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GENETIC METHOD FOR OPTIMIZING THE PROCESS OF DESULFURIZATION OF FLUE GASES FROM SULFUR DIOXIDE

I. Fedorchenko[1], A. Oliinyk[1], J.A.J. Alsayaydeh[2]. A Stepanenko[1], V. Netrebko[3] and A. Kharchenko[1]
[1]Department of Software Tools, National University Zaporizhzhia Polytechnic, Zhukovskoho str., Zaporizhzhya, Ukraine
[2]Fakulti Teknologi Kejuruteraan Elektrikdan Elektronik, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, Durian Tunggal, Melaka, Malaysia
[3]Department of Equipment and Technology of Welding Production, National University Zaporizhzhia Polytechnic, Zhukovskoho str., Zaporizhzhya, Ukraine
E-Mail: evg.fedorchenko@gmail.com

ABSTRACT

Sulfur dioxide is one of the most commonly found gases, which contaminates the air, damages human health and the environment. To reduce the damage, it is important to control the emissions on power stations, as the major part of sulfur dioxide in the atmosphere is produced during electric energy generation on power plants. The present work describes flue gas desulfurization process optimizing strategy using data mining. Determining the relationship between process parameters and the actual efficiency of the absorption process is an important task for improving the performance of flue gas desulfurization plants and optimizing future plants. To predict the efficiency of cleaning from SO2 emissions, a model of wet flue gas desulfurization was developed, which combines a mathematical model and an artificial neural network. The optimization modified genetic method of flue gas desulfurization process based on artificial neural network was developed. It affords to represent the time series characteristics and factual efficiency influence on desulfurization and increase its precision of prediction. The vital difference between this developed genetic method and other similar methods is in using adaptive mutation that uses the level of population development in working process. It means that less important genes will mutate in chromosome more probable than high suitability genes. It increases accuracy and their role in searching. The comparison exercise of the developed method and other methods was done with the result that the new method gives the smallest predictive error (in the amount of released SO_2) and helps to decrease the time in prediction of efficiency of flue gas desulfurization. The results allow to use this method to increase efficiency in flue gas desulfurization process and to reduce SO_2 emissions into the atmosphere.

Keywords: flue gas desulfurization, sulfur dioxide, artificial neural network, genetic algorithm.

INTRODUCTION

According to Nature Geoscience, NASA satellites have discovered 500 new sources of air pollution, about 40 of which are dangerous sulfur dioxide [1]. This substance is considered one of the most risky for the Earth's atmosphere. The main sources of sulfur dioxide emissions are thermal power plants running on solid and liquid fuels, as well as metallurgical enterprises. Therefore, control of SO_2 content in flue gases from coal combustion is an effective method to reduce emissions into the atmosphere [2].

SO_2 emissions can be reduced by installing sulfur treatment equipment on newly built and existing coal-fired units, as well as appropriate desulfurization efficiency requirements. To increase the efficiency of desulfurization and more effectively reduce SO_2 emissions, it is necessary to further optimize the desulfurization management system in accordance with the needs of the industry [2].

Accurate establishment of the relationship between the process parameters and the actual efficiency of desulfurization is the basis for optimizing the control system of desulfurization. Currently, a large number of local devices for analysis and monitoring of flue gases can directly control the concentration of SO_2 in the flue gases at the inlet and outlet of the equipment for desulfurization and calculate its efficiency. However, this method is only a simple feedback on the results of the desulfurization reaction process and does not reflect the monitoring results. At the same time, the monitoring equipment is strongly influenced by external factors, sometimes failures, etc., which leads to inaccurate measurement results. Therefore, the desulfurization efficiency is influenced by various factors, such as the pH value of the suspension, the temperature of the flue gases at the inlet,

Numerous approaches have been proposed in recent years, including experimental studies, mathematical models, and machine learning models, to predict desulfurization efficiency. Among them, mathematical models and machine learning models, as well as their combinations have aroused great research interest. However, predicting the efficiency of desulfurization is still difficult to fully model mathematically. Some studies simplify the system with assumptions that make errors in forecasts. In addition, the numerical solutions used in these mathematical models require large computational resources. In this context, machine learning models are useful tools for forecasting [2].

One of the promising areas for solving this problem is based on the use of artificial neural networks and genetic algorithms, as the most progressive in relation to the problems of predicting the efficiency of flue gas desulfurization. Genetic algorithms belong to a class of

search methods that iteratively improve the quality of solutions by recombination procedures and selection for survival. Due to the universality of the computational scheme, the possibilities of parallel implementation and noise resistance of HA find a successful practical application in solving many complex nonlinear multidimensional optimization problems [3].

This paper proposes a modified genetic method for optimizing the flue gas desulfurization process based on a neural network, which allows to reflect the influence of the characteristics of the time series of process parameters on the actual desulfurization efficiency and increase its forecast accuracy.

PROBLEM SOLVING

Currently, the greatest interest is the use of technologies for desulfurization of dust and gas streams that can provide effective binding of sulfur dioxide. One of the most common methods is the method of wet desulfurization [4]. The method of wet absorption purification of flue gases is based on the neutralization of sulfuric acid resulting from the dissolution of sulfur dioxide contained in the flue gases, calcium oxide hydrate $Ca(OH)_2$ (lime) or calcium carbonate $CaCO_3$ (limestone). Lime is a more expensive and scarce material, but the use of lime as a sorbent can almost halve the consumption of reagent, reduce energy consumption for the preparation of suspensions and irrigation of the absorber. The efficiency of using $Ca(OH)_2$ for gas purification depends on the temperature of the gas, its humidity and the residence time of the reagent in the system.

