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A Model for Determining Fuzzy Evaluations of Partial Indicators of Availability for High-Capacity Continuous Systems at Coal Open Pits Using a Neuro-Fuzzy Inference System

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Abstract: This paper presents a model for determining fuzzy evaluations of partial indicators of the availability of continuous systems at coal open pits using a neuro-fuzzy inference system. The system itself is a combination of fuzzy logic and artificial neural networks. The system availability is divided into partial indicators. By combining the fuzzy logic and artificial neural networks, a model is obtained that has the ability to learn and uses expert judgment for that learning. This paper deals with the ECC system (bucket wheel excavator-conveyor-crushing plant) of the open pit Drmno-Kostolac, which operates within the Electric Power Company of Serbia. The advantage of a model of this type is that it does not rely on the historical experiences of experts and usual predicted values for the fuzzy evaluation of partial indicators, which are based on the assumption that similar systems affect availability in a similar way. The fuzzy evaluation of partial indicators is based on historical data for the specific system for which the model was created. As such, it can more accurately predict continuous systems availability on the basis of expert evaluations in the appropriate time period. Another advantage of this model is that the availability is estimated on a quarterly basis, which gives a more accurate view because it uses a smaller time period with more similar characteristics and, thus, includes certain external influences which are related to the quarterly meteorological conditions.

Keywords: systems; ECC system (bucket wheel excavator-conveyor-crushing plant); mining; availability; soft computing; fuzzy logic; ANN; ANFIS

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1. Introduction

Coal is an important energy fuel in electricity production. Coal exploitation in the Kostolac Basin began in 1870. The open pit Drmno is the only active mine in the Kostolac Basin with production of 25% of coal (lignite) in Serbia (see Bugarić et al. [1]). High-capacity continuous systems are used for coal mining at the open pit Drmno-Kostolac surface mine, which operates within the Electric Power Company of Serbia. The operation of continuous systems is very important for the stable coal supply of thermal power plants. In this paper, a model is constructed for the prediction of fuzzy evaluations of availability and the ECC system (bucket wheel excavator-conveyor-crushing plant) using a neuro-fuzzy inference system.

Availability is the most commonly used term in maintenance engineering. Djenadic et al. note that, in making decisions on the life cycle of a machine, availability represents the quality of the service of the engineering system or its components with analysis of weak points (see [2]).

The application of soft computing methods is increasingly important in mining. In recent years, there has been an increasing number of studies that consider the application of soft computing methods (fuzzy logic, artificial neural network, ANFIS . . .) in mining (see [3]).

2. Literature Review

The ANFIS methodology is widely used in many branches of technology. In the field of mining, the authors applied it to address the problem of the slope stability of surface mines, the process of drilling and blasting, and the production of oil and gas.

In [4], an analysis of the slope stability of a surface mine was performed using the ANFIS model with one value based on neutrosophic numbers (SVNN-ANFIS). The stability of the surface mine slope has an important impact on the safe operation and economic benefits of the mining company. The results of applying the proposed methodology showed that the accuracy of the training was 99.20%, while the accuracy of the testing process was 97.62%. This approach provides an innovative way to assess the slope stability of a surface mine.

In [5], the size of pieces after the blasting process was performed was predicted using the ANFIS model. The main contribution of the paper was the optimization of the premises and consequent parameters of ANFIS using the frefy algorithm (FFA) and the genetic algorithm (GA). This methodological approach is completely innovative in the field of drilling and blasting.

In [6], the ANFIS model was applied to predict backbreak, which is one of the undesirable effects of the blasting process. Backbreak can cause pit-room instability, uneven fragmentation and reduced drilling efficiency. The performance of the ANFIS model was evaluated based on the root mean squared error ($RMSE$), the variance accounted for (VAF), and the correlation coefficient (R^2) computed from the measured backbreak and model-predicted values of the dependent variables. The $RMSE$, VAF, and R^2 indices were calculated to be 0.6, 0.94 and 0.95, respectively, for the ANFIS model. These indices suggest that the ANFIS model shows excellent prediction performance.

