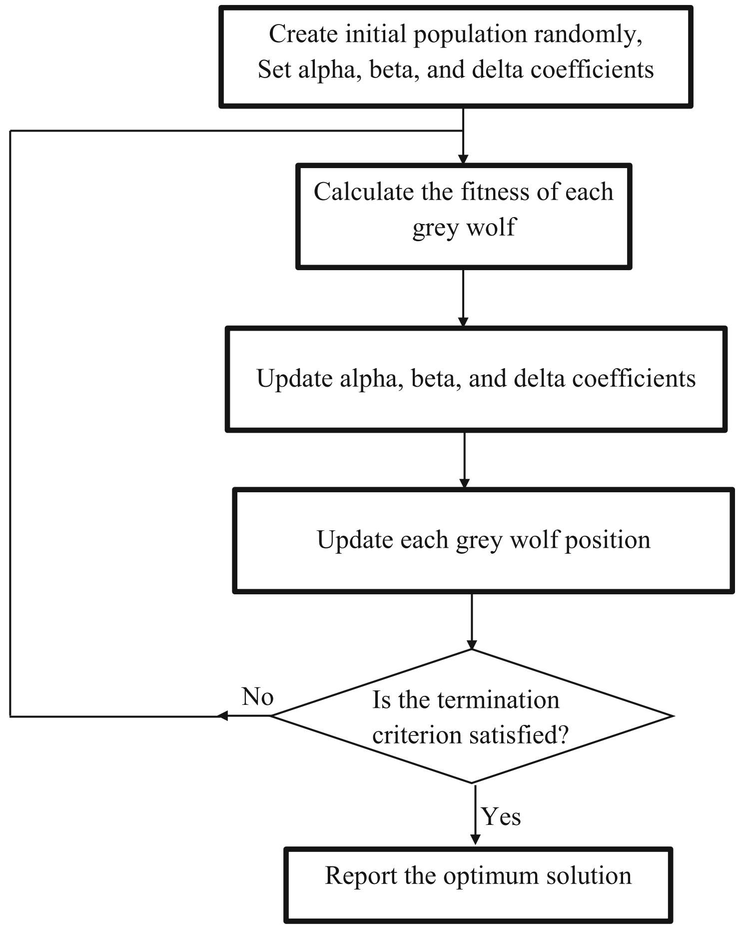


Fig. 7 Flowchart of the GWO algorithm

$$R = \frac{\left(\sum_{i=1}^{n}\left(o_k - \overline{o}_k\right)\left(y_k - \overline{y}_k\right)\right)}{\sqrt{\sum_{i=1}^{n}\left(o_k - \overline{o}_k\right)^2 \sum_{i=}^{n}\left(y_k - \overline{y}_k\right)^2}}, \quad (13)$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(o_k - y_k\right)^2}{\sum_{i=1}^{n}\left(o_k - \overline{o}_k\right)^2} \quad (14)$$

As mentioned before, setting the optimum values for the control parameters of the metaheuristic algorithms is a very difficult task. Although there is no recommended method for this problem, control parameters are determined based on the experiences obtained from previous studies. In the ABC, TLBO, and GWO algorithms, population size, run number, and maximum iteration number must be selected by the user. In addition, the limit value and quantity of employed/onlooker bees in the ABC algorithm must be determined by the user. Similarly, learning and momentum coefficient, maximum iteration number, and initial range of weights were determined by the user in the BP algorithm. However, in the GWO algorithm, $\vec{A}$, $\vec{a}$, and $\vec{C}$ are random vectors. They are determined by the GWO algorithm.

Increasing the population size in metaheuristic algorithms such as ABC, TLBO and GWO enables a more detailed search in the solution space. However, when the population size is increased, the algorithm makes more effort to find better solutions in the neighborhood of similar solutions. Therefore, the optimization becomes difficult and the optimization process prolongs. However, increasing the number of run numbers and decreasing the limit value enables more different solutions to be tried. In this way, both the efficiency of the optimization increases and the optimization process is shortened. Considering the above-mentioned situations and size of the problem, the control parameters have been determined as follows. For all algorithms, the maximum number was 500 with a run number of 10 and an MSE goal value of 8×10^{-8}. The limit value and quantity of employed/onlooker bees in the ABC algorithm were set to 100 and 25, respectively. In the ABC, TLBO, and GWO algorithms, population sizes were set to 50 for all models, and the range of parameters (unknown weights of the ANN) was set as [−1, 1]. Based on previous studies [17–19], initial weight values were selected in the range of [−0.01, 0.01] for the BP algorithm. Optimal learning and momentum ratios in the BP algorithm were determined by trial and error in the range of [0.1, 1]. The training process applies a set of input vectors to the network repeatedly, updating the network each time until certain stopping criteria are reached. The codes for the proposed algorithms have been provided in the link https://avesis.ktu.edu.tr/ergunuzlu/dokumanlar.

4 Selection of independent variables and data used

4.1 Choosing the independent variables

The most prominent indicator of a nation's economic activities is GDP, such that an increasing GDP reflects economic growth. The relationship between economic growth and the environment is often explained by the Environmental Kuznets Curve (EKC). According to the theory underlying the EKC, countries at low and very high GDP levels have less damaging effects on the environment, while developing countries tend to have highly damaging effects on the environment. According to this theory, damage to the environment varies in direct proportion to GDP in developing countries. While Gürlük and Karaer [55], Halicioglu [56], and Omay [57] have shown that the EKC is valid for Turkey, Acaravcı and Öztürk [58] and Akbostancı et al. [59] found that it was not. But all these studies have shown that GHG emission levels have consistently been shown to be closely related to GDP. Halicioglu [56] and Bölük and Mert [60] have asserted that GDP is the most important parameter influencing GHG emissions in Turkey.

The predominant source of GHG emissions in Turkey is thermal power plants that use fossil fuel combustion, following by the industry sector. According to 2018 Turkish Statistical Institute (TURKSTAT) data, energy-related emissions and industrial processes were responsible for 71.6% and 12.5% of total GHGs. Energy consumption, which results in GHG emissions, is used as an independent variable in all energy-related CO_2 prediction models in the literature [25–29, 32].