After analyzing the principle of operation of the method of wet absorption flue gas cleaning, it was found that the generalized model of the dependence of the degree of desulfurization on the reagents used with some assumption can be reduced to the form (1) [6]:

$$K_{des} = f(x_{temp\_front\_ads}, x_{temp\_after\_ads}, x_{first\_stage}, x_{second\_stage}, x_{dust}, x_{recir}, x_{water}, x_{lime}, x_{second\_reagent}), \quad (1)$$

where $x_{temp\_front\_ads}$- temperature before the adsorber, $x_{temp\_after\_ads}$- temperature after the adsorber, x_{first_stage}- volume of gas on the 1st step, x_{second_stage}- volume of gas on the 2nd step, x_{second_stage}- dustiness after the 2nd step, x_{recir}- volume of gas for recirculation, x_{water} - water consumption in the adsorber, x_{lime} - lime consumption, x_{second_reagen}- secondary reagent consumption.

Therefore, to solve this problem it is necessary to analyze the results of flue gas desulfurization, to establish the relationship between the degree of desulfurization on the amount of reagents used and create a model of this relationship, which would predict the efficiency of flue gas desulfurization, resulting in reduced SO_2 emissions and operating costs due to the optimal use of reagents in the future.

ANALYSIS OF LITERATURE DATA AND PROBLEM STATEMENT

The article [7] proposes a model for predicting the efficiency of flue gas desulfurization, based on the LSTM neural network. The authors took as a consideration the 1000MW installation in China, considering the main factors influencing the efficiency of desulfurization of wet flue gases of limestone and gypsum. A neural network with short-term memory (LSTM) is used to build a model for predicting the efficiency of desulfurization.

The general structure of the LSTM forecasting model consists of five functional modules: input level, hidden level, output level, network training and network forecasting. The input layer is responsible for the initial processing of the output time series of faults to meet the input requirements of the network. The hidden layer uses LSTM cells to build a single-layer cyclic neural network; the output layer provides the prediction results. When training the LSTM neural network, a backpropagation through time algorithm is used, which is similar to the classical backpropagation algorithm.

The advantage of the proposed model in comparison with other models is that it can reflect the influence of the characteristics of the time series of process parameters on the actual efficiency of desulfurization and increase the accuracy of prediction.

The disadvantage of the proposed model is that during training it is difficult to interpret the results, it imposes limitations on the possibility of improving the model, it is also impossible to predict when the dynamics of desulfurization will change and the model will stop working.

In [8] the prediction of the efficiency of wet desulfurization of gypsum-limestone based on the method of reference vectors (SVM) is presented. The authors take the liquid-gas ratio, flue gas velocity, oxidizing air volume, gas temperature, dust contained in the flue gas, the concentration of sulfur dioxide at the inlet, the pH of the suspension of the absorption tower, the concentration of the suspension of the absorption tower, the ratio of calcium and sulfur as independent variables, and the desulfurization efficiency as a dependent variable. The idea of the proposed method is to construct a hyperplane, which acts as a solution surface, maximally separating positive and negative examples from the learning set. The machine of reference vectors is an approximate implementation of the method of minimizing structural risk, which is based on the fact

The advantage of this method is that to solve the problem of classification, unlike most other methods, it requires a small set of data.

The disadvantage of this method is that not the whole set of samples is used for classification, but only a small part of them, which is located at the borders.

In [9] the research on data mining and optimization of wet flue gas desulfurization systems is presented. The authors proposed a comprehensive evaluation criterion using the minimum cost as a target function to obtain optimal operating conditions of the wet flue gas desulfurization system. An improved fuzzy

clustering method has been proposed to increase the accuracy of the target data mining. This algorithm used the results of the K-means method as initial conditions and the fuzzy C-means method as an analytical method. The procedure for solving the proposed method is expressed in two stages: the use of the method of K-means to obtain the initial number of clusters and their centers, as well as the use of fuzzy C-means to calculate the final results of clustering.

The advantages of the proposed method are the relative simplicity of implementation, the lack of need for expert marking of the training sample and relatively low requirements for computing power.

The disadvantage of the proposed method is its low resistance to emissions in the data, which can distort the average. As a solution to this problem may be the use of a modification of the k-median algorithm. The disadvantage is that the result of its work depends on the initial choice of centroids and in the General case, the method does not give optimal results, but allows to find only suboptimal solutions.

In [10] the solution of the problem of emission reduction for the system of forced oxidation of limestone flue gases on the basis of artificial intelligence is presented. The authors created an artificial neural network based on a multilayer perceptron (MLP) to study the relationships between input control variables and output variables. The proposed model demonstrated the ability to study the complex kinetics of the reaction between reagents. The input parameters of the model are: pH of the absorber suspension, mass SO_2 at the inlet, temperature, mass NO_x at the inlet, percentage of oxygen, volume of air for oxidation, density of the absorber suspension, volumetric moisture content, mass of dust particles as a fraction of volumetric smoke consumption gases. The initial parameters of the model are: mass of SO_2, Hg, NO_x and dust at the outlet. The model consists of a single hidden layer containing 27 neurons. Learning is done using the method of reverse error propagation. It is performed until one of the stop criteria is met, ie the convergence error is changed to 0.0000001, or the maximum number of epochs is reached during training, outside of which the error is slightly reduced.

