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MUSTAFA SEKER[1], NESLIHAN UNAL KARTAL[2], SELIN KARADIREK[3],
CEVDET BERTAN GULLUDAG[4]

The application of different optimization techniques and Artificial Neural Networks (ANN) for coal-consumption forecasting: a case study

Introduction

Energy is essential for humans to maintain their lives and meet daily needs. The demand for energy that has arisen due to industrialization, urbanization, population growth, and advanced technology has been increasing daily (Sözen and Arcaklioğlu 2007; Zaki Diab and Rezk 2017). While economic growth and social development affect this increase positively or negatively, on the global scale, the rise in energy tends to rise on a daily basis (Ediger and Tatlidil 2002). Therefore, countries need to create serious strategies to meet the increasing energy demand. These strategies can be determined by evaluating future energy

✉ Corresponding Author: Mustafa Seker; e-mail: mustafaseker@cumhuriyet.edu.tr
[1] Sivas Cumhuriyet University, Turkey; ORCID iD: 0000-0002-3793-8786;
e-mail: mustafaseker@cumhuriyet.edu.tr
[2] Burdur Mehmet Akif Ersoy University, Turkey; e-mail: nunal@mehmetakif.edu.tr
[3] Akdeniz University, Antalya, Turkey; e-mail: selinhokerek@akdeniz.edu.tr
[4] Akdeniz University, Antalya, Turkey; e-mail: bgulludag@akdeniz.edu.tr

demand forecasts using a realistic approach based on economic growth and social development (Sözen and Arcaklioğlu 2007). Many factors play a role in determining countries' future energy forecast strategies and policies. Among the most important of these factors are population growth, economic growth indicators, import and export volumes, and the consumption habits of energy users (Ozturk et al. 2004).

Today, energy needs are met through energy resources like oil, natural gas, coal, nuclear energy, hydro, and wind-solar. Among these, coal is of significant importance for its wide geographical spread and relatively low operating costs. However, due to the global-warming effects of greenhouse gases that arise from coal consumption, countries have been looking for new strategies to reduce the amount of coal they consume. Also, since coal has a limited reserve globally, humans have been searching for alternative energy resources. In this regard, the aim is to use renewable energy sources like wind and solar power as alternatives to coal (Yilmaz and Uslu 2007). However, renewable energy resources fall insufficient in meeting the high installation costs and increasing energy needs, making it unlikely for countries to give up coal consumption in the mid-term. Nuclear energy can be considered another critical alternative to coal. However, given the example of Chornobyl, governments tend to avoid this alternative since using nuclear energy has an irreparable risk factor for environmental and human health. Sources other than fossil fuels do not fail to meet increasing energy demands. However, reserves of fossil fuels also decrease day by day both in Turkey and worldwide. So, it is necessary to efficiently use energy consumption and develop planning strategies for energy resources. This matter is one of the essential key research topics for countries today.

There are many types of research on evaluating the production and consumption of fossil fuel reserves, with their significant potential among energy resources and on-demand analyses in energy balance. Yilmaz and Uslu (2007) examined the correlation between primary energy consumption and Gross National Product between 1983 and 2003 using regression analysis. They showed that if 1.33 Mtoe coal reserves are used effectively in energy production for Turkey, foreign dependency can be reduced by approximately 50%. Korkmaz et al. (2008) statistically evaluated the reserve, production, and consumption potentials of fossil fuels in Turkey. Sözen and Arcaklioğlu (2007) revealed that the future projections of energy resources in Turkey could be predicted with a high level of accuracy using an artificial neural network (ANN). They carried out ANN training using population as the input parameter of the network and net consumption (GWh), gross generation (GWh), installed electric capacity, and import and export data for energy consumption. Feng et al. (2012) examined energy consumption forecasts in China using the gray forecasting model based on actual energy consumption data from 1998 to 2006. Assareh et al. (2012) used the integration of ANN and particle swarm optimization (PSO) for energy and coal-consumption forecasts. Aydin (2015b) showed that the definition and modelling of the projections of energy resources in Turkey could be defined using appropriate regression analysis. He statistically evaluated the results using a t-test and an f-test. Aydin also evaluated coal consumption trends for many countries using a similar method (Aydin 2015a). Kim and Yoo (2016) examined the correlation between economic development and coal consumption in Indonesia using the Granger causality test and error-correction model. They presented those policies to increase economic growth, and coal consumption was simultaneously compatible with economic development. Jiang et al. (2018) found that the amount and price of coal consumption in China can be forecasted using the Autoregressive integrated moving average (ARIMA) method.

Computational Intelligence (CI) techniques have a better capability to handle nonlinear relationships between numerical data compared to statistical methods (Dreyfus 2005; Rutkowski 2008). CI methods that include Support Vector Machines (SVM), Fuzzy Logic, ANN, Genetic Algorithm (GA), and PSO techniques have been widely used in recent years for their advantages over the linear and nonlinear programming models used in energy industries (Benalcazar et al. 2017; Osowski et al. 2021). Among these approaches, ANN is an evolutionary calculation method that can be applied in various science disciplines (Kalogirou 2000; Mohandes et al. 1998). Today, ANN is widely used in production and consumption forecasts for energy resources and to determine energy policies using suitable indicator data (Sözen and Arcaklioğlu 2007; Topcu and Ulengin 2004; Palau et al. 1999; Azadeh et al. 2007).

This study presents a new forecast strategy, including an optimization-based S-curve approach, for coal consumption in Turkey. For the analysis, the appropriate parameters of the S-curve were determined using coal consumption data from 1975 to 2019. In parameter optimization, we have used GA, PSO, grey wolf optimization (GWO), and the whale optimization algorithm (WOA), which have been viral in recent years. Besides, to evaluate the suitability of the presented method, the findings were statistically compared with the coal consumption forecasts obtained by ANN. In the training of the network structure, the input parameters were chosen as population, installed capacity, gross generation, net electric consumption, and import and export data between 1975–2019 to define energy indicators in Turkey.

Furthermore, ANN structure has been performed using feed forward multilayer perceptron network. In this structure, the Levenberg-Marquardt backpropagation algorithm has been used for network training. Thus, the performance of the ANN and optimization-based S-curve approach in predicting coal consumption is statistically evaluated for the estimation of coal consumption. The obtained results in the study show that the optimization-based S-curve method has a significant advantage over ANN as it can be analyzed with fewer variables, can be easily adapted to different optimization algorithms, and has high accuracy. The novelty of this study is that the presented methodology does not need many input parameters for analysis. Furthermore, the proposed approach can easily be used to estimate coal consumption within other countries with an increasing trend in coal consumption, such as Turkey. In addition, long-term reliable coal-consumption forecasts will shed light on energy policies and contribute to the development of climate change policies. The values calculated by S-curve parameters with GWO give better results than PSO, WOA, GA, and ANN as statistically with $R^2 = 0.9881$, $RE = 0.011$, $RMSE = 1.079$, $MAE = 1.3584$, $STD = 1.5187$. The mathematical model of the presented approach, the optimization algorithms used in the study and the ANN structure are explained in detail in the following sections.

The second section offers an overview of coal consumption in Turkey and basic information about the energy indicators used in the artificial neural network training. The third section explains the forecast methodologies presented in the study. The ANN structure, the mathematical model of the S-curve, and the optimization methods are also provided in this chapter. The fourth section includes findings, discussion, and statistical comparison of forecasted values obtained by the analysis. The final section presents an overall summary of conclusions and evaluations for future studies.

1. Overview of coal consumption and energy indicators in Turkey

In Turkey, primary energy consumption has been increasing by an average annual increase rate of 3.4% over the last decade (TİK, Coal Industry Report 2019). The breakdown of the sources of this energy supply reveals that crude oil and petroleum products come first with 41.91 mtoe, followed by natural gas with 41.17 mtoe, and coal with 41.03 mtoe. In 2018, total coal consumption in Turkey was 16.55 mtoe, of which 15.12 mtoe was lignite, 0.65 mtoe was hard coal, and 0.77 mtoe was asphaltite. The figure for imported coal supply was about 24.48 mtoe, of which 23.s95 mtoe was hard coal and 0.52 mtoe was coke (EKTB 2019). As of 2018, 27.6% of Turkey's energy consumption was obtained from domestic energy sources, whereas a significant portion was met using imported sources (72.4%). As a result, the coverage ratio of domestic coal production to energy consumption was 11.52% in 2018 (TİK, Coal Industry Report 2019). In Turkey, coal remains common due to its demand in many areas like the heating and iron and steel industry and power production. In this context, there is a strong connection between coal consumption and the country's energy indicators. The values of net electric consumption, population, gross generation, installed capacity, import and export are defined as fundamental energy indicators in Turkey. Associated with coal consumption, these indicators are often used to determine future coal consumption projections (Sözen and Arcaklioğlu 2007).

The annual changes in the amount of coal consumption in Turkey between 1975–2019 are shown in Figure 1 (EIGM 2018). It is seen that coal consumption has had an increasing trend in all periods except for the crisis periods that occurred in 1994, 2001, and 2010. A graphic change of Turkey's energy indicators between 1975–2019 is presented in Figure 2.

Turkey has 139 years of coal reserves, and numerical information regarding the total coal reserves in Turkey is presented in Table 1. Due to the limited resources of fossil fuels, Turkey has turned towards renewable energy sources. Although there has been a significant increase in renewable energy sources in recent years, the decrease in coal consumption in power generation is unlikely due to higher costs in power-plant installations and the country's economic structure. In Turkey, there are sixty-eight thermal power plants generating electricity. In 2018, the shares of energy sources used in power production in Turkey were as follows: coal 37.3%, natural gas 29.8%, hydroelectric energy 19.8%, wind 6.6%, 2.6% solar energy, geothermal energy 2.5%, and other sources 1.4% (EKTB 2019).