In [7], a hybrid model was developed based on the application of the ANFIS technique and the new optimization algorithm, the Aquila Optimizer (AO). The aim of the analysis was to predict oil production in two oil fields in China and Yemen. The developed model, called AO-ANFIS, was evaluated using real data sets collected during exploitation. Comparisons with the traditional ANFIS model and several modified models were performed. The numerical results and statistics confirmed the superiority of the AO-ANFIS model compared to the traditional ANFIS and several modified variants.

Examples in the literature of the application of soft computing methods related to continuous systems and mechanization in open pit lignite mines are given below.

In the paper, "Determining the Availability of Continuous Systems at the Open Pits Applying the Fuzzy Logic" [8], Gomilanovic et al. provide solutions for the modeling of the availability of open-pit continuous systems using fuzzy logic. The model described was formed by synthesis of partial indicators of availability. The evaluation of the availability of continuous systems is based on an expert system. In this paper, the concept of availability is deconstructed into the partial indicators of reliability and maintainability. The applied fuzzy compositions in the analysis are the max-min and min-max composition. The consideration of partial indicators of availability in relation to conventional models for determining availability does not require long-term monitoring of system behavior in order to predict the state of the system.

Ivezic et al., in the paper, "A Fuzzy Expert Model for Availability Evaluation" [9], performed an analysis of the availability concept in mining machines applying fuzzy logic. The objects of the formed fuzzy model were three types of bulldozers that work in coal mines. The model integrated the reliability, maintainability and functionality of this type of auxiliary machine. On the basis of expert analysis the selected bulldozers were ranked. It was stated that the outcomes of the analysis contributed to improved maintenance, logistics and selection of bulldozer type.

The authors of the paper, "Development of the Availability Concept Using Fuzzy Theory with Ahp Correction, A Case Study: Bulldozers at the Open-Pit Lignite Mine" (see [2]), constructed a model for defining the availability of bulldozers that relied on fuzzy theory and the multi-criteria method for evaluating the AHP. The availability was defined by the selected partial indicators; for each of these, an expert evaluation was given. The assessment included three indicators which directly affected availability: reliability, sustainability and support. The experts evaluated the behavior of certain types of bulldozers based on a description of their condition. Two conditions of the machines were compared, one after two years of use and the other after seven years. In this model, the max-min composition was used. In addition to the use of fuzzy logic, a multi-criteria decision-making method (AHP method) was used in order to rank the partial indicators according to the criterion of their degree of influence on the availability for the type of bulldozer and the age of the equipment.

Milos Tanasijevic et al., in the paper, "Study of Dependability Evaluation for Multi-hierarchical Systems Based on MaxMin Composition" [10], presented a safety model of the functioning of complex technical systems, including the partial indicators of reliability, maintainability and logistic support for maintenance. In this work, the max-min composition was applied to determine the safety of functioning. The concept of performance synthesis of the safety of functioning of common components of complex technical systems was proposed.

Miletic et al., in the paper, "Adaptive Neuro-Fuzzy Prediction of the Bucket Wheel Drive Operation Based on Wear of Cutting Elements" [11], presented a model based on a combination of artificial neural networks and fuzzy logic—the ANFIS (Adaptive Neuro Fuzzy Inference System). The impact of the wear of the cutting elements on the overall behavior of the bucket-wheel excavator during operation was the main topic of this paper.

Gomilanovic and other authors, in the paper, "Predicting the Availability of Continuous Mining Systems Using LSTM Neural Network" [12], developed a model for predicting the availability of continuous systems at the surface mine using artificial neural networks. The main idea of this paper was the improvement of the analytical approach, the starting assumption of which was that the distribution of the time length of the system in failure has an exponential distribution. In this work, data related to the I ECC system of the open pit Drmno Kostolac were used. The aim of this work was to improve the model for predicting the availability of continuous systems at open pits. Based on the $RMSE$, MAE and R^2 values presented in this paper, it was concluded that the model obtained using the neural network had higher predictive power compared to the analytical approach. On the basis of the obtained model, a corresponding simulation was created showing the range of system availability. Based on the simulation, a more accurate picture of the availability of continuous systems at the open pits was provided.

The advantages of the model presented in this paper in relation to the above-mentioned works are described below.