The advantage of the proposed method is that it has a high degree of connectivity, which is implemented using synaptic connections. Also, when learning the presented neural network, due to its internal structure, it establishes patterns in connection with the input and output data, thereby as if "summarizes" the experience gained in the training sample.

The disadvantage of the proposed method is that it uses the method of backpropagation of the error, resulting in the learning process takes a long time. Excessive weight gain of the neural network can lead to its "paralysis" when the synaptic scales stop changing before reaching the end of training. The size of the step must be constantly adjusted, the network must be constantly "taught", as it gradually "forgets" the previous training sets, which it was trained.

In [11] the solution of the problem of optimization of the wet flue gas desulfurization system is presented. To predict SO_2 emissions, a modified model of wet flue gas desulphurisation was developed, combining a mathematical model and an artificial neural network. A modified PSO (Particle Swarm Optimization) with a penalty function algorithm has been proposed to increase the efficiency of the desulfurization process aimed at minimizing operating costs. The particle swarm method is based on calculating the centroid coordinates and velocities at each iteration. In essence, the problem of minimizing the fitness function is solved: the smaller the value of the fitness function at each iteration, the closer the result is to the optimal centroid of the swarm of particles. Fitness function is defined as the mean value of the Euclidean distances between the particle vector and the vector,

As a result, the operating parameters were optimized, including the pH of the lime solution, the temperature, the density of the lime solution and the number of operating circulating pumps. The results show that PSO with a fine function provides satisfactory convergence performance to reduce operating costs under constraints.

The disadvantage of this method is that it easily falls into the local optimum in multidimensional space and requires a lot of time to find a solution.

In [12] the forecasting and optimization of the desulfurization system using a neural network and a genetic algorithm are presented. The authors, taking the desulfurization factor and economic value as two goals, created a forecasting model with ten inputs and two outputs. A modified genetic algorithm was created to build a model and optimize the cost of the desulfurization process. The genetic algorithm consists of two stages. At the first stage, the HA finds the suboptimal architecture of the ANN. In the second stage, suboptimal values of weight coefficients and SHNM shifts are determined. The first stage can be considered a preparatory stage of training, which simplifies the further task of determining weights and displacements. The authors used the following approach: the chromosome was built from the number of neurons in the hidden layer, the impulse, learning speed, type of activation function and learning algorithm of ANN and several other parameters. Due to the variety of these parameters, it is generally impossible to use the inversion operator in them. The number of additional genes included a vector that characterizes the occurrence of a variable in the learning array. Zeros and ones were distributed at loci randomly with the only remark that the number of zeros should not exceed half of the original number of variables. The introduction of this type of gene into the chromosome was performed to identify the suboptimal set of variables. After defining the ANN architecture, the network training is started. Then a number of vectors of weights and displacements reduced to the size $n \times 1$, and a vector of a standard error of training is formed. From a number of vectors (chromosomes) the initial population is created,

The advantage of the proposed method is to increase the accuracy of classification using the GA-

modified approach. GA allows to experimentally select the best combination of the main features of ANN, which can vary not only in different tasks, but also when changing the statistical parameters of the data. Thus, this approach allows to optimize the desulfurization process.

The disadvantages of this method include the consumption of a much larger amount of computing resources. Therefore, the presented GA can be used only if have access to distributed computing resources.

The paper [13] presents a neural network modeling of sulfur dioxide removal by activated carbon sorbent. The authors have developed a neural network with three hidden layers to predict the efficiency of removing sulfur dioxide (SO_2) from a flue gas stream (SO_2 + air) in a fixed bed reactor using a granular sorbent with activated carbon. The input layer has six neurons, the initial SO_2 concentration, reaction temperature, flue gas flow rate; sorbent particle size, layer height and reaction time are used as input parameters. The output layer has one neuron and represents the SO_2 removal efficiency. Back propagation algorithm with two hidden layers was used for training and testing of the neural network.

The predictions of the neural network have shown an excellent agreement with the experimental data based on the category of MSE for both training and testing. The neural network is shown to give comparable predictive capability when used for interpolation and extrapolation, for a variety of reactions.

The disadvantage of this model is its “black box” character, high computational load, tendency to retraining, as well as relatively large time costs.

The paper [14] presents the application of an improved BP neural network based on the LM algorithm in Desulfurization System of Thermal Power Plant. In this paper, the improved BP neural network prediction model of LM algorithm is established by analyzing the influencing factors of desulfurization efficiency and the network weights and threshold value were adjusted repeatedly. The five variable factors are used as inputs to the BP neural network, and the output is desulfurization efficiency. The dynamic method is used to determine the number of neurons in the hidden layer. In the beginning, fewer hidden layer neurons were selected. If the effect was not good after training for a certain number of times, then the hidden layer neurons were added until the more reasonable number of hidden neurons was reached.