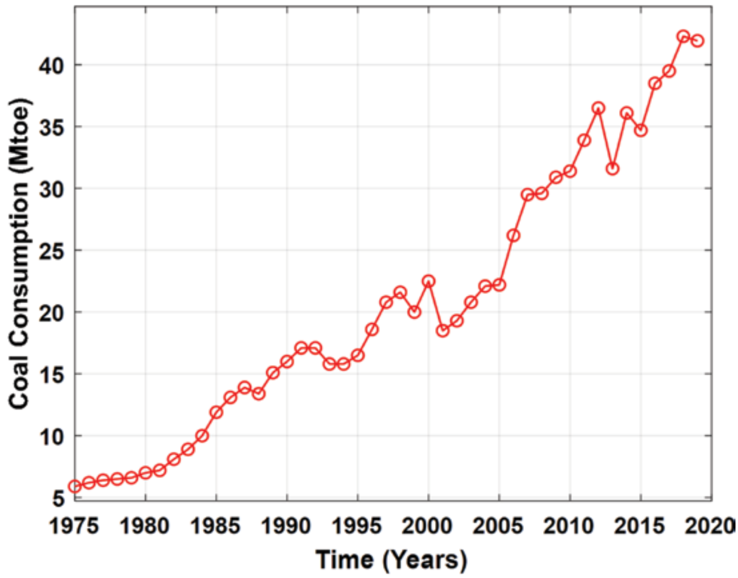

Fig. 1. The annual changes in the amount of coal consumption in Turkey (EIGM 2018)

Rys. 1. Roczne zmiany wielkości zużycia węgla w Turcji

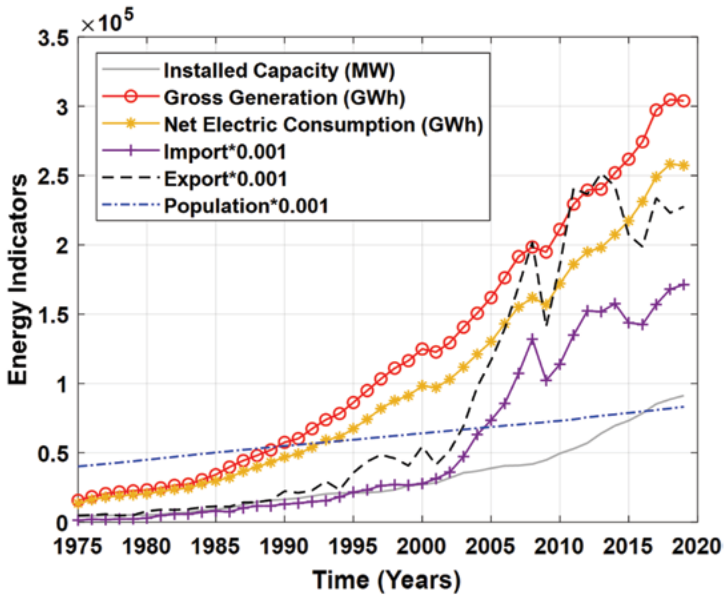

Fig. 2. Turkey's energy indicators between 1975–2019 (Sözen and Arcaklioğlu 2007)

Rys. 2. Wskaźniki energetyczne Turcji w latach 1975–2019

Table 1. Total proven reserves for Coal at the end of 2019

Tabela 1. Całkowite potwierdzone zasoby węgla na koniec 2019 r.

Country	Anthracite and bituminous (Million tons)	Sub-bituminous and lignite (Million tons)	Total (Million tons)	Share of Total	R/P ratio
Turkey	551	10,975	11,526	1.1%	139

Source: Statistical Review of World Energy 2020.

2. Method

This chapter explains the mathematical expression of the S-curve used in the coal-consumption forecast methodology. The GA and meta-heuristic optimization methods like PSO, GWO, and WOA for optimizing the S-curve are defined, and the details of how they are used in the coal-consumption forecast are described.

In addition, a general explanation of the ANN approach is presented in this section. More detailed explanations about the ANN approach are given in Section 4. In particular, the performance of the proposed approach in forecasting coal consumption was examined and the results were evaluated statistically using different optimization techniques and ANN findings. The data used in the forecasting models were obtained from the BP Statistical Review of World Energy 2020 (BP 2020). For forecasting coal consumption using ANN, the net electric consumption, population, gross generation, installed capacity, and import and export values as related indicators for coal consumption in Turkey have been used and these indicators are presented in Figure 2.

2.1. Artificial neural network (ANN)

ANNs have been developed with inspiration from the biological nerve cell. ANNs are used in many engineering and multidisciplinary fields like optimization, control, classification and forecast generation (Osowski et al. 2021; Kalogirou 2000; Mohandes et al. 1998). Used in many fields, ANN gives very successful results in complex problems that cannot be solved by the limitations of traditional methods (Bechtler et al. 2001).

The fundamental functional element of an ANN is a neuron. In biological terms, a neuron receives information, processes it, and transmits the outcome to the output of the nerve cell. The structure of ANNs consists of five main components: input, weights (w_i), sum function, activation function, and output (forecast parameter).

The ANN does not need any prior knowledge of input and output variables. By giving input information corresponding to the information, the network is able to learn the relationship between the input and output variables. This learning process is called supervised learning. This study used the backpropagation approach from supervised learning methods to estimate coal consumption. The learning of an artificial neural network by a backpropagation algorithm consists of forwarding and backward calculation strategies. First, the input values coming to the network are processed with weight matrices in the forward calculation process, and the output value is calculated. Then the network weights are arranged with the backward propagation of the network based on minimizing the error value between the output value produced by the network and the actual value. Finally, this process continues until the network makes the desired output.

Each input is summed by multiplying it by its weight function. The outcome is processed with the total activation function and the output value is obtained. The learning ability of an ANN cell depends on the suitable adjustment of the weights in the chosen learning algorithm. The number of hidden layers in the network structure should also be determined correctly (Basheer and Hajmeer 2000). The transfer function, which often includes algebraic equations, can be linear or nonlinear (Kalogirou 2000).

2.2. Mathematical expression of the S-curve

Turkey is a country with an increasing trend in coal consumption. This increase can be expressed with the S-curve depending on the country's coal reserves. As can be seen in Figure 3, the S-curve consists of the following three main components (Şeker 2021).

1. Minimum Hyper-growth (*minHG*): this refers to the year in which 10% of the saturation point of the parameter to be forecasted is reached. In the coal consumption forecast, this value is considered to be 10% of the coal reserve of Turkey, and it is assumed that the increasing trend of coal consumption will accelerate after this year.
2. Ramp Period (Take-over [*TO*] Time) refers to the increase period between 10% and 90% of the region's saturation point.
3. Saturation Time (*ST*): after reaching 90% of the saturation point, coal consumption in the region slows down.

The S-curve describes a sigmoid function. The function must be minimized to solve the S-curve using optimization problems (Willis 2005; Tursun et al. 2016). We are examining the graph for coal consumption in Turkey (Figure 1); a correlation similar to that between electricity consumption and the peak load value of the region can be defined between coal consumption and Turkey's total coal reserves (Şeker 2021).

The solution of S-curves using the optimization problem is defined by Equation (1). Equation (1) also refers to the fitness function of the optimization approach (Tursun et al. 2016).

$$\min\left[\sum_{t=t_0-t}^{T}\left(S_{t,i}-TB_t\right)^2+\sum_{t=t_0-t}^{T}\left(S_{t,i}-TB_t\right)^2\cdot pen_t+\left(S_{t,i}-S_{t_0,i}\right)^2\cdot pen_{t_0}\right] \tag{1}$$

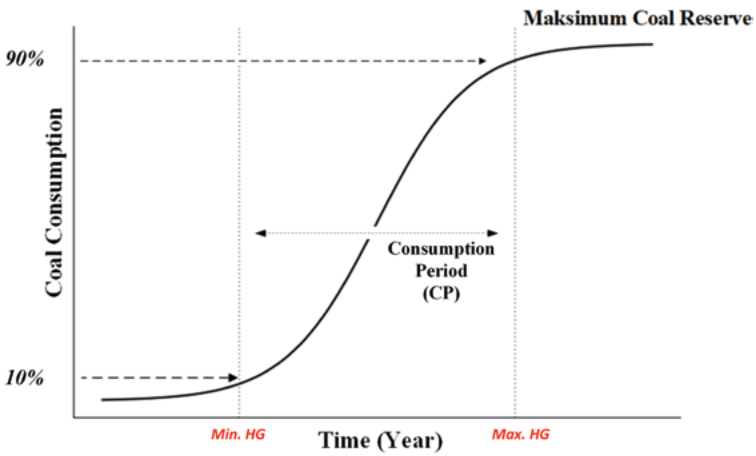

Fig. 3. S-curve approach in coal consumption forecast (Tursun et al. 2016; Şeker 2021)

Rys. 3. Ujęcie krzywej S w prognozie zużycia węgla

In Equation (1), $S_{t,i}$ denotes the demand value of the S-curve in the i^{th} demand forecast year, TB_t denotes the total consumption value defined by coal consumption projection, t_0 denotes the start year of the projection, and t represents the index year. Finally, T is the last year forecasted. pen_t and $pent_0$ are the error factors for t and t_0, respectively, and the error factor is defined by Equations (2–4).

$$If\left(\frac{\left|S_{t,i}-TB_t\right|}{TB_t}\cdot 100\right) > \varepsilon\, then\, Pen_t = PC \tag{2}$$

$$If\left(\frac{\left|S_{t,i}-TB_t\right|}{TB_t}\cdot 100\right) \leq \varepsilon\, then\, Pen_t = 0 \tag{3}$$

and

$$Pen_{t0} = PC \tag{4}$$

In Equations (2) and (4), PC is defined as a penalty constant. This constant forces the S-curve of the demand value to fit with historical coal consumption according to the ε value. Depending on these constraints, the general mathematical expression of the S-curve is defined by Equation (5).

$$s_t = \frac{ST}{1+81^{\left(\frac{HG+\frac{TO}{2}-t}{TO}\right)}} \tag{5}$$

In Equation (5), ST is the maximum coal reserve value for the region of coal-consumption forecast, TO is take-over time, and HG is the start time of the hyper-growth period. Therefore, to solve the S-curve using the optimization problem, the lower and upper limit values of the HG and TO levels depending on the region's development should be determined using the equations below (6 and 7).

$$MinHG \leq HG \leq MaxHG \tag{6}$$

$$MinTO \leq TO \leq MaxTO \tag{7}$$

In these equations, Equation (6) expresses the time interval when coal consumption is in growth to solve the presented problem. Equation (7) is defined as the duration of the ramp period.