Two other important parameters affecting GHG emissions are population and urbanization rate. In general, greater rural-to-urban migration is a characteristic of increasing population, and urban populations have a greater impact on energy consumption, and thus GHG emissions, than rural populations. Cities account for more than two-thirds of global energy use and emit 70% of global GHG emissions, and increasing urbanization has been identified as an underlying cause of increasing GHG emissions in Turkey [61]. The urbanization rate is the urban population divided by the total population.

Renewable energy can both ensure electricity supply sustainability and reduce GHG emissions. Electricity production from renewable sources represents a key means of reducing GHG emissions in Turkey, which due to its primarily fossil-based energy production produces 71.6% of the amount of GHGs released into the atmosphere in Turkey. Bölük and Mert [60] and Pata [61] found that the EKC hypothesis is valid for Turkey and that an increase in the production of renewable energy can reduce GHG emissions.

Many other parameters affect GHG release, including emissions from vehicles and heating of buildings, as well as gases formed as a result of the decay of vegetation on lake bottoms and gases released by animals. However, it would be very difficult to develop a model that encompasses all of these parameters. Moreover, the effects of these parameters on GHG release are quite low comparatively. Thus, the present modeling assumes that GHG emission levels are mostly affected by the five included parameters.

4.2 Data employed

GDP, energy consumption, population, urbanization rate, and renewable energy production amounts were used as independent variables to estimate Turkey's GHG emission levels. Historical data from the period of 1990–2011 were used for training, while data from the period of 2012–2017 were reserved for evaluating trained network performance. As shown in Fig. 8, six categories of data were collected from distinct sources.

Population and GHG emission data were obtained from TURKSTAT [62]. GDP, energy consumption, urbanization rate, and renewable energy production data were taken Republic of Turkey Presidency of Strategy and Budget [63], Ministry of Energy and Natural Resources [64], Republic of Turkey Ministry of Environment and Urbanization [65], and Turkish Electricity Transmission Corporation [66], respectively.

To increase the performance of the algorithms used in ANN training and to find the best ANN weights in a short time, all data were normalized to the interval [0.1, 0.9] by applying Eq. 6 [67]. Results of chosen activation functions change generally in a [0, 1] interval [19]. A range of [0.1, 0.9] was selected to produce more effective results from the activation functions used in the ANN input and output layers.

$$\text{Normalized value} = \left[\frac{\text{Raw value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}}\right] \times (0.9 - 0.1) + 0.1 \qquad (15)$$

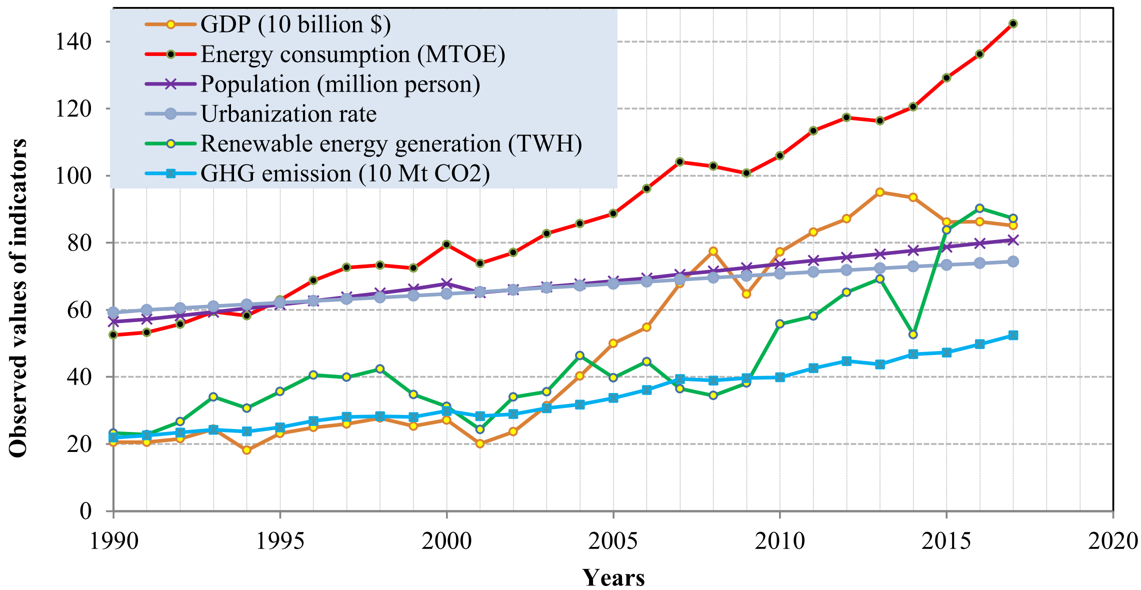


Fig. 8 Variations in GHG and predictor variables [62–66]

5 Development and performance evaluation of the forecasting model

The three-layer network with a hidden layer shown in Fig. 2 was selected for this study. GDP, energy consumption, population, urbanization rate, and renewable energy production values were employed in the network's input layer. GHG, the variable being predicted, was in the output layer. BP, ABC, TLBO, and GWO algorithms were used to train the network. ANN architectures and best ANN training convergence, that is, those with the minimum MSE values, for the three methods are shown in Table 1.