By modeling data from a thermal power plant in real time, the authors have shown that the model can overcome the inherent disadvantages of the BP neural network, the convergence rate is higher, the forecast accuracy is higher, which is of some importance for improving the desulfurization system of thermal power plant.

The disadvantage of the proposed model for predicting the efficiency of desulfurization is the lack of the ability to observe the hidden patterns in the time series under study.

The paper [15] compared regression and MLP models to develop an accurate, efficient and simple method for predicting air pollutants such as SO2. Artificial neural networks have been developed to investigate the complex nonlinear relationship between predictor variables and predicted parameters such as daily SO2 concentration. In this study, the back-propagation (BP) training algorithm was used owing to its simplicity, widespread, and powerful nonlinear technique applications The logarithmic sigmoid and linear activation functions were applied to adjust the network. In the first step, the input data set were weighted in the first layer and passed to the middle layer, then was calculated the output weight through connections between the middle and the output layer and lastly, results were indicated in the output layer.

As well as, the air quality can be improved after suitable decisions for controlling the effective parameters which are the one-day time delay, park indicator, the season of the year, and the total area of parks. Furthermore, the results of various studies confirmed that the ANN model demonstrated that it could be fully used in environmental research including the prediction of air pollution under different conditions, due to air pollution seriously impacting human health and the environment.

The proposed method has some disadvantages, such as low convergence rate, local minimum value, which leads to the loss of the global optimal solution.

The analysis of works [7 - 15] allows us to state that conducting research on optimization and forecasting the efficiency of flue gas purification from nitrogen oxides is quite an urgent task. Also in the course of work it was found that the most effective method for solving this problem is the use of neural networks. Because they have advantages such as the ability to adapt to change, which allows them to work even in a critical situation, self-learning, speed (forecasting and planning can be much faster than using accurate algorithms), as well as high resistance to noise and the ability to use an unlimited number of independent variables. In this case, despite their obvious advantages, the main disadvantage is the difficulty of choosing an effective teaching method and creating a training data set, as well as the complexity of the correct weight distribution of the matrix at the initial stage, under conditions of uncertainty. To solve this problem, the genetic method is well suited; the advantage of this method is greater accuracy and reduce the amount of time spent on training. It is effective for training neural networks such as "multilayer perceptron", "ANN with general regression", "Kohonen networks" and others. The use of evolutionary genetic algorithms at the learning stage helps to reduce the number of training cycles by using the parameters that have the greatest weight. It is effective for training neural networks such as "multilayer perceptron", "ANN with general regression", "Kohonen networks" and others. The use of evolutionary genetic algorithms at the learning stage helps to reduce the number of training cycles through the use of the parameters that have the greatest weight. It is effective for training neural networks such as "multilayer perceptron", "ANN with general regression", "Kohonen networks" and others. The use of evolutionary genetic algorithms at the learning stage helps to reduce the number of training cycles by using the parameters that have the greatest weight.

Therefore, in order to solve the problems that arise when using the studied methods, it was decided to develop a modified genetic method to adjust the weights of the artificial neural network to increase the efficiency of flue gas desulfurization and reduce SO2 emissions into the atmosphere.

THE PURPOSE AND OBJECTIVES OF THE STUDY

The object of study - desulfurization systems at coal-fired power plants.

The subject of research - methods for predicting the efficiency of flue gas desulfurization.

Research methods - traditional models (decision trees, nearest neighbor method, ant colony method), neural networks, combined methods (neural networks and genetic algorithms, neural networks and multi-agent systems).

The purpose of the study is to develop a mathematical model for solving the problem of optimizing the process of desulfurization of flue gases from sulfur dioxide using a neural network.

To achieve the goal of the study it was necessary to solve the following tasks:

- to develop a modified genetic method of learning the neural network using adaptive mutations to predict the effectiveness of flue gas desulfurization;
- to present an experimental study of the proposed genetic method.

DEVELOPMENT OF A GENETIC METHOD FOR OPTIMIZING THE PROCESS OF DESULFURIZATION OF FLUE GASES FROM SULFUR DIOXIDE

The most well-known of the evolutionary methods at present is the genetic algorithm for finding the global extremum of a multiextreme function. It consists in parallel processing of a set of alternative decisions, thus search concentrates on the most perspective of them. This indicates the possibility of using genetic algorithms in solving any optimization and decision-making problems, so it was chosen to adjust the synaptic weights of the neural network [13].

First, the proposed method is the initialization of the initial population of chromosomes containing information about the values of the weights of the network of a given structure. The chromosome consists of G genes that contain the values of the weights and displacements of all neurons in the network. The developed method uses real coding to represent the values of weights in chromosomes. The best way to encode the scales in this representation of the topology is to encode using a matrix whose size is equivalent to the size of the matrix of the ANN topology. The elements of this matrix are the weights of the corresponding connection. The length of the chromosome is calculated by formula (2):

$$\lambda = Q_1(T+1) + \sum_{l=1}^{L} Q_l(Q_{l-1}+1) \quad (2)$$

where Q_l is the number of neurons on the l-th layer; T - the number of features in the training sample; L is the number of layers of the neural network [13].