2.2.1. Optimization techniques used in the parameter estimation of S-curves

In this section, the genetic algorithm (GA), particle swarm optimization (PSO), meta-heuristic optimization algorithm, the grey wolf algorithm (GWO), and the whale optimization algorithm (WOA) are explained; these are used to determine parameter values of S-curve. These algorithms have been selected because they are widely used in solving many optimization problems that have been very popular in recent years. Furthermore, all algorithms are compiled and run-on MATLAB. Therefore, it is very important to determine the population and maximum iteration numbers of the algorithms presented in determining the S-curve parameters. Choosing these values high causes an increase in the time taken to reach the optimal solution. By contrast, if it is selected low, it will decrease the performance of catching the global value of the algorithm. For this reason, these two values should be determined by trial and error or by considering the experience (Elmas 2007). Therefore, in solving the presented problem, all algorithm population sizes and maximum iteration numbers have been selected as 100 and 1000, respectively.

2.2.1.1. Genetic algorithm

Genetic algorithms are research algorithms developed to obtain optimal solutions for complex problems, and they have emerged from Darwin's principles of natural selection and survival of the fittest. The first step in GA usually begins with creating an initial population containing the available solutions. The population size is generally designed to have between 30 and 100 chromosomes. However, this value can be chosen more or less depending on the type of problem. Then, a fitness function must be found to solve the problem. The fitness value allows the evaluation of solutions within the algorithm. For example, suppose the fitness value of the possible solution in the initial population is at the desired value or close to the solution. In this case, this potential solution is passed on to the next generation. However, if it is not at the desired value, it is removed from the population or changed. These changes are done with the help of genetic operators called crossover and mutation.

The crossover operator shows a one-to-one similarity to natural life. It is based on the principle of bringing together the best traits among individuals in the population. Thus, the formation of the population for the purpose of the fitness function is ensured. By contrast, the mutation operator evaluates each solution in the population within itself, and the chromosome exposed to the mutation is replaced. In this way, a new possible solution is created. Then, these solutions are forced to evolve to achieve the optimal solution at an acceptable error rate (Elmas 2007). During this process, starting from an initial population, previous data is used based on the condition that the strongest in the gene pool survive. This process continues iteratively until the optimal solution value for the complex problem intended to be solved is achieved.

The genetic algorithm approach can also be applied to curve fitting problems by determining the most optimal solution for the S-curve. The error value "ε" used in the genetic algorithm is used to force the S-curve to keep the actual values defined historically. Firstly, to apply the genetic algorithm to Equation (3), the lower and upper limit values are expressed as vectors, as presented in Equation (8).

$$S_1 = \left[\left(HG_{\min}, TO_{\min} \right), \left(HG_{\max}, TO_{\max} \right) \right] \tag{8}$$

As can be seen in this equation, two parameters are to be determined to forecast coal consumption using the optimization of the S-curve. First, the start year of *HG* and *TO* are optimization parameters of the S-curve. The next step is to generate a second-generation solution population from those selected via genetic operators (crossover [i.e., recombination] and mutation), as shown in Figure 4. Single gene mutation operation and partially matched crossover operation have been used to achieve this goal. This process ultimately results in a different population from the first generation. This production process is repeated until the maximum number of iterations defined by the planner is reached.

The solution steps with the genetic algorithm can be summarized as follows (Figure 4):

1. ***Generating the initial population:*** an initial population (generation) is created from individuals (chromosomes), which are usually random and represent possible solutions to the problem.
2. ***Calculating the fitness values:*** the fitness values of each individual in the generation are calculated.
3. ***Test stop criterion***
   - If not, create a new generation and return to step two:
     - Selecting by fitness values – selection is made according to the calculated fitness values of each individual in the old generation.
     - Adaptation of selected individuals: selected individuals are adapted by genetic processes (crossover, mutation, etc.).
   - Choosing the most suitable solution, if available: the best individual (chromosome, solution) is selected according to the fitness values calculated in the population.

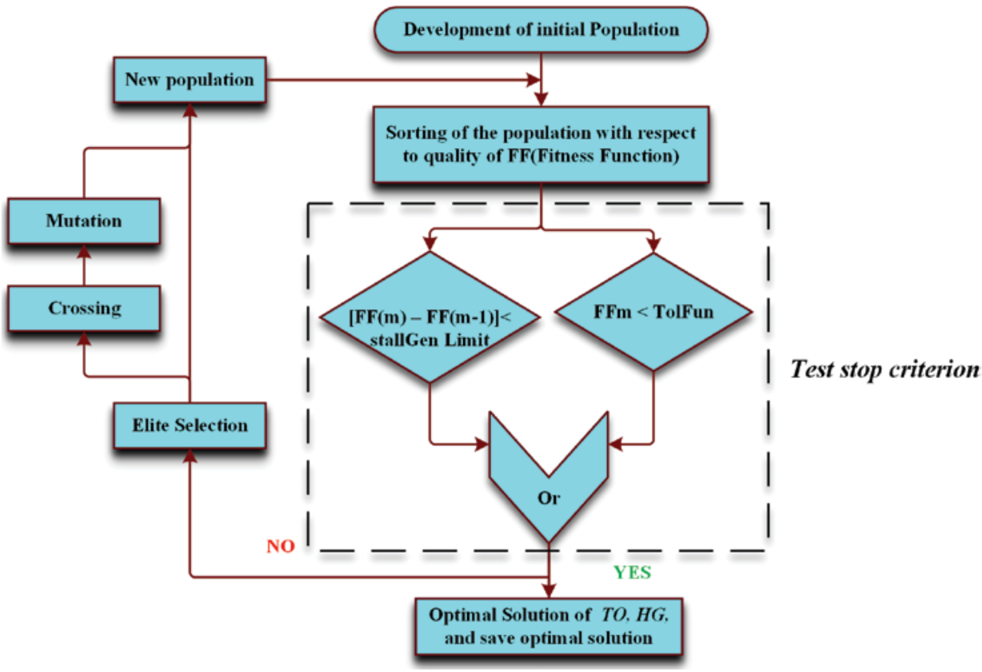

Fig. 4. Flow chart for the solution of the parameters of the S-curve by genetic algorithm (Tursun et al. 2016)

Rys. 4. Schemat blokowy rozwiązania parametrów krzywej S za pomocą algorytmu genetycznego

The algorithm flow chart used to optimize the S-curve using GA is shown in Figure 4 and optimization parameters are presented in Table 2 (Tursun et al. 2016). In Table 2, TolFun and TolCon are defined as Function termination tolerance and Constrain tolerance. The GA algorithm runs until the average relative change in the fitness function value over Stall-Generation is less than the function termination tolerance. Constrain tolerance determines feasibility concerning linear constraints.

Table 2. GA parameter values used in finding the optimal solution of S-curves

Tabela 2. Wartości parametrów GA wykorzystane do znalezienia optymalnego rozwiązania krzywych S

Parameter	Definition	Value
Pop_Ini	Number of initial populations	≤10e2
EliteCount	The number of best individuals alive for the next generation	%10*Pop_Ini
Crossover Fraction	The rate of genes exchanged among individuals	50%
StallGen_Limit	Number of generations in which the cumulative change in the objective function value is less than TolFun	10e3
TolFun	Function Termination tolerance	10e-6
TolCon	Constraint tolerance	10e-6

Source: Tursun et al. 2016.

2.2.1.2. Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) development by Eberhart and Kennedy is a population-based swarm optimization technique inspired by the social behaviors of birds flock or fish training. This technique solves many complex optimization problems (Eberhart and Kennedy 1995; Anand et al. 2019). In PSO, each agent or particle is related to the position vector $X(t)$ and the velocity vector $V(t)$. The PSO approach aims for the individuals in the swarm to improve themselves depending on the velocity and position vectors (Mashayekhi et al. 2019).

In PSO, through examination, each particle's velocity and position vectors in each swarm are evaluated, seeking the most relevant result in the research algorithm. Then, according to the velocity and position vectors, the general mathematical expression of the PSO algorithm is defined by Equation (9) and Equation (10) (Zhou et al. 2009).

$$V_{i,j}^{k+1} = \omega \cdot V_{i,j}^{k} + r_1 \cdot c_1 \cdot \left[P_{i,j}^{k} - X_{i,j}^{k} \right] + r_2 \cdot c_2 \left[G_j^k - X_{i,j}^{k} \right] \tag{9}$$

$$X_{i,j}^{k+1} = X_{i,j}^{k} + V_{i,j}^{k+1} \tag{10}$$

The general notations used in this expression are expressed as follows.

$r_1 \cdot c_1 \cdot \left[P_{i,j}^{k} - X_{i,j}^{k} \right]$: Cognitive component,

$r_2 \cdot c_2 \cdot \left[G_j^k - X_{i,j}^{k} \right]$: Social component,

$\omega \cdot V_{i,j}^{k}$: Inertia term.