In this work, when determining the fuzzy evaluation of partial indicators for the availability of continuous systems, the experience of experts is not used. Instead, the assessment of fuzzy evaluation is based on historical data for the specific ECC system for a period of three years; in this way a better prediction of the availability of the system itself is enabled. Furthermore, the presented model evaluates availability on a quarterly basis and, thus, includes external influences (e.g., meteorological conditions) affecting the system itself.

Availability is generally not a time-dependent function, but is an umbrella term. Availability is a term that comprises a number of indicators, including reliability and maintainability. Availability can be mathematically expressed as a coefficient, but this does not provide an in-depth picture of the behavior of the engineering system. The model developed in this paper offers exactly that possibility.

For the first time, through this work, the possibility of realizing the conditional-consequential relationship of the availability and meteorological conditions for machines working outdoors is provided.

In the field of the exploitation and maintenance of technical systems used in mining, models are mainly based on the application of the theory of fuzzy logic and neural networks. The model presented in this paper has an innovative character and represents an overarching framework based on previous scientific achievements.

3. Case Study: I ECC System of the Coal Open Pit Drmno Kostolac

Continuous surface mining systems are systems where the flow of material is continuous. They are characterized by excavating during the entire work cycle, in contrast to discontinuous ones, where excavating only takes place for part of the time of one cycle. This enables them to achieve high capacity, which is why they are often used in the energy sector in surface coal mines because they can meet the large fuel needs of thermal power plants. Apart from coal mining, they are widely used in overburden mining due to their capacity and the low unit costs of mining, transporting and disposal of tailings (waste).

The mechanization that is applied is very complex and most often designed according to special requirements because continuous systems must be adapted to the specific conditions of the working environment and the technological requirements regarding the quantity and quality of mineral raw materials [13].

Continuous surface mining systems usually consist of a bucket wheel excavator, a belt conveyor and a spreader, in the case of tailings systems, or a stacker-reclaimer, in the case of coal [14].

The main objective of continuous systems in coal production is the realization of stable and reliable production of a suitable capacity. These systems are connected in a series, as shown in Figure 1 [12].

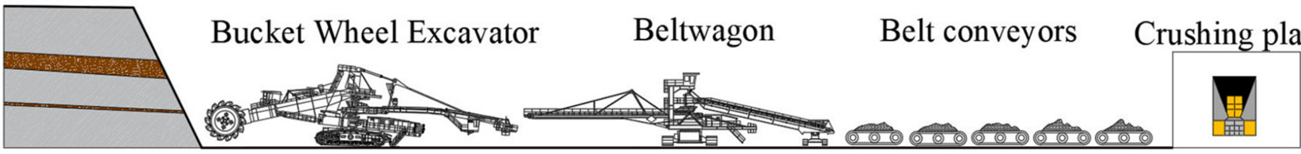

Figure 1. Overview of the ECC system [12].

This paper presents a case study for determination of the fuzzy evaluation of the partial availability indicators of the continuous coal system (I ECC system) of the open pit Drmno Kostolac, which consists of the following elements (subsystems):

- Bucket wheel excavator SRs 400.14/1.5
- Beltwagon BRs 2400
- Belt conveyors
- Crushing plant

Figure 2 shows the equipment that makes up the I ECC System at the coal open pit Drmno Kostolac.

Figure 2. I ECC system at the coal surface mine Drmno Kostolac (photo M. Gomilanovic).

4. Methods

The time state picture is the basis for calculating the availability, in which the times when the system is up alternate with the times when the system is down. Figure 3 shows the time picture of the system state. The time when the system is in a correct state can be divided into the inactive time, that is, the time when the system is waiting for operation (stand-by) (t_{11}), and the time when the system is in operation (t_{12}). The time when the system is in failure is divided into the organizational time (t_{21}), the logistic time (t_{22}), and the active repair time (t_{23}), which can be the time for corrective repairs (t_{231}) and the time for preventive repairs (t_{232}), see [2,12].