After formation, the chromosomes of the current population are evaluated, for which purpose each chromosome of the population is decoded into a set of neural network weights. Next, the value of the fitness function is calculated, which evaluates the quality of the selected architecture by the value of the learning error of the neural network by formula (3) and (4):

$$F_{opt} = \min(F), \quad (3)$$

$$F = \frac{1}{2C_t}\sum_{i=1}^{C_t}(O_i - R_i)^2 \quad (4)$$

where C_i is the power of the set of training pairs; O_i - the value of the output neuron obtained by means of a network at the i-th set of training; R_i is the required value of the original neuron in the i-th set of training [14].

As can be seen, the fitness function will evaluate the error as the difference between the received network output and the required one, which determines how much the obtained network output differs from the required one. Therefore, the smaller this error, the higher the value of suitability, ie it is necessary to reduce the matrix to a form in which the learning error neural network will be minimal.

Based on the obtained values of fitness function, individuals are selected to generate new solutions using rank selection. To do this, the current population was sorted according to the values of fitness function; each chromosome is assigned a number that determines its place in the rank of the sorted population, rather than its absolute value. This approach allows to control the selective pressure and limit the number of offspring on one chromosome. Selection pressure coefficient [15]

Linear ranking of all chromosomes is performed using formula (5):

$$P_{sl}(Pos) = 2 - SP + 2\cdot(SP-1)\cdot\frac{Pos-1}{C-1}, \quad (5)$$

where Pos is the position of the chromosome in the population (Pos = 1 has the chromosome with the lowest value of fitness function F_{min}, and Pos = C has the chromosome with the highest value of fitness function Fmax.); C - the number of chromosomes (individuals) in the population; SP is the selection pressure coefficient, which is calculated by formula (6):

$$SP = \frac{F_{\max}}{F_{avg}}, \quad (6)$$

where F_{max} is the chromosome with the highest value of fitness function, F_{avg} is the average value of fitness function of the whole population [16].

The advantage of the rank method is the possibility of its application both to maximize and to minimize the function. It also does not require scaling due to the problems of premature convergence, which is relevant for the roulette method.

The crossing operator in the proposed genetic method generates two offspring from two parental chromosomes, ie from two vectors of real numbers the formation of two new vectors is carried out. The SBX is used as a basis - a crossover that simulates the operation of a binary crossing operator. Let $P_1 = (p_{11}, p_{12},\ldots, p_{1\lambda})$ and $P_2 = (p_{12}, p_{22},\ldots, p_{2\lambda})$ chromosomes of two ancestors, then the genes of progeny chromosomes are found by formulas (7) and (8):

$$c_j^1 = \frac{1}{2}\left((1-\omega)\cdot p_j^1 + (1+\omega)\, p_j^2\right), \quad (7)$$

$$c_j^2 = \frac{1}{2}\left((1+\omega)\cdot p_j^1 + (1-\omega)\, p_j^2\right), \quad (8)$$

where $j = 1,2,\ldots, \lambda$; λ is the length of the chromosome; p_{j1}, p_{j2} - genes of the first and second parents, respectively; ω is a number obtained by formula (9):

$$\omega = \begin{cases} (2v)^{\frac{1}{b+1}}, v \le 0,5 \\ \left(\frac{1}{2(1-v)}\right)^{\frac{1}{b+1}}, v > 0,5 \end{cases}, \quad (9)$$

where ν is a random number distributed according to the uniform law $\nu \in (0.1)$; b is a parameter that affects the probability of the appearance of offspring away from the parental individuals $b \in [2, 5]$. During the study, it was found that small values of b allow generating offspring significantly distant from the parents, while an increase in b causes the appearance of offspring near the parent pairs [17].

In evolutionary algorithms, the mutation operator is responsible for extensive search and capture of new areas of search space. To configure it, the user additionally has to decide which value of the mutation probability should be used. With a low mutation, the algorithm will rarely capture new areas of search space and converge more quickly to local extremes. With a high mutation, the algorithm will more often examine different areas of the search space, but will not localize promising areas of the search space. Thus, the choice of the mutation operator directly affects the quality of the method and the solutions it receives.

To solve this problem, a method of changing the probability of mutation was implemented. Initially, each iteration is the level of population development, i.e. the average value of the fitness function of all individuals, after which the value obtained is compared with the value of the fitness function of each individual. If the value of the fitness function of the individual is less than the average value of the fitness function of all individuals, then there is a jump in the probability of mutation, ie the worse the value of fitness function, the higher the probability of mutation. The probability of chromosome mutation is calculated by formula (10):

$$\beta_{mut} = \begin{cases} 0.5\frac{F_{\max}(e) - F(P(e))}{F_{\max}(e) - F(e)}, if\ F(P(e)) \ge \bar{F}(e), \\ 0.5, if\ F(P(e)) < \bar{F}(e) \end{cases} \quad (10)$$

where $F_{max}(e)$ is the largest value of the fitness function of the current population, $\bar{F}(e)$ is the average value of the fitness function of the current population [18].

If the pj gene is mutated, then its new modified value pjnew is determined by formula (11):

$$p_j^{new} = p_j + b\left(o_j - p_j\right)\left(1 - \frac{e}{e_{\max}}\right)^{\xi}, \quad (11)$$

where b is a randomly generated number from the interval [0,1]; o_j - randomly generated from the set $\{p_{min}, p_{max}\}$, where p_{min}, and p_{max} - the lower and upper limit of the possible change in the value of the variable p_j; e - current generation number; e_{max} - the maximum number of generations; ξ is a refinement parameter that depends on the convergence of the iterative process, after reaching a steady state, when the best of the individuals has not changed during the last e generations, the value is halved, which expands the search area and thus overcomes local extremum traps [19].