In Equation (9), $P_{i,j}^{k}$ defining as P_{best} value and represent a personal best j^{th} component of i^{th} individual. The G_j^k point out j^{th} component of the best individual of the population up to iteration k. Then, in the same equation, r_1 and r_2 are randomly chosen between 0 and 1, ensuring ∈ R+. c_1 and c_2 provides information exchange within the swarm, chosen between 0 and 2.5, ensuring ∈ R+. How c_1 and c_2 are determined is defined by Clerc and Kennedy (Clerc and Kennedy 2002) which is based on a metaphor of social interaction, has been shown to perform well, researchers have not adequately explained how it works. Further, traditional versions of the algorithm have had some undesirable dynamical properties, notably the particles' velocities needed to be limited in order to control their trajectories. The present paper analyzes a particle's trajectory as it moves in discrete time (the algebraic view and mathematically expressed by Equation (11) and Equation (14).

$$0 \le r_1 \le 1 \quad \text{and} \quad 0 \le r_2 \le 1 \tag{11}$$

$$0 \le c_1 \le 2.5 \quad \text{and} \quad 0 \le c_2 \le 2.5 \tag{12}$$

$$k = \frac{2}{\left|2 - \phi - \sqrt{\phi^2 - 4\phi}\right|} \tag{13}$$

$$\phi = c_1 + c_2 \quad \text{and} \quad \phi > 4 \tag{14}$$

In Equations (12–14), c_1 and c_2 values must be chosen to the best optimal values as 2.05. In the problems, determining the value of Φ in the range of $4.1 \le \phi \le 4.2$ has provided better results (Vlachogiannis and Lee 2006; Zhu 2015).

Determining the inertia weight of "ω" in PSO is very important for finding the optimal solution. In the literature, many functions have been defined to determine the inertia weight of ω (Shi and Eberhart 1995; Feng et al. 2007; Fan and Chiu 2007; Gao et al. 2008; Yang et al. 2015; Feng et al. 2012). This study uses the strategy of chaotic random inertia weight to optimize S-curves. The chaotic random inertia weight is expressed by Equation (15). In Equation (15), z values are defined between 0 and 1 as a uniformly distributed positive real number.

$$z = 4 \cdot z \cdot (1 - z), \quad \omega = \frac{1}{2} rand(.) + (0.5) \cdot z \tag{15}$$

Experiments show that the inertia weight strategy accelerates the convergence of particle swarm in the early time when it is selected between 0.4 and 0.8. This method can find quite a good result with mostly function. In this study, inertia weight ranges have been examined. The maximum and minimum inertia weight coefficients were selected in the 0.35 and 0.8 range.

The following steps are followed to find the optimal solution for the PSO algorithm (Alam et al. 2015).

- Set parameters of PSO (n, ω_1, ω_2, c_1, and c_2).
- Initialize the population of particles according to positions (X) and velocities (V).
- Evaluate the initial fitness of each particle.
- Select P_{best} and G_{best}.
- Set iteration k.
- Calculate the inertia weight.
- Update to velocity and position of particles

$$V_{i,j}^{k+1} = \omega \cdot V_{i,j}^{k} + rand() \cdot c_1 \cdot \left[P_{i,j}^{k} - X_{i,j}^{k} \right] + rand() \cdot c_2 \left[G_{j}^{k} - X_{i,j}^{k} \right]; \quad \forall_j \text{ and } \forall_i$$

$$X_{i,j}^{k+1}(t) = X_{i,j}^{k} + V_{i,j}^{k} + V_{i,j}^{k}; \quad \forall_j \text{ and } \forall_i$$

- Evaluate the fitness.
- Update the P_{best} of population $\forall_i$.
- *Update the* G_{best} of the population.
- *If* $k <$ maximum iteration, then $k = k + 1$ and go to step 6; else, go to step 12.
- Print the optimal solution of the S-curve (*TO and HG*).

The flow chart of the above PSO algorithm used to optimize S-curves is shown in Figure 5. Additionally, PSO parameters used to optimize S-curves are presented in Table 3.

Table 3. PSO parameter values used for the optimization of S-curves

Tabela 3. Wartości parametrów PSO wykorzystane do optymalizacji krzywych S

Parameter	Value
Maximum iterations	1,000
Number of populations (n)	100
Cognitive coefficient (c_1)	2.05
Social coefficient (c_2)	2.05
Maximum inertia value (ω_2)	0.80
Minimum inertia value (ω_1)	0.35

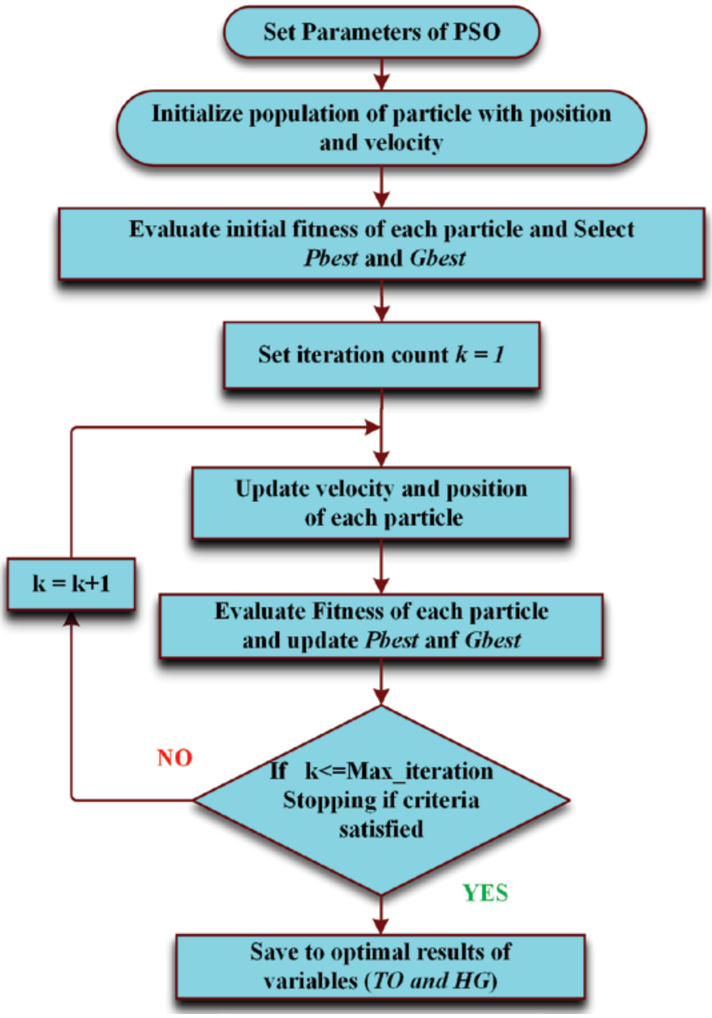

Fig. 5. PSO flow chart is used to optimize the S-curve
According to (Alam et al. 2015)

Rys. 5. Schemat blokowy PSO służący do optymalizacji krzywej S

2.2.1.3. Grey Wolf Optimization (GWO)

As a meta-heuristic algorithm, the GWO algorithm has been used in many optimization problems (Mirjalili et al. 2014). It was developed based on wolves' social hierarchy and hunting techniques (Pradhan et al. 2018, 2016; Ma and Zhang 2009). Grey wolves hunt in packs, and there is a hierarchical structure in the community.

In this hierarchy, α is at the top of the pyramid (Pradhan et al. 2018). In the mathematical definition of the GWO algorithm, α provides the best optimal solution in a hierarchical order.

β follows the α. δ and ω follow the β and define other solutions mathematically (Sahoo and Chandra 2017). The hunting strategy of grey wolves includes three main processes and these strategies are classified as surrounding prey, hunting prey, and attacking prey.

1. Surrounding the Prey

Grey wolves first surround the prey during the hunt. This surrounding is defined by Equations (16 and 17).

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)\right| \tag{16}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{17}$$

Where, t is the current iteration value $\vec{A}$ and $\vec{C}$ are coefficient vectors. $\vec{D}$ is calculated depending on $\vec{X}_p$ and $\vec{X}$ vectors. $\vec{X}_p$ is the location vector of the prey and $\vec{X}$ indicates the position vector of a grey wolf. $\vec{A}$ and $\vec{C}$ vectors are calculated using Equations (18 and 19).

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{18}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{19}$$

In these equations, the value of is defined to decrease linearly from 2 to 0 depending on the number of iterations. $\vec{r}_1$ are $\vec{r}_2$ the values in the range of 0 to 1 and are assigned randomly.

2. Hunting

Grey wolves can recognize and surround prey. The prey is usually led by the alpha when hunted by the grey wolves. Sometimes, β and δ also participate in hunting. After all, α is the closest wolf to the prey, and it provides the best optimum solution. β or δ contain information about the location of the prey. The GWO algorithm records the first best solution obtained in the hunting strategy for α, β, or δ. It then forces all research agents (including omegas) to update their location against top search agents. Equations (20–23) define this update process mathematically.

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{20}$$

$$\vec{X}_1 = \left|\vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha\right| \tag{21}$$

$$\vec{X}_2 = \left|\vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta\right| \tag{22}$$

$$\vec{X}_3 = \left|\vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta\right| \tag{23}$$

Where, $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ give the three best solutions in the iteration process and the $\vec{D}_\alpha, \vec{D}_\beta$ and $\vec{D}_\delta$, and parameters are calculated by Equations (24–26).

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \tag{24}$$

$$\vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \tag{25}$$

$$\vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \tag{26}$$

3. Attacking Prey

Grey wolves finish the hunt by attacking the prey when it stops moving. To mathematically model approaching the prey, we decrease the value of $\vec{a}$. The fluctuation range of A is also decreased by $\vec{a}$. A value is expressed by Equation (27). In this equation, $|A| < 1$ forces the wolves to attack the prey.

$$A = 2 - 2 \cdot \left(\frac{t}{Mak}\right) \tag{27}$$

Where t represents the number of times, the algorithm is run between zero to the maximum iteration number (Max). In accordance with the approach described above, the flow chart used to optimize S-curves using the GWO algorithm is shown in Figure 6.