Based on the error values obtained with the training set (Table 1), it can be seen that the GWO algorithm performs better than the BP, ABC, and TLBO algorithms in ANN training. When the convergence values obtained for the BP and TLBO algorithms are compared, the TLBO algorithm performs better than the BP algorithm, except for cases with 5 and 15 neurons in the hidden layer. On the other hand, the ABC algorithm performs better than the BP and TLBO algorithms, except for cases with 5 and 10 neurons in the hidden layer. The best convergence (minimum MSE) values were 3.058 for the ANN-BP (4–5–1) model, 3.156 for the ANN-ABC (4–20–1), 3.178 for the ANN-TLBO (4–20–1) model, and 2.275 for the ANN-GWO (4–5–1) model. According to these values, the GWO algorithm performed 25.60%, 27.92%, and 28.41% better in ANN training than did the BP, ABC, and TLBO algorithms, respectively. However, error values calculated for the training set of the developed ANN models cannot alone indicate the predictive power of the network given that problems such potential sticking in a local solution or memorizing can yield apparently good performance, but low predictive power. Therefore, the ANN model with the smallest training error may not always have the greatest predictive power. Thus, test set error values were determined for all ANN models (Table 2) to identify the model with the highest predictive power.

According to the error values in Tables 1 and 2, although ANN-BP (4–5–1) has the minimum MSE value for the training set, the lowest mean RE, RMSE, and MAE values for the testing set were obtained from ANN-BP (4–20–1). Therefore, the best model among ANN-BP models is clearly the ANN-BP (4–20–1), which contains 20

Table 1 The model results for the training set

ANN architecture	MSE			
	BP algorithm	ABC algorithm	TLBO algorithm	GWO algorithm
4–5–1	3.058	4.925	**4.855**	**2.275**
4–10–1	6.253	6.352	5.837	4.784
4–15–1	3.452	3.230	3.551	3.447
4–20–1	**3.186**	**3.156**	3.178	3.096

The bold value is the error value for the proposed model

Table 2 The model results for the testing set

ANN architecture	Average relative error (%) in the testing set				RMSE for the testing set				MAE for the testing set			
	BP	ABC	TLBO	GWO	BP	ABC	TLBO	GWO	BP	ABC	TLBO	GWO
4–5–1	2.953	2.030	1.298	**1.047**	3.853	2.806	1.556	**1.454**	3.296	2.202	1.453	**1.136**
4–10–1	2.423	2.256	2.395	1.626	2.919	3.020	3.039	2.177	2.736	2.551	2.657	1.839
4–15–1	1.948	1.910	1.721	1.790	2.458	2.482	2.216	2.326	2.126	2.073	1.868	1.943
4–20–1	1.545	1.618	1.531	1.670	2.095	2.120	2.081	2.146	1.716	1.804	1.706	1.859

The bold values are the error values for the proposed model

neurons in its hidden layer. A similar situation exists among the ANN-TLBO models. Although the smallest training set error value was obtained from ANN-TLBO (4–20–1), the smallest test set error values were found for ANN-TLBO (4–5–1). In this case, ANN-TLBO (4–5–1) is the ANN-TLBO model with the highest predictive power. When the error values calculated for the ANN-ABC and ANN-GWO models were examined, the minimum error values for the training and test sets were both obtained from the same model. The best models for ANN-ABC and ANN-GWO are ANN-ABC (4–20–1) and ANN-GWO (4–5–1) models with 20 and 5 neurons in the interlayer, respectively. The average RE, RMSE, and MAE error values obtained from the ANN-GWO (4–5–1) model with the test set data were 1.047%, 1.454, and 1.136, respectively. ANN-GWO (4–5–1) is the model with the smallest training and test set error values among all of the examined ANN models. Considering the average RE values calculated for test set data, it was determined that the ANN-GWO (4–5–1) model outperformed the ANN-ABC (4–20–1), ANN-BP (4–20–1), and ANN-TLBO (4–5–1) models, respectively, by 35.29%, 32.23%, and 19.33%. Comparisons of the performances of ANN-BP (4–20–1), ANN-ABC (4–20–1), ANN-TLBO (4–5–1), and ANN-GWO (4–5–1) for the training set are presented in Fig. 9. According to the data described above and Fig. 10, the best model is clearly the ANN-GWO (4–5–1) model, which has 5 neurons in its hidden layer. The R and U-statistic values calculated with the training set data (0.991 and 0.018, respectively) and with the test set data (0.993 and 0.008, respectively) confirmed the accuracy of the proposed ANN-GWO (4–5–1) model, thus affirming that its predictive power is acceptable. In addition to R and U-statistic values, NSE values were calculated using training and test set data to test the statistical significance of the proposed ANN-GWO (4–5–1) model. The NSE coefficient takes values between 1 and $-\infty$. As the NSE value approaches 1, the accuracy of the model increases. An NSE value equal to 1 indicates that the model has a perfect predictive power. But an NSE value less than 0 suggests that the model's prediction performance is poor and it cannot be used. The NSE values of the ANN-GWO (4–5–1) model were calculated as 0.966 and 0.936 for the training and test sets, respectively. NSE value, R value, U-statistic, and calculated error values show that the results are statistically significant. The performance of the proposed ANN-GWO (4–5–1) model for test data is presented in Fig. 10.

The ANN-GWO technique gives very good results not only for the data set in this study but also for different data sets and problems. For example, Uzlu [68] used the ANN-GWO technique to estimate Turkey's future energy consumption. GDP, population, import, and export data were used as independent variables and total energy consumption data were used as the dependent variable in the model. The ANN-GWO model was compared with the ANN-BP and ANN-ABC models to test the accuracy of the proposed model. The ANN-GWO model gave better results than the ANN-BP and ANN-ABC models. The results obtained for different data sets and problems agree with the results in this study. Therefore, the ANN-GWO technique is a method with high predictive power and reliability.