This adaptive mutation allows to maintain the required balance between two different-scale changes (mutations) of genes in the process of implementation of GA (evolution), because the initial steps of the method were mainly dominated by large-scale changes (providing a wide range of search), while in the final stage due to the reduction of mutations) there was a refinement of the decision.

The use of an adaptive mutation for each individual is necessary, but not sufficient to prevent population convergence in the local optimum. Suppose the i-th individual has a mutation probability of 97%. On the one hand, such a high mutation in the generation of the i-th individual of the population is equivalent to the generation of a chromosome with completely random parameters that do not carry useful information about previous evolution. On the other hand, the i-th individual remains in the population due to the high value of the

adaptation function, displacing subsequent generations with smaller values. In order to completely avoid convergence, we introduce selection that will thin the population and weed out individuals with a high probability of mutation by formula (12):

$$if\ \beta_{mut}\left(P^i\right) > \delta : removed\ P^i, \quad (12)$$

where β_{mut} is the probability of mutation of the P_i chromosome; δ is the selection threshold which determines the degree of mutations and eliminates individuals "incompatible with life" [20-21].

The developed method stops its work at achievement of the maximum number of epochs of functioning which is set by the user.

The presented genetic method is able to fully explore the search space, avoid local extremes at the stage of genetic search and effectively use the found "good" solutions, ie gradually improve the results based on intermediate solutions.

THE RESULTS OF THE GENETIC METHOD FOR OPTIMIZING THE PROCESS OF DESULFURIZATION OF FLUE GASES FROM SULFUR DIOXIDE

To build a model for predicting process efficiency desulphurization of flue gases used experimental data of the coal boiler capacity 1000 MW from 07:00 on May 24, 2020 to 06:00 on December 31, 2020. The set consists of 11 attributes and 5330 instances:

- input SO_2 content (mg / m3);
- temperature before the adsorber (C);
- temperature after the adsorber (C);
- volume of gas on the 1st step (m^3 / h);
- volume of gas on the 2nd step (m^3 / h);
- dustiness after the 2nd step (mg / nm^3);
- volume of gas for recirculation (m^3 / h);
- water consumption in the adsorber (m^3 / h);
- lime consumption (t / h);
- consumption of secondary reagent (t / h);
- SO_2 content at the outlet (mg / m^3).

To solve this problem, a software environment based on the Python programming language was chosen, and for easy work with data arrays and the formation of datasets, the NumPy library was used - the Python package for scientific calculations. The Keras library [22] and Theano library [23] were chosen to build and work with neural network models.

An important requirement for data for modeling is their quality. If the data contains the so-called "noise", seasonal component, emissions, omissions - this negatively affects the accuracy of forecasts and the quality of models. Also, data intended for use as training datasets for ANN should be normalized to reduce error and improve training quality.

Processing of raw data before the presentation of the model takes place in the following sequence [24]:

- clear datasets with undefined or empty key fields;
- processing gaps in these predictors;
- processing of predicate data anomalies;
- removal of the seasonal component from time series;
- reduction of data to the types used in calculations;
- data normalization.

When processing data gaps, empty values are replaced by the median value calculated by formula (13):

$$M_e = X_{Me} + i_M \frac{\frac{\sum f}{2} + S_{Me-1}}{f_{Me}}, \quad (13)$$

where X_{Me} is the lower value of the median interval; i_M - median interval; S_{Me} - the sum of observations that were accumulated before the median interval; f_{Me} - the number of observations in the median interval. Thus, the minimum statistical error from the values of the series is provided. Processing anomalies in the data is to clean a set of variables from abnormally high or low values. Cleaning from the seasonal component of the time series is by the method of decomposition [25].

The normalized value of the variable x is calculated by formula (14):

$$z(x) = \frac{x - \min(x)}{\max(x) - \min(x)}. \quad (14)$$

The created network was trained for 100 epochs. During testing, the method of dividing the data sample into training and test samples in the percentage of 75/25% was used.

Mean Absolute Error (MAE) and Mean Square Error (MSE) are used to assess the quality of predictive models [26].

Figure-1 and Figure-2 present the results of the workfully connected perceptron with one hidden layer.

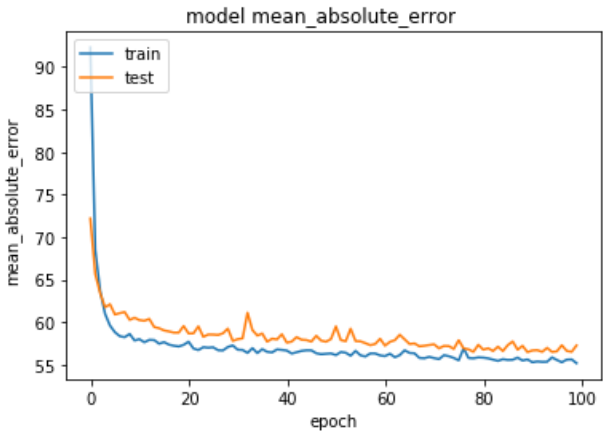

Figure-1. The value of the network metric (MAE) for a fully connected perceptron with one hidden layer.