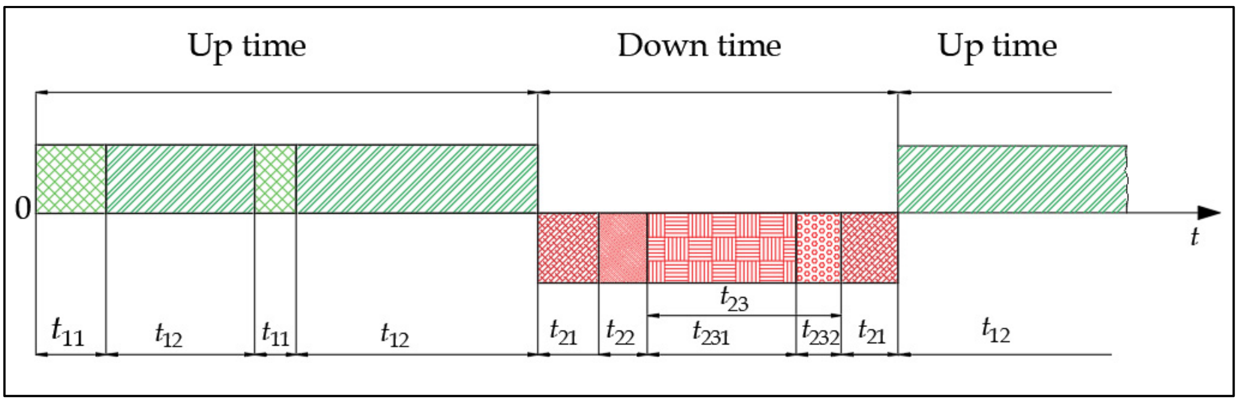

Figure 3. Time picture of the technical system state (see [2,12]).

In [2,12], it is noted that "The availability is determined as the quotient of the total time during which the system is in a correct state and total time that makes up the time in the correct state and time in failure (operational availability)".

$$A(t) = \frac{\sum t_{11}, t_{12}}{\sum t_{11}, t_{12}, t_{21}, t_{22} t_{231}, t_{232}} \tag{1}$$

Development of the Adaptive Neuro-Fuzzy Inference System for Determining the Fuzzy Evaluations of Partial Indicators of the Availability of Continuous Systems

The ANFIS (Adaptive Neuro-Fuzzy Inference System) represents a synthesis of artificial neural networks and fuzzy logic. These systems were developed in the early 1990s, (see [15,16]). The advantages of these systems are reflected in the combination of positive properties of the artificial neural network, which primarily includes the ability to learn, and use of fuzzy logic, which involves expert knowledge assessments.

The structure of the ANFIS system is similar to the structure of artificial neural networks in which an appropriate fuzzy inference system is formed based on the input-output data set and the parameters of the membership functions that define the fuzzy numbers.

The training process is based on determination of the parameter values, adjusted according to the training data [17]. The back-propagation method is the basic means of system training that is used. This algorithm tries to minimize the error between the network and the desired output. The disadvantages of this algorithm are the somewhat longer time required for training and the tendency to "forget" in the local minimum [15]. In order to eliminate the disadvantages of the back-propagation algorithm, a hybrid learning model was developed based on a combination of the back-propagation algorithm with the method of least squares [16]. The ANFIS structure has five layers.

The first layer of the ANFIS system implies the transformation of evaluations obtained by expert assessment into the corresponding fuzzy system where the membership functions are defined by certain continuous functions. It is usual to define the membership functions with the bell-shaped membership function:

$$\mu_A(x) = \frac{1}{1 + \left[\left(\frac{x-a}{b}\right)\right]^2}, \tag{2}$$

Gaussian membership function:

$$\mu_A(x) = \exp\left[-\left(\frac{x-a}{b}\right)^2\right], \tag{3}$$

or the Sigmf (sigmoid) membership function:

$$\mu_A(x) = \frac{1}{1 + \exp(-ax + b)}, \tag{4}$$

where a and b are the real parametric and $b \neq 0$ that need to be estimated. Accordingly, the output data of the first layer are determined by:

$$O_{1d,i} = \mu_{A_{d,i}}(x), \;\; i = 1,2,3 \tag{5}$$

where x is the input parameters of the first layer and (A_{d1}, A_{d2}, A_{d3}) are the corresponding linguistic variables corresponding to the partial indicator d.

The next layer of the ANFIS model combines the output arguments of the previous layer; so, the output data are determined by:

$$O_{2,d_1,d_2,i,j} = \omega_{2,d_1,d_2,i,j} = \mu_{A_{d_{1,}i}}(x) * \mu_{A_{d_{2,}j}}(y), \; i,j = 1,2,3 \tag{6}$$

The above operation represents the AND operator in the fuzzification process.