6 Future predictions of energy consumption

Using the proposed model, Turkey's GHG emission values were estimated for time years of 2018–2030 for three different scenarios. Scenario 1 represents stagnation of economic activities, scenario 2 represents a continuation of the current trends for all conditions, and scenario 3 represents a greater increase in economic activities than is currently expected. In summary, scenario 1, scenario 2, and scenario 3 represent minimum, expected, and maximum GHG emission values, respectively. The population and energy consumption data used in these scenarios reflect TURKSTAT population projections [69] and Tefek et al.'s results [70], respectively. The values used in these scenarios for GDP, renewable energy production, and urbanization rate

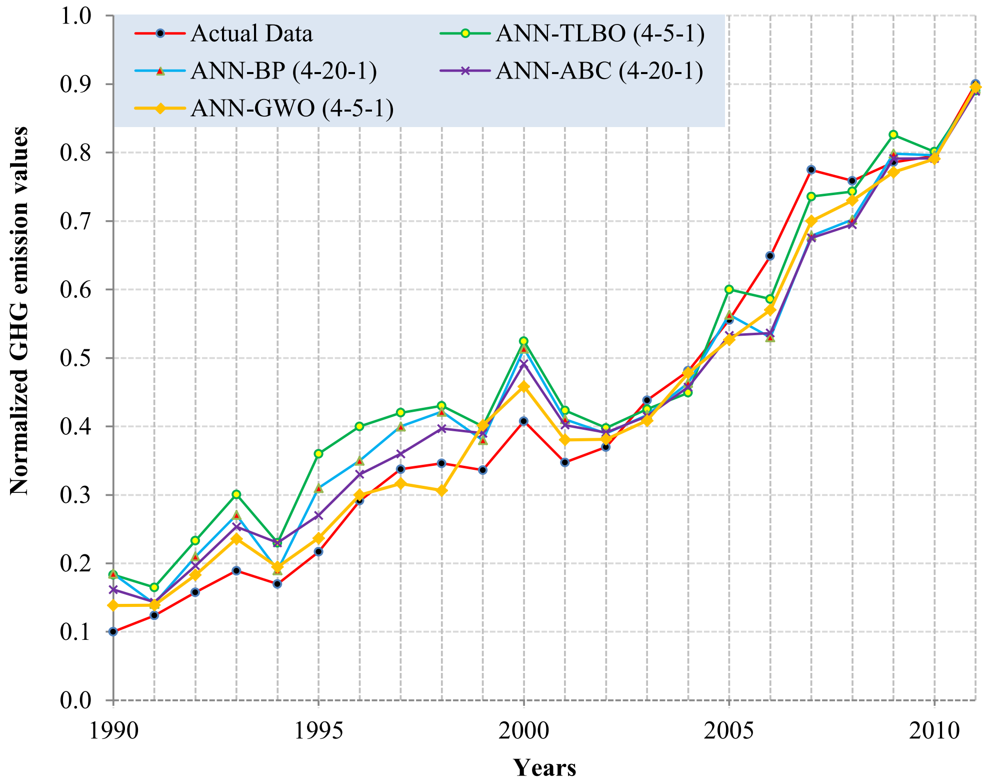
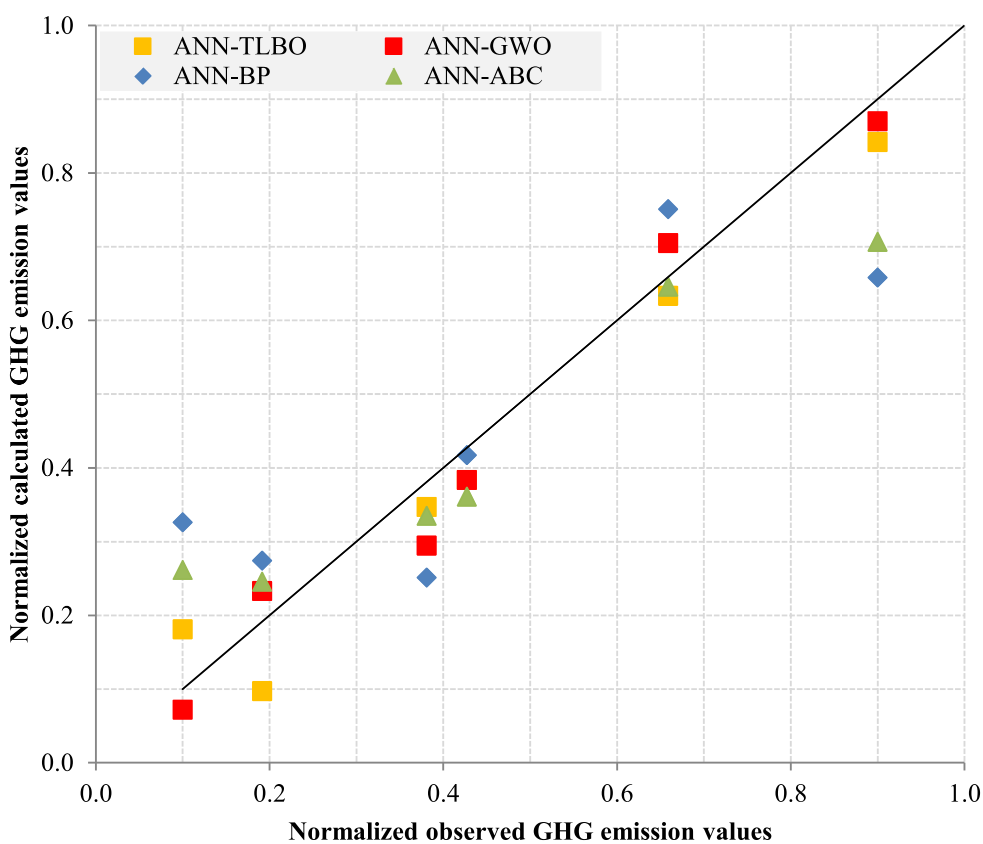


Fig. 9 Performances of the ANN-BP (4–20-1), ANN-ABC (4–20–1), ANN-TLBO (4–5–1), and ANN-GWO (4–5–1) for the training set

Fig. 10 Performance of the proposed ANN-GWO (4–5–1) model for test data



reflect average growth rates: 6.37%, 1.16%, and 0.84%, respectively. The data and scenarios used in the scenarios are presented in detail in Tables 3 and 4, respectively.