From Figure-1 it can be seen that the best MAE values of this model were 59.85% and from the 10th epoch

there is an almost constant value during the training of a fully connected perceptron with one hidden layer.

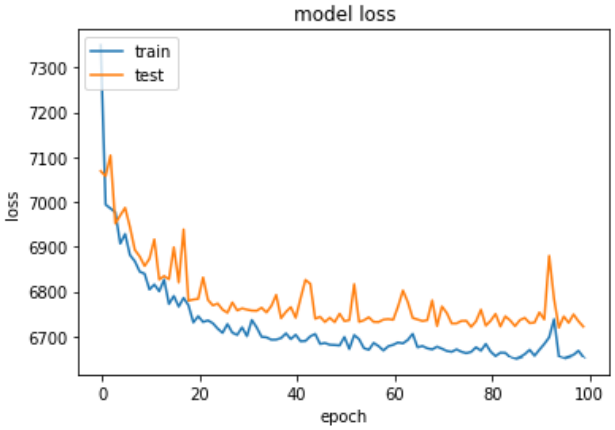

Figure-2. The value of the network metric (MSE) for a fully connected perceptron with one hidden layer.

From Figure-2, we can see that there is a gradual decrease in the value of MSE, and in the 20th epoch it almost becomes a constant value and is equal to 6785.

Figures 3and 4 present the results of the work a fully connected perceptron with two hidden layers [26 - 35].

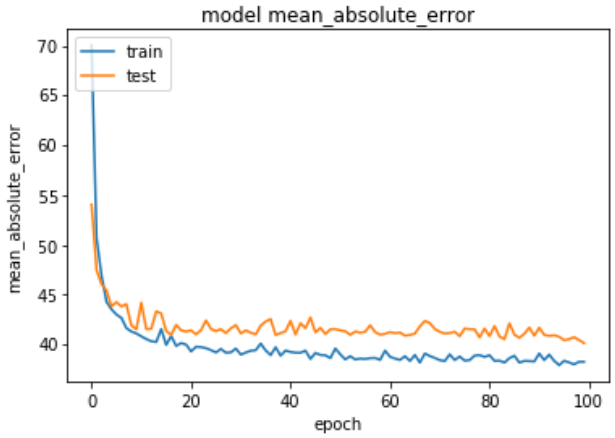

Figure-3. The value of the network metric (MAE) for a fully connected perceptron with two hidden layers.

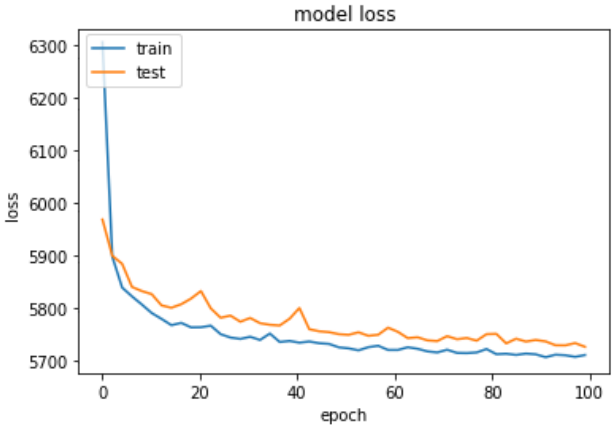

Figure-4. The value of the network metric (MSE) for a fully connected perceptron with two hidden layers.

From Figure-4 it can be seen that there is a gradual decrease in the value of the error and in the area of 10-15 epochs of training reaches a local extreme and is equal to 5795. The locality of the minimum error may indicate a further gradual decrease in network error [36 - 50].

Figure-5 and Figure-6 presents the results of the work a fully connected perceptron with two hidden layers and a genetic method with an adaptive mutation.

From Figure-5 it can be seen that the MAE value for a fully connected perceptron with two hidden layers and a genetic method with an adaptive mutation is equal to23.95 and since the 5th era almost constant value, therefore, it can be assumed that a global minimum of error is reached during training, and the network is considered trained.

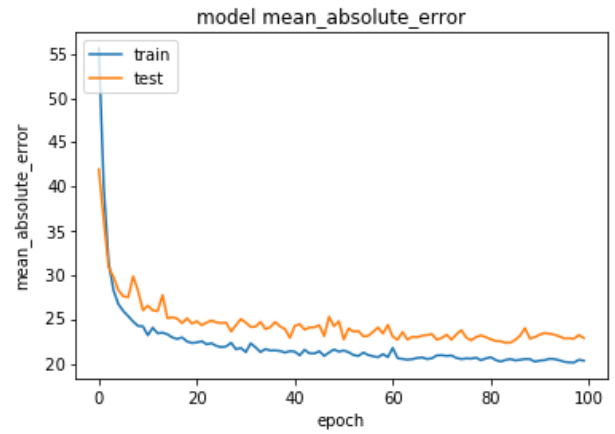

Figure-5. The value of the network metric (mae) for a fully connected perceptron with two hidden layers and a genetic method with an adaptive mutation.