The next layer includes the process of normalization of the values obtained in the second layer; so, the output data are determined by:

$$O_{3,d_1,d_2,i,j} = \overline{\omega_{d_1,d_2,i,j}} = \frac{\omega_{d_1,d_2,i,j}}{\sum_{d_1 \neq d_2} \sum_{k=1}^{3} \sum_{l=1}^{3} \omega_{d_1,d_2,i,j}},\ i,j = 1,2,3 \tag{7}$$

The next layer is a layer that combines the normalized values from the previous layer and the first-order polynomials. Namely,

$$O_{4,d_1,d_2,i,j} = \overline{\omega_{d_1,d_2,i,j}} f_{d_1,d_2,i,j} = \overline{\omega}_{d_1,d_2,i,j} \left(p_{d_1,d_2,i,j} x + q_{d_1,d_2,i,j} y + r_{d_1,d_2,i,j} \right),\ i,j = 1,2,3 \tag{8}$$

In the last layer, the normalized values of the previous layer are added using the following formula:

$$O_{5 d_1,d_2,i,j} = \sum_{i,j,d_1,d_2,} \overline{\omega_{d_1,d_2,i,j}} f_{d_1,d_2,i,j} = \frac{\sum_{d_1,d_2,i,j} \omega_{d_1,d_2,i,j} f_{d_1,d_2,i,j}}{\sum_{d_1,d_2,i,j} \omega_{d_1,d_2,i,j}} \tag{9}$$

Figures 4–6 show the functions used in the model. Figure 7 shows the ANFIS layers.

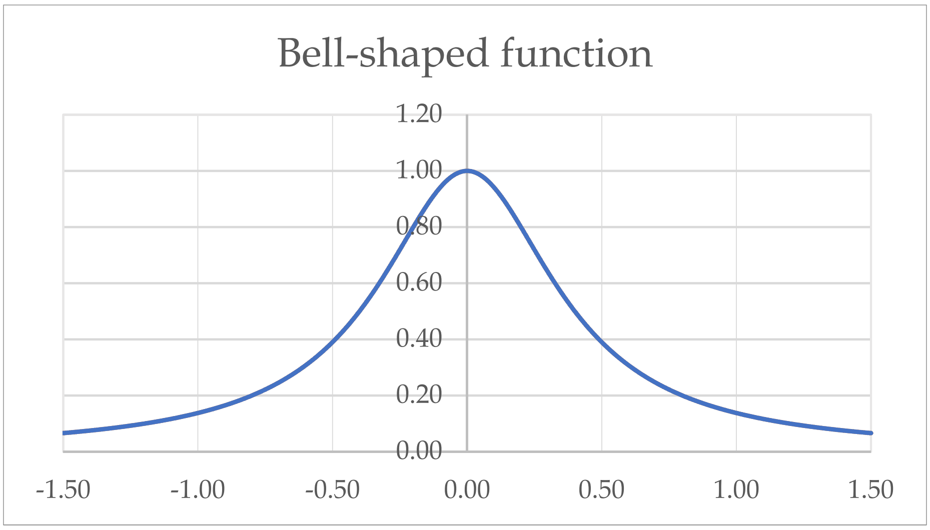

Figure 4. Bell-shaped function for *a* = 0 and *b* = 1.