GHG emission values predicted by ANN-GWO modeling with official projections committed to by Turkey at the Paris Climate Summit are compared in Table 5 and Fig. 11 [54]. Because emission values in scenario 2 are higher than in scenario 1 and less than in scenario 3 (Table 5), scenarios 1, 2, and 3 can be called low, expected, and high scenarios, respectively. Notably, the GHG emission values obtained for all scenarios in this study are higher than the values in the official projection (Fig. 11). According to this study, Turkey's GHG emissions should be within the range of 956.97–1170.54 Mt CO_2 in 2030, whereas the official projection [65] suggests they will be only 929 Mt CO_2 equivalent in 2030, to which Turkey committed at the Paris Climate Summit. According to Pabuçcu and Bayramoğlu's [30] projection, Turkey's GHG emissions values will be 740.33, 1039.32, and 1244.13 Mt CO_2 equivalent in 2020, 2025, and 2030, respectively. The officially projected GHG emission amounts for the years 2020, 2025, and 2030 are 599.00, 790.00, and 929.00 Mt CO_2, respectively [65]. When these values are compared, it is seen that Pabuçcu and Bayramoğlu's [30] estimates are considerably higher than the official projection values [65]. However, the closeness of the predictions made by Pabuçcu and Bayramoğlu [30] to the values obtained for scenario 3 in this study should increase confidence in the accuracy of the proposed model.

While Turkey's GHG emissions values are under the EU's average GHG values up to 1997–1998, Turkey's GHG values are now outpacing EU levels at a widening rate. The targeted average GHG emissions for EU countries in 2030 is 151.75 Mt CO_2 [30]. According to the projection obtained from this study, this value planned for EU countries corresponds to 12.9–15.8% of Turkey's projected 2030 GHG emissions, indicating that Turkey's future GHG emissions are on course to far exceed the EU average. In addition, more than 70% of Turkey's GHG emissions are derived from energy consumption and Turkey, as a developing country, is bound to increase its energy consumption. Meanwhile, however, it is important to limit or mitigate environmental destruction. Given these considerations, Turkey needs to increase its energy efficiency and renewable energy use to fulfill the commitments it made at the Paris Climate Summit. If Turkey does not improve these factors, its economic growth will result in the deterioration of its environmental conditions.

7 Conclusions

Predictions of GHG values under different scenarios are critical to environmental policy development because GHG emissions are a key component of environmental pollution. In addition, GHG forecasts can be utilized to assist in decisions that will affect substantial capital investments related to national energy policy. The presently developed ANN-GWO model based on the indicators of GDP, energy consumption, population, urbanization rate, and renewable energy production data predicts GHG emission levels better than the ANN-BP, ANN-ABC, and ANN-TLBO models, according to all error metrics. Average RE, RMSE, and MAE values of 1.047%, 1.454, and 1.136, respectively, were obtained for the test set data with the proposed ANN-GWO (4–5–1) model. Other advantages of the GWO algorithm are that the GWO algorithm can be easily applied to any optimization problem thanks to its easy coding, converges to the optimum solution quickly thanks to its simple structure and high predictive ability, and saves time and effort. Therefore, ANN-GWO methodology was used to forecast Turkey's GHG emissions from 2018 through 2030. Compared with the official projections committed to by Turkey at the Paris Climate Summit [65], the present forecasts, as well as those published by Pabuçcu and Bayramoğlu [30], predict substantially higher GHG values. According to the results of the present study, Turkey's GHG emission level will be between 956.97 and 1170.54 Mt CO_2 in 2030. Thus, to fulfill its commitment to the Paris Climate Summit agreement, Turkey must improve its energy efficiency and renewable energy use. If there is inaction in this regard, Turkey's economic growth will be accompanied by serious degradation of environmental quality.

In the GWO algorithm, wolves are classified as alpha, beta, delta, and omega. The increase in the number of parameters due to this classification can be seen as a disadvantage. Reducing these parameters with appropriate methods can make the algorithm more useful. In addition, choosing appropriate values for control parameters is a big problem in the GWO algorithm as with other metaheuristic algorithms. This problem has not been investigated sufficiently in the literature. Therefore, tuning the control parameters of GWO can be addressed as a searching subject in future studies. It is noteworthy that the codes for the proposed ANN-GWO technique have been provided in the link https://avesis.ktu.edu.tr/ergunuzlu/dokumanlar. Thanks to the shared code, the above-mentioned shortcomings of the method can be eliminated and the technique further developed. In addition, using the shared code, the proposed technique can be easily applied to different problems. Future use of the GWO algorithm in ANN

Table 3 The data for GDP, population, energy consumption, renewable energy generation, and urbanization rate amounts used in scenarios

Year	GDP (Billion $)			Population (10^6)	Energy consumption (Mtoe)			Renewable energy generation (TWh)			Urbanization rate		
	Growth rate 4.87%	Growth rate 6.37%	Growth rate 7.87%	TURKSTAT [69]	Tefek et al. [70] low scenario	Tefek et al. [70] expected scenario	Tefek et al. [70] high scenario	Growth rate 1.13%	Growth rate 1.16%	Growth rate 1.20%	Growth rate 0.64%	Growth rate 0.84%	Growth rate 1.04%
2018	89.349	90.627	91.905	81.867	138.10	139.60	144.20	98.607	101.557	104.716	74.839	74.988	75.136
2019	93.701	96.400	99.138	82.890	142.30	144.20	150.30	111.426	118.192	125.659	75.318	75.618	75.918
2020	98.264	102.541	106.940	83.900	146.60	149.00	156.70	125.912	137.552	150.791	75.800	76.253	76.707
2021	103.049	109.073	115.357	84.910	151.00	154.00	163.30	142.280	160.082	180.949	76.285	76.893	77.505
2022	108.068	116.021	124.435	85.910	155.60	159.20	170.30	160.777	186.304	217.138	76.773	77.539	78.311
2023	113.331	123.411	134.228	86.910	160.30	164.50	177.60	181.677	216.821	260.566	77.265	78.190	79.126
2024	118.850	131.272	144.792	87.890	165.20	170.10	185.30	205.296	252.336	312.679	77.759	78.847	79.948
2025	124.638	139.635	156.187	88.840	170.20	175.90	193.40	231.984	293.668	375.215	78.257	79.510	80.780
2026	130.708	148.529	168.479	89.780	175.40	182.00	201.90	262.142	341.771	450.258	78.758	80.177	81.620
2027	137.073	157.991	181.738	90.700	180.80	188.20	210.80	296.220	397.753	540.310	79.262	80.851	82.469
2028	143.749	168.055	196.041	91.600	186.30	194.70	220.20	334.729	462.905	648.372	79.769	81.530	83.327
2029	150.749	178.760	211.470	92.480	192.00	201.50	230.00	378.244	538.729	778.046	80.279	82.215	84.193
2030	158.091	190.147	228.112	93.330	198.00	208.50	240.30	427.415	626.973	933.655	80.793	82.906	85.069