2.2.1.4. Whale Optimization Algorithm (WOA)

As a meta-heuristic optimization technique, WOA is based on modeling the feeding strategies of humpback whales (Mirjalili and Lewis 2016). Humpback whales explore the area to find the location of their prey at first (Hekimoğlu et al. 2019). Humpback whales have two different hunting strategies. After the exploration, they attack their prey by encircling the prey in shrinking circles or using the helix location update strategy (Watkins and Schevill 1979; Hof and Van Der Gucht 2006). When whales search for prey, the time frame is called the search space exploration. The period during which they attack their prey is called the exploitation of the space where they can find probable solutions for the optimization problem.

1. Exploration Phase

Humpback whales search for their prey randomly according to each other's location. Except for the reference whale, all whales must be forced to move away from a randomly selected reference whale to search for the prey. Unless this is achieved, the exploration phase cannot be carried out. The mathematical expression for this is defined by Equation (28). The position vector $\overrightarrow{X}(t+1)$ is calculated using Equation (29) according to Equivalence (28).

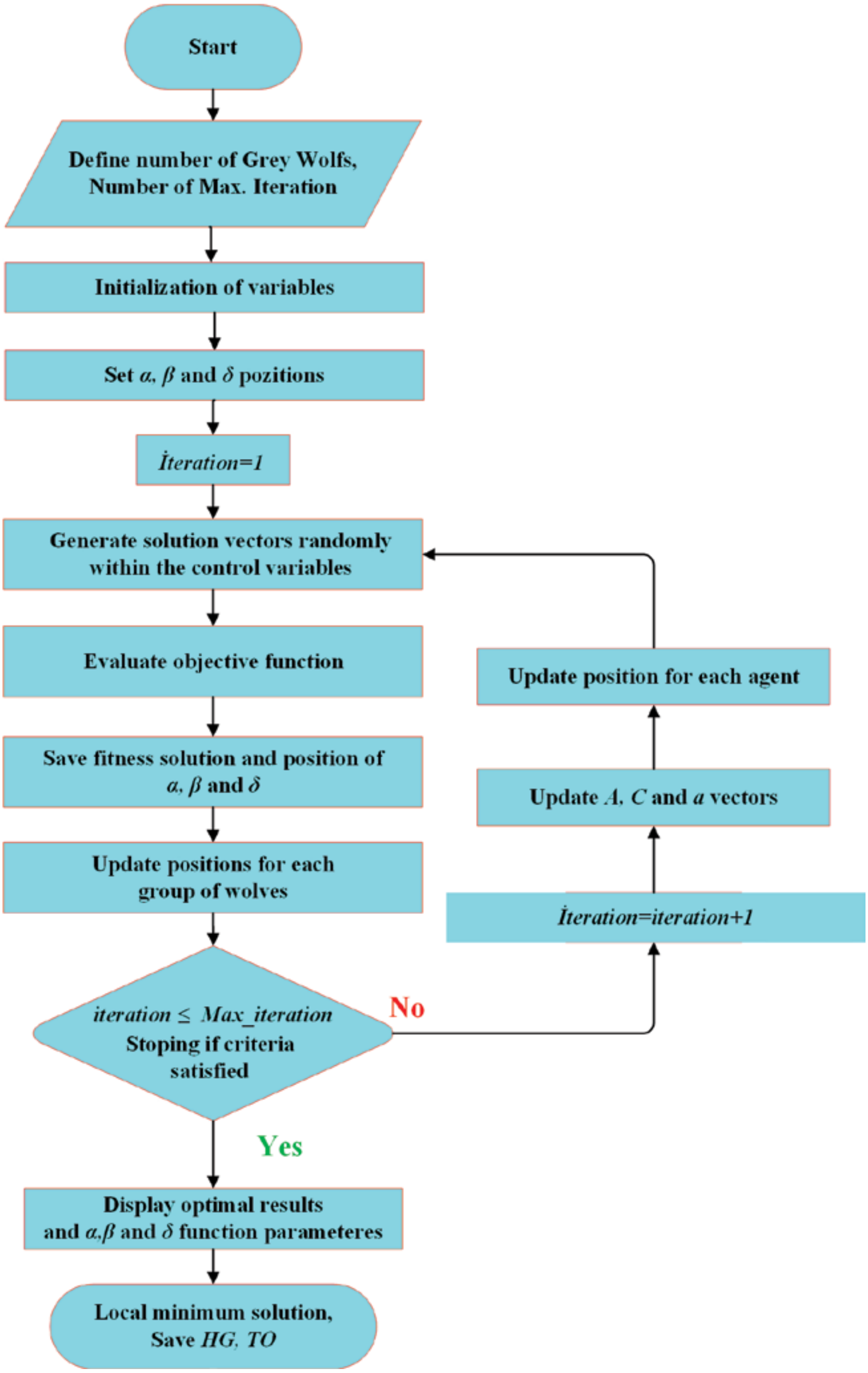

Fig. 6. GWO flow chart is used to optimize the S-curve (Şeker 2021)

Rys. 6. Schemat blokowy GWO służący do optymalizacji krzywej S

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{28}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} \tag{29}$$

Where $\vec{A}$ and $\vec{C}$ are coefficient vectors, and t indicates the current iteration. $\vec{X}$ (t) is defined as a position vector. $\overrightarrow{X^*}$ denotes the position vector of the best solution obtained. $\vec{A}$ and $\vec{C}$ vectors are calculated using Equations (30–31).

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \tag{30}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{31}$$

In these equations, $\vec{a}$ vector represents a number decreasing from 2 to 0 during the optimization steps. $\vec{r}$ is a random vector defined in the range of [0,1].

2. Bubble-net attacking method (exploitation phase)

The WOA algorithm uses the two approaches to mathematically model the bubble-net behavior of humpback whales as follows:

- Surrounding the prey by shrinking encircling

From Equation (30), it is seen that $\vec{A}$ vector will be in the range of [–a, a]. In this case, the exploration phase of the search space is only available when | $\vec{A}$ | > 1. During the exploitation phase, | $\vec{A}$ | ≤ 1 and the whale encircles in a decreasing spiral. This behaviour is achieved by decreasing the value of the vector in Equation (30). When the $\vec{a}$ vector is decreased, the fluctuation range of $\vec{A}$ is decreased too. In other words, $\vec{A}$ is a random value in the interval [–a, a]. Where a is decreased from 2 to 0 throughout the iteration. By setting random values for $\vec{A}$ between the range of [−1,1], the new position of a search agent can be defined anywhere in between the original position of the agent and the status of the current best agent.

- Spiral updating position relative to the prey

In the spiral updating position relative to the prey, the distance between the whale and the prey should be calculated first. Then, to mimic the spiral movements of the humpback whales, a spiral updating mechanism between the whale's location and the prey's location is made using Equation (32).

The spiral position of humpback whales is calculated by Equation (33) in accordance with Equation (32).

$$\vec{D}' = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{32}$$

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) \tag{33}$$

In this equation, vector describes the distance between a whale and the target prey. b is a constant value used to define the spiral shape generated logarithmically, and l is a random number in the range of [–1, 1].

In the bubble-net attacking method of the humpback whale, the two hunting strategies mentioned above are used simultaneously. In the optimization algorithm, when the probability of the realization of each case is evaluated as equal, the optimization process, as mathematically, is defined by Equation (34) for equal probability selection.

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} & \text{if} \quad p < 0.5 \\ \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) & \text{if} \quad p \geq 0.5 \end{cases} \tag{34}$$

Where p is a random number in the range 0 to 1.

3. The search for prey (Exploration phase)

Humpback whales randomly search according to each other's position. When $|\vec{A}| > 1$, the exploration phase of the search space is available. In this case, the WOA algorithm allows performing a global search. For this case, the mathematical model is expressed as follows.

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{X_{rand}} - \vec{X} \right| \tag{35}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A} \cdot \vec{D} \tag{36}$$

Where, $\overrightarrow{X_{rand}}$ is a random population position (a random whale) vector chosen from the current population.

In accordance with the aforementioned explanations, the flow chart of the WOA algorithm used to optimize S-curves for coal-consumption forecast analysis is shown in Figure 7.