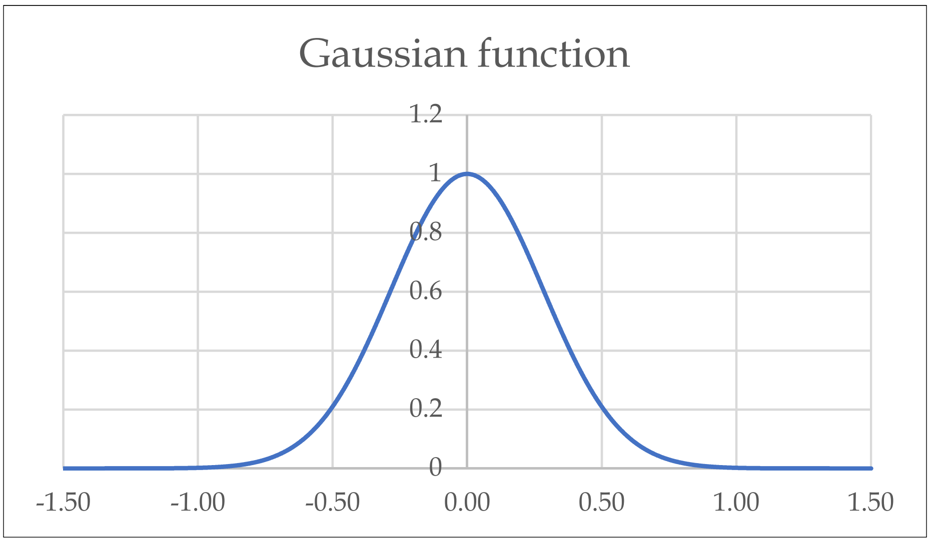

Figure 5. Gaussian function for *a* = 0 and *b* = 1.

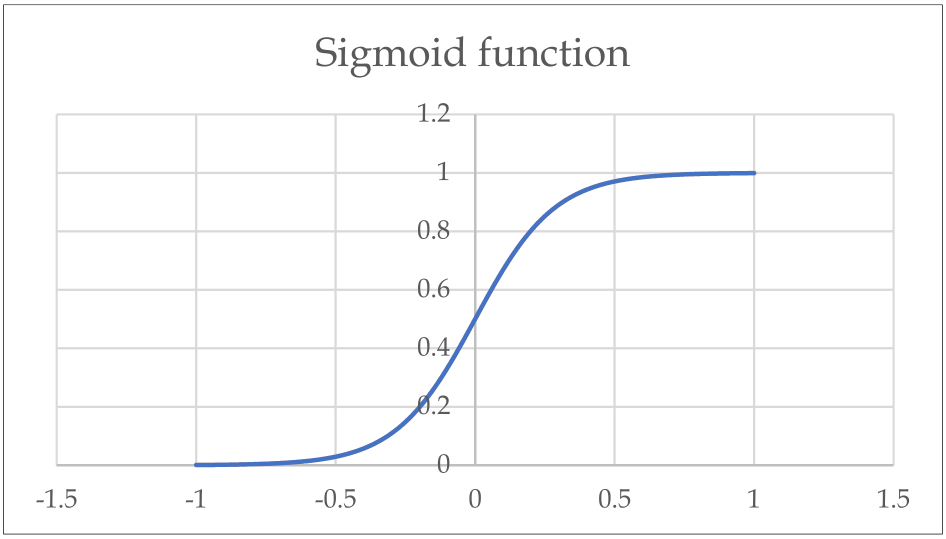

Figure 6. Sigmoid function for $a = 1$ and $b = 0$.