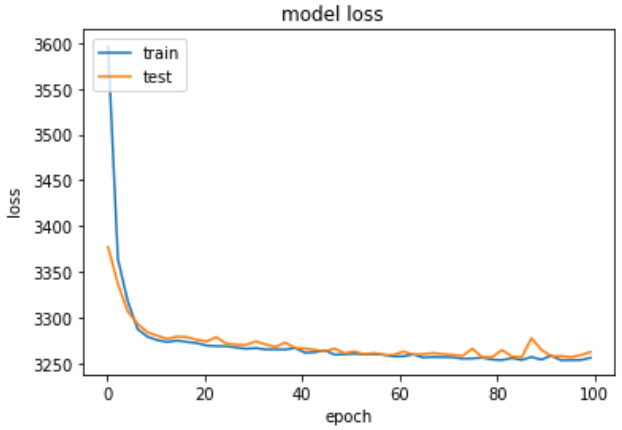

Figure-6. Value of the network metric (MSE) for a fully connected perceptron with two hidden layers and a genetic method with adaptive mutation.

From Figure-6, we can see that there is a gradual decrease in the value of the error, and in the 20th epoch it practically becomes a constant value and is equal to 3253. A comparative analysis of the results of the developed models with such methods as: linear regression, polynomial regression, logistic regression, the method of the nearest neighbor, random forest, the method of an ant colony. The evaluation criteria were the metrics MAE (Mean Absolute Error), MSE (Mean Squared Error) and execution time (Table-1).

Table-1. Comparative analysis of the results of the developed method for predicting the efficiency of flue gas desulfurization.

Method	MAE	MSE	Time, s
Linear regression	79.24	9103	363
Polynomial regression	77.84	9031	401
Logistic regression	78.56	9041	374
The method of the nearest neighbor	75.76	7421	428
Random forest	74.15	7201	469
Ant colony method	73.89	7523	393
Multilayer perceptron with one hidden layer	59.85	6785	864
Multilayer perceptron with two hidden layers	40.98	5795	964
Multilayer perceptron with two hidden layers and developed GA	24.95	3253	564

From the Table-1, we can see that the best results on the accuracy of prediction were obtained in a multilayer perceptron with two hidden layers, its mean absolute error was 24.95, and the root mean square error is 3253. The worst results were obtained in the method of linear regression, its average absolute error is 79.24, and the root mean square error is 9103.

DISCUSSION OF THE RESULTS OF THE DEVELOPMENT OF A GENETIC METHOD FOR SOLVING THE PROBLEM OF OPTIMIZING THE PROCESS OF DESULFURIZATION OF FLUE ASES FROM SULFUR DIOXIDE

Analyzing the results of experiments (Table-1), we can see that the use of neural networks in comparison with regression models gives an advantage in accuracy, for example, the value of the average absolute error of a multilayer perceptron with one hidden layer or two hidden layers was 59.85 and 40.98, respectively, and the value of the average absolute error predicting linear regression and logistic regression, respectively is 79.24 and 78.56. Thus, neural networks can achieve higher prediction accuracy than regression models because they are much better able to handle nonlinear behavior, but neural networks are inferior in execution time. The execution time of the multilayer perceptron with one hidden layer is 864s, and the polynomial regression is 401s. To overcome this problem, a modified genetic method with an adaptive mutation was developed, which allows to increase the accuracy of prediction and reduce the learning time of the neural network. During testing, it showed the lowest value of the root mean square prediction error, it was 3253, which is 54% less than the random forest method and 43% less than the multilayer perceptron with two hidden layers. Also, the execution time of a multilayer perceptron with two hidden layers and developed HA is 564s, which is 34% less than a multilayer perceptron with one hidden layer and 41% less than a multilayer perceptron with two hidden layers. Based on the work, it can be concluded that the use of evolutionary algorithms is promising for the learning of ANN, as their application allows to reduce the training time and achieve a deeper minimum error of learning ANN.

CONCLUSIONS

The solution of the problem of optimization of the strategy of the flue gas desulfurization process from sulfur dioxide using heuristic methods was considered in the work. A modified genetic method for predicting the efficiency of flue gas desulfurization based on the created neural network was developed. The fundamental difference between the proposed genetic method from existing analogues is the use of adaptive mutation, which uses in the process of its work the level of population development. In it, the least significant genes are more likely to mutate in chromosomes than those with high fitness, which increases accuracy and increases their role in the search. That is, the worse the adapted individual, the farther it is from the optimum, therefore, it is given an increase in the probability of mutation so that it can move away from the current suboptimal position. The presented genetic method is able to fully explore the search space, avoid local extremes at the stage of genetic search and effectively use the found "good" solutions, i.e., gradually improve the results based on intermediate solutions. It also allows to display the influence of the characteristics of the time series of process parameters on the actual efficiency

of desulfurization and increase its forecast accuracy. A comparative analysis of the proposed method and known ones was carried out, during which it was found that the developed method gives the smallest error in predicting the SO_2 content at the outlet after flue gas desulfurization (mean absolute error is 24.95 and root mean square error is 3253, which is less than models, built using other methods) and gives the lowest execution time (model learning time was 564 s). Practical use of the developed method will increase the efficiency of the flue gas desulfurization process and reduce SO_2 emissions into the atmosphere.

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