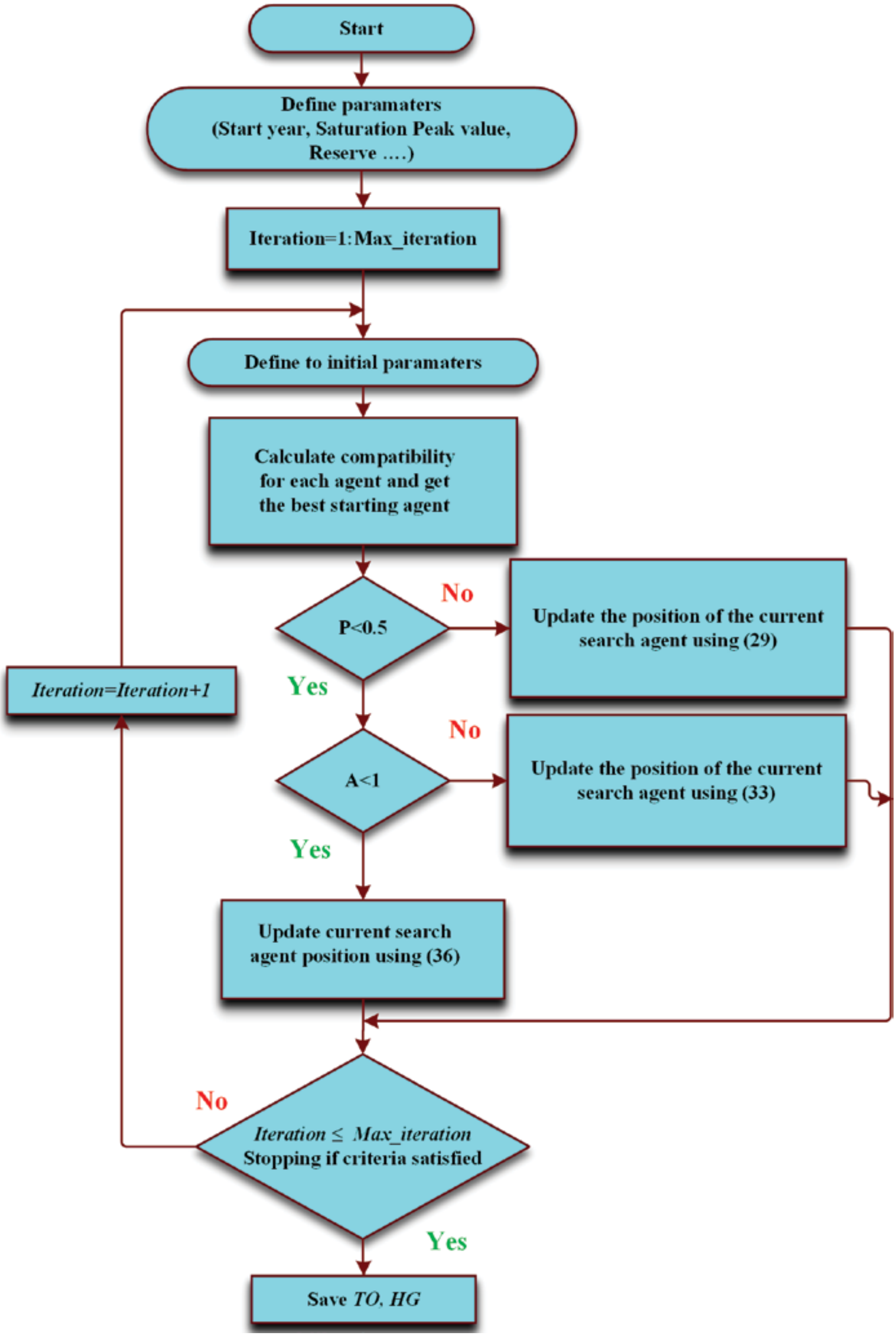

Fig. 7. WOA flow chart used for the optimization of the S-curve

Rys. 7. Schemat blokowy WOA wykorzystany do optymalizacji krzywej S

2.2.2. Fitness Function

To compare the suitability of the GA, PSO, GWO, and WOA algorithms to coal consumption data, a fitness function was defined to keep total squared errors at a minimum. The fitness function is mathematically expressed by Equation (37).

$$F = \int_{0}^{T} \left[V\left(t, \overline{x}\right) - V_m\left(t\right) \right]^2 dt \tag{37}$$

↳ F – Sum of squared errors,
T – Time on the S-curves (years),
$V(t, \overline{x})$ – The values of the S-curve are dependent upon time,
$V_m(t)$ – Coal consumption values are dependent upon time,
$\overline{x}$ – Variable vector state of the S-curve.

When considering Equation (37) in a discrete form, it can be defined by Equation (38).

$$F = \sum_{k=1}^{N} \left[v\left(k \cdot \Delta t, x\right) - v_m\left(k \cdot \Delta t\right) \right]^2 \cdot \Delta t \tag{38}$$

↳ N – the number of discrete-time samples,
Δt – the sampling time.

3. Results and discussion

In this chapter, the coal consumption values calculated by the S-curve using ANN and GA, PSO, GWO, and WOA algorithms for coal consumption forecast in Turkey are statistically compared with actual coal consumption values. All analyses and calculations were performed using MATLAB.

The feed-forward NNs ensure better estimation accuracy than cascade-forward neural networks (Orlowska-Kowalska et al. 2008). For this reason, The ANN structure used in the coal-consumption forecast is defined using the feed forward multilayer perception (FFMLP) network structure. First, the values of installed capacity, gross generation, net electric consumption, import, export, and population (6 input parameters) for 1975–2019 (Figure 2) were used as the input variables of the network. Coal consumption was then selected as the output parameter of the network. Considering the studies in the literature, we see that ANN models with a single hidden layer shorten the optimization time and give better results (Kankal and Uzlu 2017). Therefore, a single hidden layer was used in this analysis. The FFMLP network topology for coal-consumption forecast analysis using ANN modelled as six input parameters, one hidden layer with ten neurons, and one output parameter is shown in Figure 8.

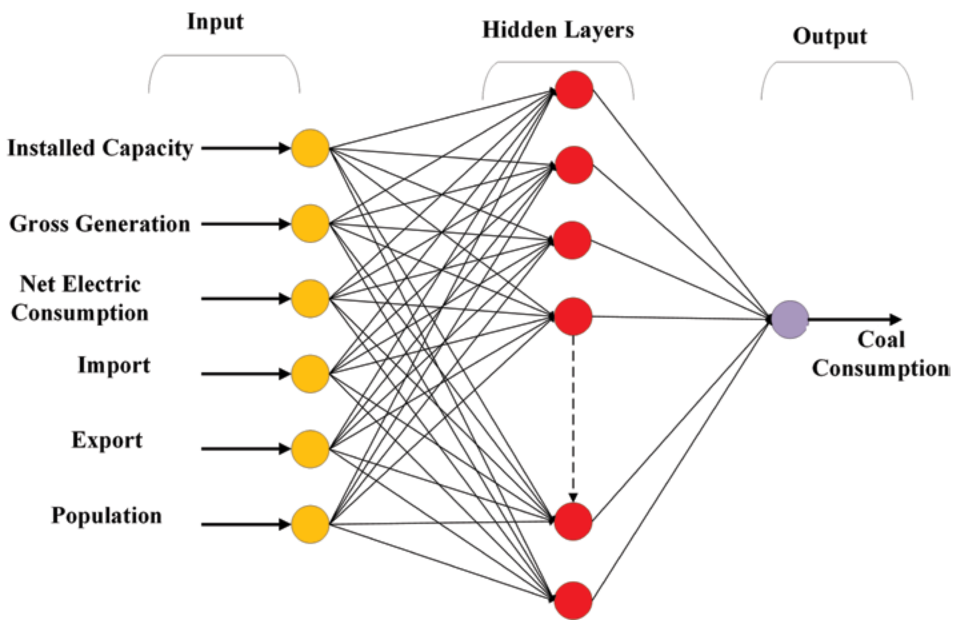

Fig. 8. FFMLP ANN topology for coal consumption forecast in Turkey

Rys. 8. Topologia FFMLP SSN dla prognozy zużycia węgla w Turcji

In this structure, the activation function for neurons has been defined as the logistic sigmoid function and is expressed mathematically by Equation (39).

$$f(z_i) = \frac{1}{1+e^{-z_i}} \tag{39}$$

In this equation, z_i is the total weight of inputs. x_j is the signal coming directly from the neuron j. $w_{i,j}$ is the weights that are directly connected from neuron j to neuron i. According to $w_{i,j}$ *and* x_j, z_i is defined with Equation 40.

$$z_i = \sum_{j=1}^{n} w_{i,j} \cdot x_j + \beta_i \tag{40}$$

Mean squared error (MSE) performance and network training status resulting from ANN training using the network structure and energy indicator data in Figure 9 are given in Figures 10 and 11, respectively. Levenberg-Marquardt (LM) backpropagation has been used to train data inputs. Coal-consumption data from 40 years (1975–2014) have been used as the training set, and coal-consumption data from 2015–2019 was used as test data. Coal-consumption data and the regression analysis of the consumption values by ANN training are given in Figure 12. As shown in Figure 9, the best validation performance was obtained in 17. epoch according to MSE. As shown in Figure 11, the training data was trained with 99.98% accuracy according to the regression analysis. The regression accuracy of the test data, by contrast, was calculated as 99%.