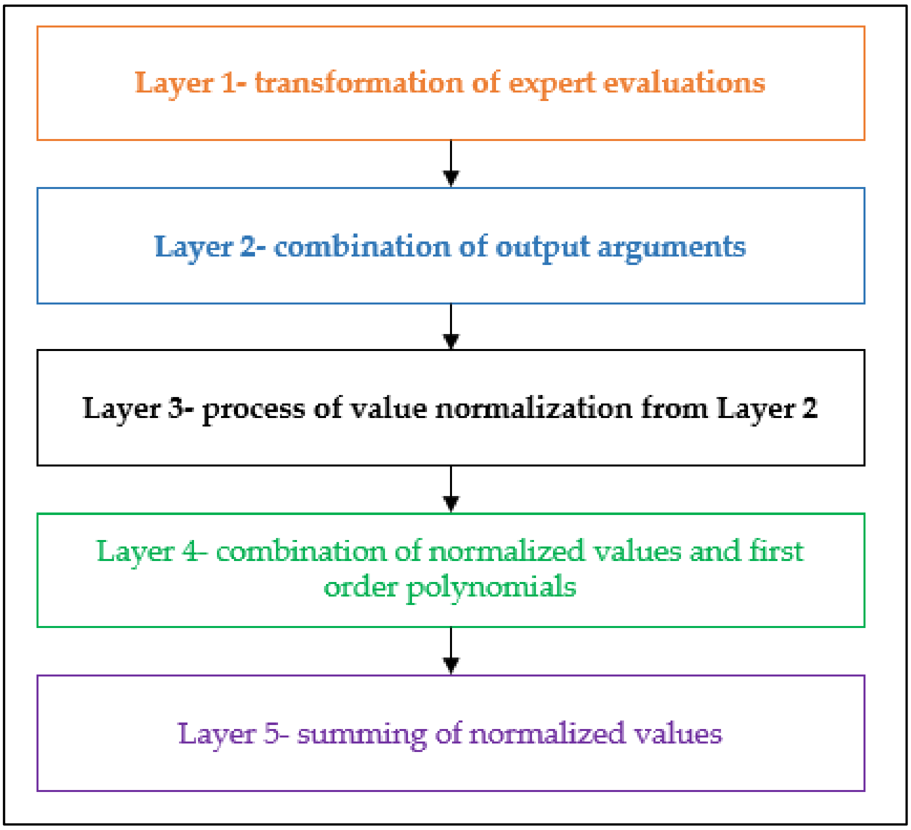

Figure 7. ANFIS layers [18].

Figure 8 shows the architecture of the ANFIS model.

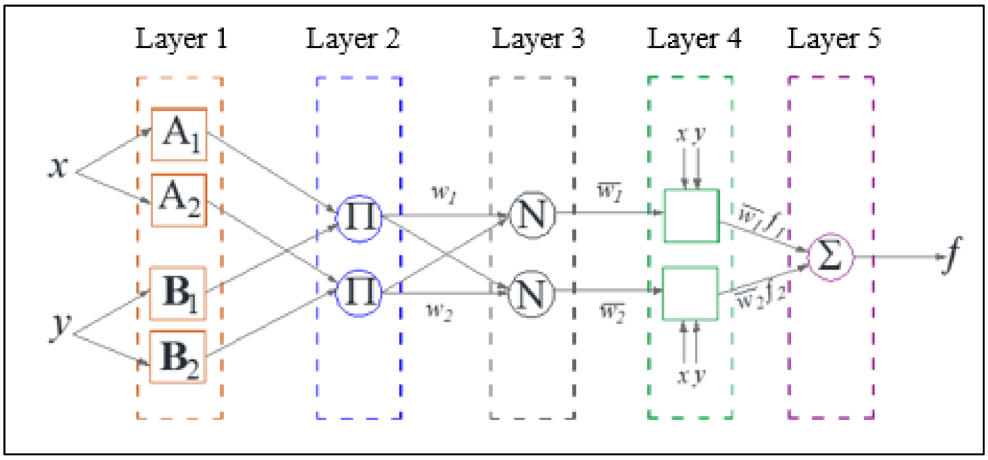

Figure 8. Architecture of the ANFIS model.

The neuro-fuzzy system training is best performed using a hybrid algorithm (Figure 9). The essence of this approach is the extension forward to the fourth layer, where the estimation of the resulting parameters is carried out using the method of least squares. When spreading back to the first layer, data on the size of the error are transferred, which updates the premise parameters using the gradient descent method. When the input membership function parameters are set, the output from the ANFIS model is calculated as follows:

$$\begin{gathered} f = \frac{w_1}{w_1+w_2} \cdot f_1 + \frac{w_2}{w_1+w_2} \cdot f_2 = \overline{w_1} \cdot f_1 + \overline{w_2} \cdot f_2 \\ f = (\overline{w_1} \cdot x) \cdot p_1 + (\overline{w_1} \cdot y) \cdot q_1 + (\overline{w_1}) \cdot r_1 + (\overline{w_2} \cdot x) \cdot p_2 + (\overline{w_2} \cdot y) \cdot q_2 + (\overline{w_2}) \cdot r_2 \end{gathered} \tag{10}$$

The assessment of unknown parameters that configure in the described model is made with certain corrections in order to match the actual and estimated value of the desired parameter to the greatest extent. The $RMSE$ (root mean square error) and MAE (mean absolute error) statistics, defined by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^a - y_i^p\right)^2},\ \ MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i^a - y_i^p\right|, \tag{11}$$

where $y_1^a, y_2^a, \ldots, y_n^a$ are real values, and $y_1^p, y_2^p, \ldots, y_n^p$ are values predicted by the model.