Table 4 Scenarios for Turkey's GHG emission

Scenarios	GDP	Population	Energy consumption	Renewable energy generation	Urbanization rate
Scenario 1	The growth rate (about 4.87%)	The population data obtained from TURKSTAT [69]	Tefek et al. [70] low scenario	The growth rate (about 1.13%)	The growth rate (about 0.64%)
Scenario 2	The growth rate (about 6.37%)	The population data obtained from TURKSTAT [69]	Tefek et al. [70] expected scenario	The growth rate (about 1.16%)	The growth rate (about 0.84%)
Scenario 3	The growth rate (about 7.87%)	The population data obtained from TURKSTAT [69]	Tefek et al. [70] high scenario	The growth rate (about 1.20%)	The growth rate (about 1.04%)

Table 5 Future projections of energy consumption in 10 Mt CO_2 according to scenarios, official projection [65]

Year	Scenario 1	Scenario 2	Scenario 3	Official projection [65]
2018	54.860	55.600	56.800	53.500
2019	60.270	61.870	63.210	56.700
2020	66.930	68.500	69.120	59.900
2021	72.560	73.540	76.030	63.800
2022	76.130	78.900	83.250	67.700
2023	80.088	83.800	88.690	71.700
2024	83.580	87.840	94.448	75.350
2025	85.780	92.020	99.077	79.000
2026	87.970	95.930	103.692	81.780
2027	90.160	99.781	108.296	84.560
2028	92.343	102.405	111.890	87.340
2029	93.921	104.550	114.875	90.120
2030	95.697	106.070	117.054	92.900

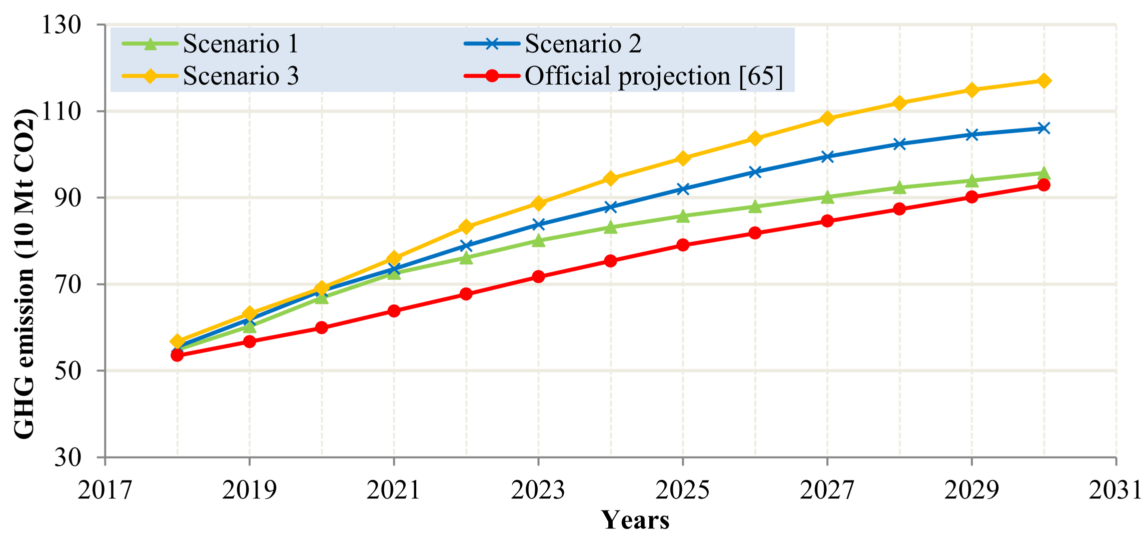


Fig. 11 Comparison of the three scenarios, and official projection [65] for Turkey's GHG emission amount

training for GHG modeling applications is thus encouraged and can be recommended based on the present demonstration that the GWO algorithm yields satisfactory results.

Declarations

Conflicts of interest The author declares that there are no conflicts of interest regarding the publication of this paper.