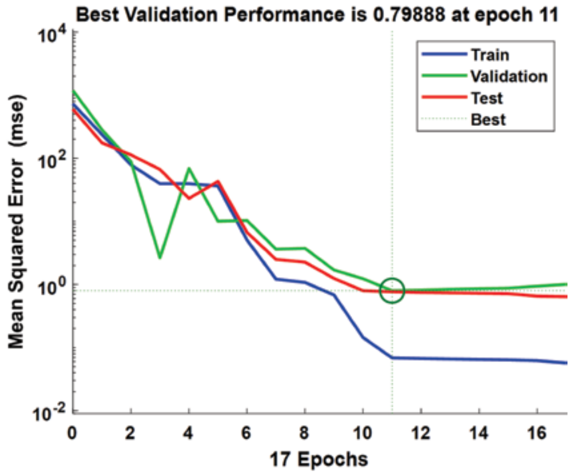

Fig. 9. MSE performance of ANN Model for forecasted output

Rys. 9. Wydajność MSE Modelu SSN dla prognozowanej produkcji

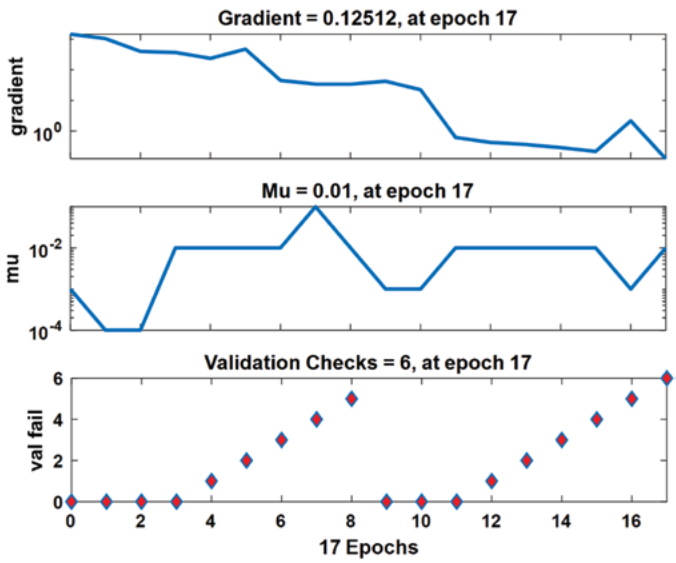

Fig. 10. Training state of ANN

Rys. 10. Stan wyszkolenia SSN

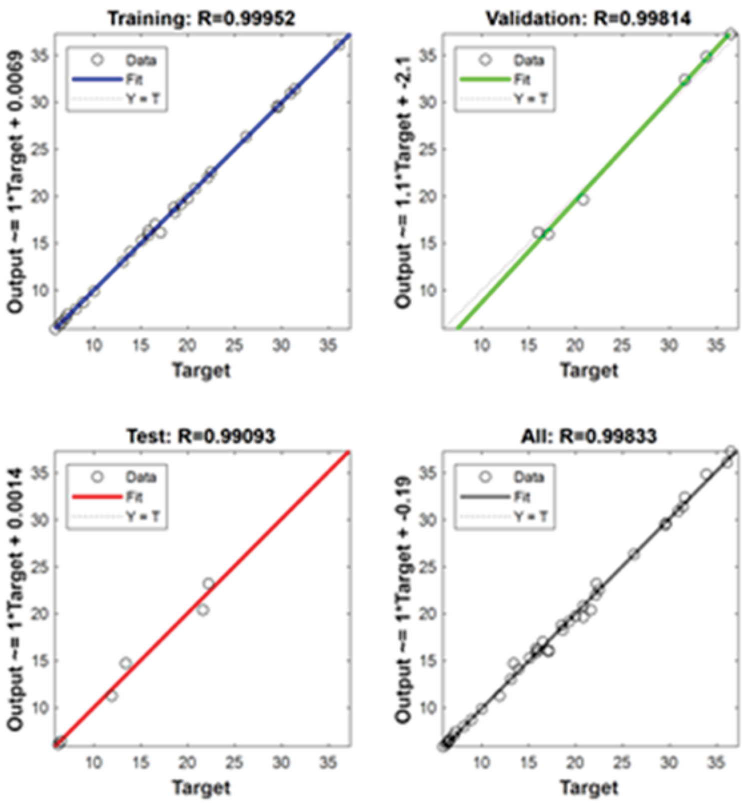

Fig. 11. Comparison of regression analysis between coal consumption values and forecasted

Rys. 11. Porównanie analizy regresji pomiędzy wartościami zużycia węgla a prognozami

The coal forecast S-curve calculated using GWO based on the coal reserve in Turkey is shown in Figure 12. For a visual representation of the analysis findings, the S-curves for coal consumption between 1965 and 2019 calculated using ANN and GA, PSO, GWO, and WOA are shown in Figure 13.

The saturation value of the S-curve is the total coal reserves in Turkey, and the total amount of the reserves is 11,525 mt, according to the BP data. The forecasted time-over period for the coal reserves in Turkey is 139 years, as presented in Figure 12. The upper and lower band limit values used in the optimization were determined as *t* for the *TO* base on the reserve amount. Optimization parameters presented in Table 2 and optimization settings shown in Table 4 were used for GA. The parameter values given in Table 3 were used for PSO while determining *HG* and *TO* parameters that define the characteristics of the S-curve was achieved using optimization methods. The number of agents is selected as 100 in GWO and WOA to test the performances of all algorithms under equal conditions. Each algorithm was repeated 1000 times for the same parameters in the calculation processes.

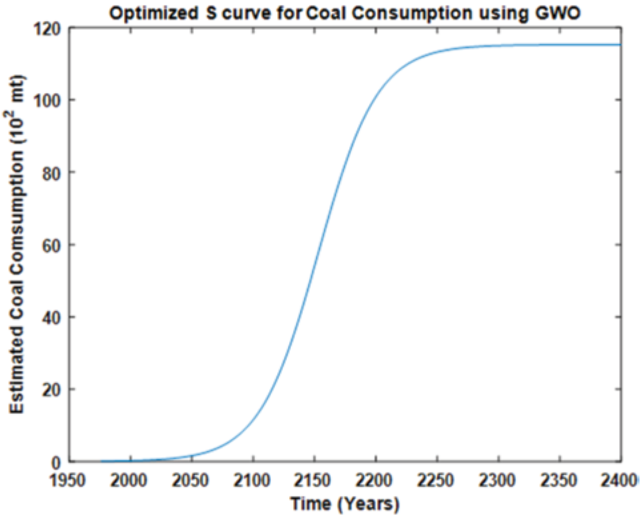

Fig. 12. Optimized S-curve for future projection of coal consumption using GWO to calculate takeover 136 years and hypergrowth 2100

Rys. 12. Zoptymalizowana krzywa S dla przyszłej projekcji zużycia węgla z wykorzystaniem GWO do obliczenia przejęcia 136 lat i hiperwzrostu 2100

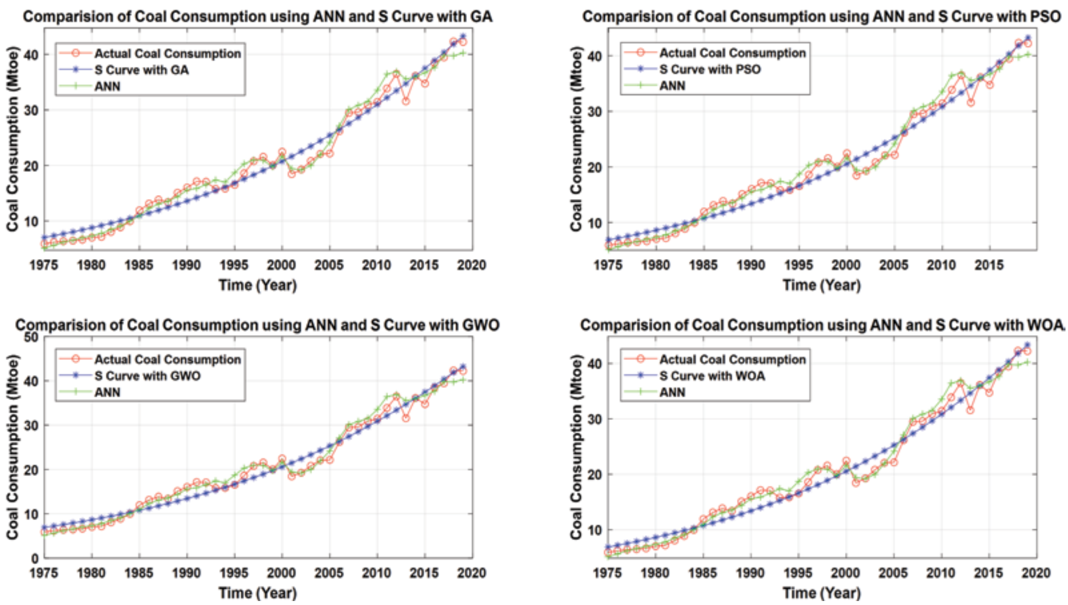

Fig. 13. Comparison of the actual coal consumption values with S-curves obtained by using optimization algorithms and ANN

Rys. 13. Porównanie rzeczywistych wartości zużycia węgla z krzywymi S uzyskanymi za pomocą algorytmów optymalizacyjnych i SSN

Table 4. Optimization settings used for GA

Tabela 4. Ustawienia optymalizacji stosowane dla GA

CrossoverFrac	0.5
Max_Population_Size	100
TolCon	0.000001
TolFun	0.000001
EliteCount Multiplier	0.1

Source: Tursun et al. 2016.

The consumption values between 1975 and 2019 were used as test data to examine the suitability of coal consumption values calculated using the S-curve by optimization and ANN. Consumption values for the period between 2009–2019 and the consumption values calculated using S-curve optimization are presented in Table 5.

Table 5. Coal consumption in Turkey between 2009–2018 and consumption forecast calculated using S-curve optimization and ANN

Tabela 5. Zużycie węgla w Turcji w latach 2009–2018 oraz prognoza zużycia obliczona z wykorzystaniem optymalizacji krzywej S i SSN

Years	Actual Consumption	ANN	Forecasted Consumption with S-curve			
			GA	PSO	GWO	WOA
2009	31,43800	30.900	29.371	30,905	29.713	29.705
2010	33,87880	31,398	30,991	30,851	30,905	30,851
2011	36,49500	33,900	32,211	32,083	32,136	32,082
2012	31,56420	36,939	33,469	33,353	33,406	33,353
2013	36,12600	34,384	34,765	34,663	34,715	34,663
2014	34,73999	36,097	36,100	36,013	36,063	36,012
2015	34,73999	36,705	37,474	37,402	37,402	37,452
2016	38,45745	37,645	38,887	38,832	38,831	38,880
2017	39,45931	39,819	40,340	40,302	40,301	40,348
2018	42,30865	39,742	41,832	41,813	41,811	41,857
2019	42,22403	40,240	43,264	43,243	43,361	43,200

The R^2 test has been used to evaluate the results obtained depending on the parameter values calculated with the ANN, GA, PSO, GWO, and WOA algorithms and the actual coal consumption values in Table 5. The R^2 value, which is obtained according to the Pearson product-moment correlation coefficient, is an expression with Equation (41)

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \overline{y})^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{41}$$

Where y_i values are the actual coal consumption values over the years, $\hat{y}_i$ are values determined from the regression equation, and $\overline{y}$ is the average value of coal consumption. R^2 is between [0, 1]. Values closer to 1 indicate the similarity of the data set, while those closer to zero indicate that the data sets come from different sampling. R^2 statistical values calculated according to the consumption values obtained by ANN and optimization algorithms and actual coal consumption values between 1975 and 2019 are presented in Table 6.