References

1. Republic of Turkey Ministry of Environment and Urbanization. Turkey environmental performance review report. https://webdosya.csb.gov.tr/db/ab/icerikler/oecd-epr-tr-20190228120557.pdf
2. Turkish Statistical Institute (TURKSTAT). Greenhouse gas emission statistics 1990–2018. https://webdosya.csb.gov.tr/db/iklim/icerikler/turk-ye-istat-st-k-kurumu-sera-gazi-em-syon-istat-st-kler–1990-2018-20200506122539.pdf
3. Natural Gas Distribution Companies Association of Turkey. Carbon emission report. https://www.gazbir.org.tr/uploads/page/Karbon%20Emisyonu-Rev-Son.pdf
4. Choi CS, Abdullah L (2016) Prediction of carbon dioxide emissions using two linear regression-based models: a comparative analysis. J Appl Eng 4:305–312
5. Pao HT, Tsai CM (2011) Modeling and forecasting the CO_2 emissions, energy consumption, and economic growth in Brazil. Energy 36:2450–2458
6. Lotfalipour MR, Falahi MA, Bastam M (2013) Prediction of CO_2 emissions in Iran using grey and ARIMA models. Int J Energy Econ Policy 3:229–237
7. Wang ZX, Li Q (2019) Modelling the nonlinear relationship between CO_2 emissions and economic growth using a PSO algorithm-based grey Verhulst model. J Clean Prod 207:214–224
8. Ding S, Dang YG, Li X, Wang JJ, Zhao K (2017) Forecasting Chinese CO_2 emissions from fuel combustion using a novel grey multivariable model. J Clean Prod 162:1527–1538
9. Yu Y, Deng YR, Chen FF (2018) Impact of population aging and industrial structure on CO_2 emissions and emissions trend prediction in China. Atmos Pollut Res 9:446–454
10. Zhao X, Han M, Ding L, Calin AC (2018) Forecasting carbon dioxide emissions based on a hybrid of mixed data sampling regression model and back propagation neural network in the USA. Environ Sci Pollut Res 25:2899–2910
11. Chen Z, Ye X, Huang P (2018) Estimating carbon dioxide (CO_2) emissions from reservoirs using artificial neural networks. Water 10:1–16
12. Zhou J, Du S, Shi J, Guang F (2017) Carbon emissions scenario prediction of the thermal power industry in the Beijing-Tianjin-Hebei region based on a back propagation neural network optimized by an improved particle swarm optimization algorithm. Pol J Environ Stud 26:1895–1904
13. Tian L, Gao L, Xu P (2010) The evolutional prediction model of carbon emissions in china based on bp neural network. Int J Nonlinear Sci 10:131–140
14. Appiah K, Du J, Appah R, Quacoe D (2018) Prediction of potential carbon dioxide emissions of selected emerging economies using artificial neural network. J Environ Sci Eng 7:321–335
15. Radojevic D, Pocajt V, Popovic I, Grujic AP, Ristic M (2013) Forecasting of greenhouse gas emissions in Serbia using artificial neural networks. Energy Sources Part A Recovery Util Environ Eff 35:733–740
16. Santibanez-Gonzalez E, Del R, Robson MG, Pacca LH (2011) Solving a public sector sustainable supply chain problem: a genetic algorithm approach. In: Proc. of Int. Conf. of Artificial Intelligence (ICAI), Las Vegas, USA, pp. 507–512
17. Uzlu E, Akpınar A, Öztürk HT, Nacar S, Kankal M (2014) Estimates of hydroelectric generation using neural networks with the artificial bee colony algorithm for Turkey. Energy 69:638–647
18. Uzlu E, Kankal M, Akpınar A, Dede T (2014) Estimates of energy consumption in Turkey using neural networks with the teaching–learning-based optimization algorithm. Energy 75:295–303
19. Kankal M, Uzlu E (2017) Neural network approach with teaching–learning-based optimization for modeling and forecasting long-term electric energy demand in Turkey. Neural Comput Appl 28:737–747
20. Li W, Gao S (2018) Prospective on energy related carbon emissions peak integrating optimized intelligent algorithm with dry process technique application for China's cement industry. Energy 165:33–54
21. Sangeetha A, Amudha T (2018) A novel bio-inspired framework for CO_2 emission forecast in India. Procedia Comput Sci 125:367–375
22. Hong T, Jeong K, Koo C (2018) An optimized gene expression programming model for forecasting the national CO_2 emissions in 2030 using the metaheuristic algorithms. Appl Energy 228:808–820
23. Pintea CM, Pop PC, Hajdu-Macelaru M (2013) Classical hybrid approaches on a transportation problem with gas emissions constraints. Adv Intell Syst Comput 188:449–458
24. Say NP, Yücel M (2006) Energy consumption and CO_2 emissions in Turkey: empirical analysis and future projection based on an economic growth. Energy Policy 34:3870–3876
25. Aydin G (2015) The development and validation of regression models to predict energy-related CO_2 emissions in Turkey. Energy Sources Part B 10:176–182
26. Şahin U (2019) Forecasting of Turkey's electricity generation and CO_2 emissions in estimating capacity factor. Environ Prog Sustain Energy 38:56–65
27. Köne AÇ, Büke T (2010) Forecasting of CO_2 emissions from fuel combustion using trend analysis. Renew Sustain Energy Rev 14:2906–2915
28. Ayvaz B, Kusakci AO, Temur GT (2017) Energy-related CO_2 emission forecast for Turkey and Europe and Eurasia a discrete grey model approach. Grey Syst Theory Appl 7:437–454
29. Hamzacebi C, Karakurt I (2015) Forecasting the energy-related CO_2 emissions of Turkey using a grey prediction model. Energy Sources Part A Recovery Util Environ Eff 37:1023–1031
30. Pabuçcu H, Bayramoğlu T (2016) CO_2 emissions forecast with neural networks with: the case of Turkey. Gazi Univ J Fac Econ Adm Sci 18:762–778
31. Sözen A, Gülseven Z, Arcaklioğlu E (2009) Estimation of GHG emissions in Turkey using energy and economic indicators. Energy Sources Part A 31:1141–1159
32. Özceylan E (2016) Forecasting CO_2 emission of Turkey: swarm intelligence approaches. Int J Glob Warm 9:337–361
33. Uzlu E (2019) Application of Jaya algorithm-trained artificial neural networks for prediction of energy use in the nation of Turkey. Energy Sources Part B 14:183–200
34. Kalemci EN, İkizler SB, Dede T, Angin Z (2020) Design of reinforced concrete cantilever retaining wall using grey wolf optimization algorithm. Structures 23:245–253
35. Gaafary AAM, Mohamed YS, Hemeida AM, Al-Attar A, Mohamed AA (2015) Grey wolf optimization for multi input multi output system. Univers J Commun Netw 3:1–6

36. Hadavandi E, Mostafayi S, Soltani P (2018) A Grey Wolf Optimizer-based neural network coupled with response surface method for modeling the strength of siro-spun yarn in spinning mills. Appl Soft Comput 72:1–13
37. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61
38. Mirjalili S (2015) How effective is the grey wolf optimizer in training multi-layer perceptrons. Appl Intell 43:150–161
39. Rumelhart DE, Hinton GE, Williams RJ (1986) Learning representations by back-propagating errors. Nature 323:533–536
40. Kankal M, Uzlu E, Nacar S, Yüksek Ö (2018) Predicting temporal rate coefficient of bar volume using hybrid artificial intelligence approaches. J Mar Sci Technol 23:596–604
41. Cinar D, Kayakutlu G, Daim T (2010) Development of future energy scenarios with intelligent algorithms: case of hydro in Turkey. Energy 35:1724–1729
42. Adak MF, Yumusak N (2016) Classification of e-nose aroma data of four fruit types by ABC-based neural network. Sensors 16:1–13
43. Sonmez M, Akgüngör AP, Bektaş S (2017) Estimating transportation energy demand in Turkey using the artificial bee colony algorithm. Energy 122:301–310
44. Xu Q, Chen J, Liu X, Li J, Yuan C (2017) An ABC-BP-ann algorithm for semi-active control for magnetorheological damper. KSCE J Civ Eng 21:2310–2321
45. Karaboga D (2005) An idea based on honey bee swarm for numerical optimization. Technical Report-TR06. Erciyes University Engineering Faculty Computer Engineering Department
46. Uzlu E, Kömürcü Mİ, Kankal M, Dede ÖHT (2014) Prediction of berm geometry using a set of laboratory tests combined with teaching–learning-based optimization and artificial bee colony algorithms. Appl Ocean Res 48:103–113
47. Ozkan C, Kisi O, Akay B (2011) Neural networks with artificial bee colony algorithm for modeling daily reference evapotranspiration. Irrig Sci 29:431–441
48. Dede T, Ayvaz Y (2015) Combined size and shape optimization of structures with a new meta-heuristic algorithm. Appl Soft Comput 28:250–258
49. Rao RV, More KC (2015) Optimal design of the heat pipe using TLBO (teaching–learning-based optimization algorithm). Energy 80:535–544
50. Rao RV, Savsani VJ, Vakharia DP (2011) Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. Comput Aided Des 43:303–315
51. Moattari M, Moradi MH (2020) Conflict monitoring optimization heuristic inspired by brain fear and conflict systems. Int J Artif Intell 18:45–62
52. Precup RE, David RC, Petriu EM, Szedlak-Stinean AI, Claudia-Adina BD (2016) Grey wolf optimizer-based approach to the tuning of pi-fuzzy controllers with a reduced process parametric sensitivity. IFAC-PapersOnLine 49(5):55–60
53. Faris H, Aljarah I, Al-Betar MA, Mirjalili S (2018) Grey wolf optimizer: a review of recent variants and applications. Neural Comput Appl 30:413–435
54. Keshtegar B, Heddam S (2018) Modeling daily dissolved oxygen concentration using modified response surface method and artificial neural network: a comparative study. Neural Comput Appl 30:2995–3006
55. Gürlük S, Karaer F (2004) On the examination of the relation between economic growth and environmental pollution. Turk J Agric Econ 10:43–54
56. Halicioglu F (2009) An econometric study of CO_2 emissions, energy consumption, income and foreign trade in Turkey. Energy Policy 37:1156–1164
57. Omay RE (2013) The relationship between environment and income: regression spline approach. Int J Energy Econ Policy 3:52–61
58. Acaravcı A, Öztürk İ (2010) On the relationship between energy consumption, CO_2 emissions and economic growth in Europe. Energy 35:5412–5420
59. Akbostancı E, Aşık ST, Tunç Gİ (2009) The relationship between income and environment in Turkey: is there an environmental Kuznets curve? Energy Policy 37:861–867
60. Bölük G, Mert M (2015) The renewable energy, growth and environmental Kuznets curve in Turkey: An ARDL approach. Renew Sustain Energy Rev 52:587–595
61. Pata UK (2018) Renewable energy consumption, urbanization, financial development, income and CO_2 emissions in Turkey: testing EKC hypothesis with structural breaks. J Clean Prod 187:770–779
62. Turkish Statistical Institute (TURKSTAT). Main statistics, Population and Demography, Population Statistics, Population by Years, Age Group and Sex, Census of Population - ABPRS. http://www.turkstat.gov.tr/UstMenu.do?metod=temelist
63. Republic of Turkey Presidency of Strategy and Budget (SBB). http://www.sbb.gov.tr/ekonomik-ve-sosyal-gostergeler/#1540021349004-1497d2c6-7edf
64. Republic of Turkey Ministry of Energy and Natural Resources (MENR): General Directorate of Electricity Affairs. Statistics, balance sheets. https://www.eigm.gov.tr/tr-TR/Denge-Tablolari/Denge-Tablolari?page=2
65. Republic of Turkey Ministry of Environment and Urbanization. https://cevreselgostergeler.csb.gov.tr/kentsel—kirsal-nufus-orani-i-85670
66. Turkish Electricity Transmission Corporation (TEIAS). Turkey's gross electric generation by the electricity utilities and exports-imports-gross demand. https://www.teias.gov.tr/tr-TR/turkiye-elektrik-uretim-iletim-istatistikleri
67. Ertuğrul ÖF, Kaya Y (2017) Determining the optimal number of body-worn sensors for human activity recognition. Soft Comput 21:5053–5060
68. Uzlu E (2019) Estimates of energy consumption using neural networks with the grey wolf optimizer algorithm for Turkey. Gazi Üniv Fen Bilim Derg Part C Tasar ve Teknol 7:245–262 (**[in Turkish]**)
69. Turkish Statistical Institute (TURKSTAT). https://data.tuik.gov.tr/Bulten/Index?p=Nufus-Projeksiyonlari-2018-2080-30567
70. Tefek MF, Uğuz H, Güçyetmez M (2019) A new hybrid gravitational search–teaching–learning-based optimization method for energy demand estimation of Turkey. Neural Comput Appl 31:2939–2954

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.