Table 6. Statistical R^2 results of ANN and optimization algorithm with actual coal consumption

Tabela 6. Statystyczne wyniki R^2 SSN i algorytmu optymalizacji z rzeczywistym zużyciem węgla

	ANN	GA	PSO	GWO	WOA
R^2	0.9863	0.9741	0.9861	0.9881	0.9868

Statistical evaluation of the test results between 2015–2019 obtained by ANN, GA, PSO, GWO, and WOA optimization analyses are presented in Table 7. To support the statistical values obtained with R^2 test, standard deviation (STD), average relative error (RE), mean absolute error (MAE), and root mean square error (RMSE) values are used in statistical evaluation. These statistical values are calculated using Equations (42–45).

$$STD = \sqrt{\frac{\sum_{i=1}^{n_r}\left(P_i - \overline{P}_{i,t}\right)^2}{n_r - 1}} \tag{42}$$

$$RE = \sqrt{\frac{\sum_{i=1}^{n_r}\left(P_i - P_{i,t}\right)}{P_{ort}}} \cdot 100 \tag{43}$$

$$MAE = \frac{\sum_{i=1}^{n_r}\left|P_i - P_{i,t}\right|}{n_r} \tag{44}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n_r}\left(P_i - P_{i,t}\right)^2}{n_r}} \tag{45}$$

Table 7. Statistical results of optimization algorithm results using test data between 2015–2019

Tabela 7. Wyniki statystyczne wyników algorytmu optymalizacji z wykorzystaniem danych testowych w latach 2015–2019

	RE	MAE	RMSE	STD
ANN	0.015	1.536	1.7400	1.9460
GA	0.116	1.112	1.3964	1.5613
PSO	0.022	1.102	1.3767	1.5392
GWO	0.011	1.079	1.3584	1.5187
WOA	0.023	1.090	1.3771	1.5397

In these equations, n_r denotes the number of elements in the array. stands for the actual coal-consumption value corresponding to i^{th} iteration. is the coal consumption value calculated by S-curve optimization for the i^{th} iteration value.

By examining the statistical results in Table 6 and Table 7 and the changes in the charts, it can be seen that coal consumption can be forecasted using the S-curve approach together with optimization algorithms. The forecast values obtained by GWO, PSO and WOA methods are more consistent with actual values compared to those obtained by the GA method. Furthermore, as a meta-heuristic optimization algorithm, GWO has higher accuracy than PSO and WOA algorithms, while WOA reaches the solution faster in convergence speed values.

The approach presented here is easier to implement and more straightforward than ANN. The essential advantage of the method is that the analysis does not need many input parameters. As a result, the S-curve method has high accuracy for coal-consumption forecasting, and this approach, with the appropriate optimization algorithm, can be used to forecast different data sets.

Conclusion

There is a direct relationship between coal consumption, increased energy production and greenhouse gas emissions. Therefore, forecasting coal consumption is very important in evaluating decision processes in the energy sector and greenhouse gas emissions. Moreover, since the global population is predicted to increase significantly within the next twenty years, the depletion rate of energy resources will possibly increase. Therefore, accurate forecasts must preserve, plan, and consume energy sources obtained from fossil fuels. Therefore, proper modeling is necessary to make accurate forecasts. Furthermore, coal is at the forefront of local power generation as a fossil fuel since Turkey is rich in coal reserves.

This study presents a new forecast strategy, including an optimization-based S-curve approach, for coal consumption in Turkey. For the analysis, the appropriate parameters of the

S-curve have been determined using GA, PSO, GWO and WOA optimization algorithms, and coal consumption data from 1975 to 2019. In the analysis of the S-curve, the saturation point is taken as 11,526 million tons, which is the total reserve amount of Turkey. Based on this value, *TO* and *HG* times were calculated with optimization algorithms. In addition to the presented optimization-based S-curve approach, the ANN approach, which is widely used in the literature, is used to estimate coal consumption in Turkey.

In the ANN model, the installed capacity, gross generation, net electric consumption, import, export, and population parameters, which determine the energy indicators in Turkey, were used as input parameters. The ANN structure was performed using a feed forward multilayer perceptron network. For the network training of ANN, the Levenberg-Marquardt backpropagation algorithm has been used.

In the analysis, the S-curves findings calculated using ANN and optimization algorithms have been evaluated statistically compared with actual consumption values. The results show that the coal-consumption forecast obtained by GWO, which is a meta-heuristic optimization technique, has better performance than GA and ANN. The values calculated S-curve parameters with GWO give better results than PSO and WOA as statistically with $R^2 = 0.9881$, $RE = 0.011$, $RMSE = 1.079$, $MAE = 1.3584$, $STD = 1.5187$. Turkey's remaining coal reserve, which was 139 years, was calculated as 136 years in the GWO algorithm analysis. Therefore, it is seen that the ANN approach presented in the literature can have a higher level of accuracy. However, in this study, the optimization-based S-curve approach has better performance in solving the problem. Besides comparing the approach presented here with ANN in terms of coal-consumption forecast projections for Turkey, the S-curve method has a significant advantage over ANN. It can be analyzed with fewer variables and easily adapted to different optimization algorithms with high accuracy.

In the future, coal consumption may decrease from time to time due to the increase in the use of renewable energy sources and economic factors. However, the S-curve defines the increase in consumption in accordance with the amount of reverse. In such a case, the forecasting strategy presented using the correlation between the decreased amount compared to the previous year and the S forecast curve can be used. Therefore, to overcome this problem, we recommend that the presented approach be repeated at an interval of 3–5 years to achieve higher accuracy. Long-term reliable coal-consumption forecasts will shed light on energy policies and enable the development of climate-change policies. The presented approach can also estimate coal consumption in other countries with an increasing trend.

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The authors declare that they have no conflict of interest.

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APPLICATION OF DIFFERENT OPTIMIZATION TECHNIQUES AND ARTIFICIAL NEURAL NETWORK (ANN) FOR COAL CONSUMPTION FORECASTING: A CASE STUDY

Keywords

coal consumption, meta-heuristic optimization, grey wolf optimization, particle swarm optimization, whale optimization

Abstract

The demand for energy on a global scale increases day by day. Unlike renewable energy sources, fossil fuels have limited reserves and meet most of the world's energy needs despite their adverse environmental effects. This study presents a new forecast strategy, including an optimization-based S-curve approach for coal consumption in Turkey. For this approach, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and Whale Optimization Algorithm (WOA) are among the meta-heuristic optimization techniques used to determine the optimum parameters of the S-curve. In addition, these algorithms and Artificial Neural Network (ANN) have also been used to estimate coal consumption. In evaluating coal consumption with ANN, energy and economic parameters such as installed capacity, gross generation, net electric consumption, import, export, and population energy are used for input parameters. In ANN modeling, the Feed Forward Multilayer Perceptron Network structure was used, and Levenberg-Marquardt Back Propagation has used to perform network training. S-curves have been calculated using optimization, and their performance in predicting coal consumption has been evaluated statistically. The findings reveal that the optimization-based S-curve approach gives higher accuracy than ANN in solving the presented problem. The statistical results calculated by the GWO have higher accuracy than the PSO, WOA, and GA with R^2 = 0.9881, RE = 0.011, $RMSE$ = 1.079, MAE = 1.3584, and STD = 1.5187. The novelty of this study, the presented methodology does not need more input parameters for analysis. Therefore, it can be easily used with high accuracy to estimate coal consumption within other countries with an increasing trend in coal consumption, such as Turkey.

ZASTOSOWANIE RÓŻNYCH TECHNIK OPTYMALIZACJI I SZTUCZNYCH SIECI NEURONOWYCH (SSN) DO PROGNOZOWANIA ZUŻYCIA WĘGLA: STUDIUM PRZYPADKU

Słowa kluczowe

zużycie węgla, optymalizacja metaheurystyczna, optymalizacja szarego wilka, optymalizacja roju cząstek, optymalizacja wielorybów

Streszczenie

Zapotrzebowanie na energię w skali globalnej rośnie z dnia na dzień. W przeciwieństwie do odnawialnych źródeł energii, paliwa kopalne mają ograniczone rezerwy i zaspokajają większość światowego zapotrzebowania na energię pomimo ich niekorzystnego wpływu na środowisko. Niniejsze opracowanie przedstawia nową strategię prognozowania, w tym oparte na optymalizacji podejście oparte na krzywej S dla zużycia węgla w Turcji. W tym podejściu algorytmy optymalizacji genetycznej (GA) i optymalizacji roju cząstek (PSO), optymalizacja *Gray Wolf* (GWO) i algorytm optymalizacji wielorybów (WOA) należą do metaheurystycznych technik optymalizacji stosowanych do określenia optymalnych parametrów krzywej S. Ponadto algorytmy te oraz sztuczna sieć neuronowa (SSN) zostały również wykorzystane do oszacowania zużycia węgla. Przy ocenie zużycia węgla za pomocą SSN jako parametry wejściowe wykorzystuje się parametry energetyczne i ekonomiczne, takie jak moc zainstalowana, produkcja brutto, zużycie energii elektrycznej netto, import, eksport i energia ludności. W modelowaniu SSN wykorzystano strukturę *Feed Forward Multilayer Perceptron Network*, a do uczenia sieci wykorzystano propagację wsteczną Levenberg-Marquardt. Krzywe S zostały obliczone za pomocą optymalizacji, a ich skuteczność w przewidywaniu zużycia węgla została oceniona statystycznie. Wyniki pokazują, że podejście oparte na optymalizacji opartej na krzywej S zapewnia większą dokładność niż SSN w rozwiązaniu przedstawionego problemu. Wyniki statystyczne obliczone przez GWO mają wyższą dokładność niż PSO, WOA i GA z R^2 = 0,9881, RE = 0,011, $RMSE$ = 1,079, MAE = 1,3584 i STD = 1,5187. Nowość tego badania, prezentowana metodyka nie wymaga dodatkowych parametrów wejściowych do analizy. Dzięki temu może być z łatwością wykorzystany z dużą dokładnością do oszacowania zużycia węgla w innych krajach o tendencji wzrostowej zużycia węgla, takich jak Turcja.