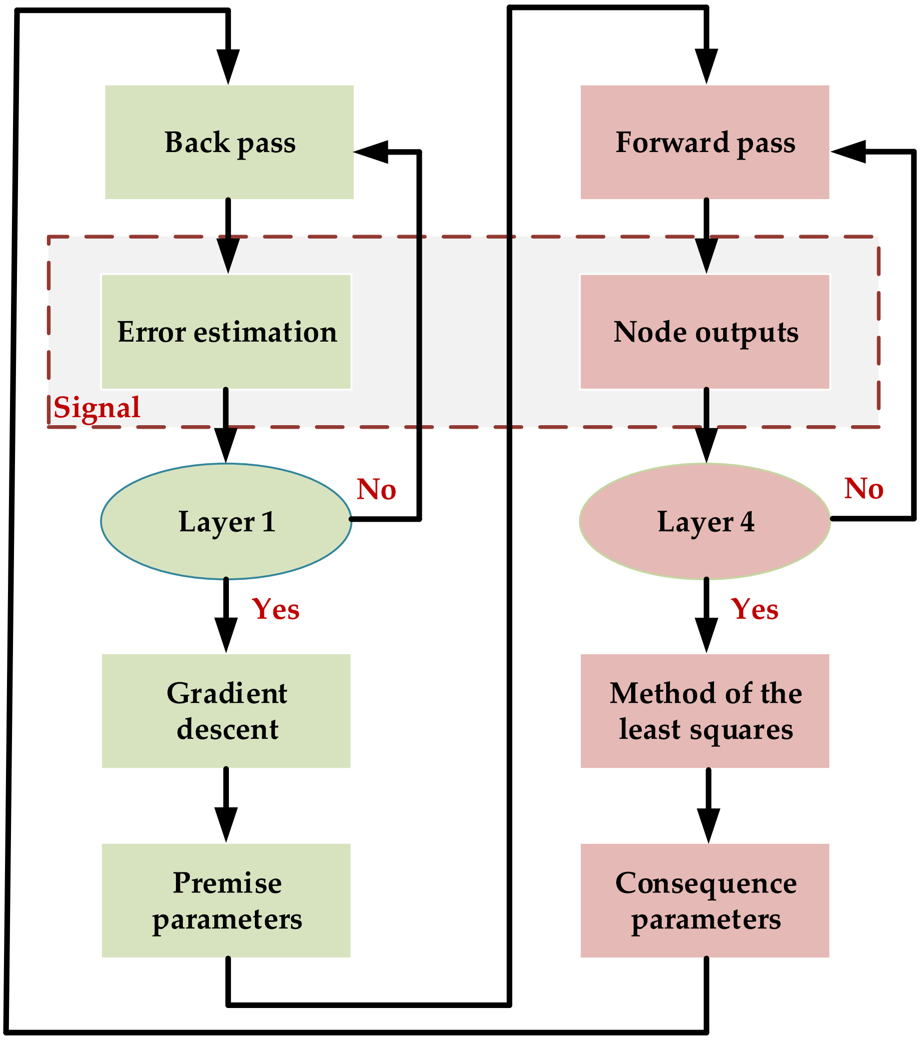

Figure 9. Hybrid algorithm of the ANFIS system training.

5. Results of Expert Assessment

In the literature, most often the availability as a measure of system functioning security is decomposed into the partial indicators, reliability and maintainability. Maintainability is also a complex term that can be described by partial indicators, among which the most important are the following: E-tools and equipment, D-diagnosis, M-manipulability, S-standardization and unification.

Reliability represents the probability that the system will successfully perform the function for which it is intended in a given time interval.

The maintainability depends significantly on the tools and equipment that provide high quality maintenance if they are well chosen. Adequate diagnostics reduce the time it takes to identify and locate the failure, which shortens the total time the system is in failure.

Manipulability is a characteristic of technical systems that describes their ability to be quickly and efficiently transported to a service point, either as a whole or in parts (see [19]).

Standardization and unification include a wide range of system maintenance measures that enable reduction in downtime, and the definition of procedures, technical and organizational measures. In addition to reducing downtime, they improve the quality of maintenance.

Determination of the availability of the continuous system and its partial indicators was derived from the results obtained in a questionnaire related to the expert assessment of the partial indicators of availability. In this model, the availability is divided into the following partial indicators (Figure 10).

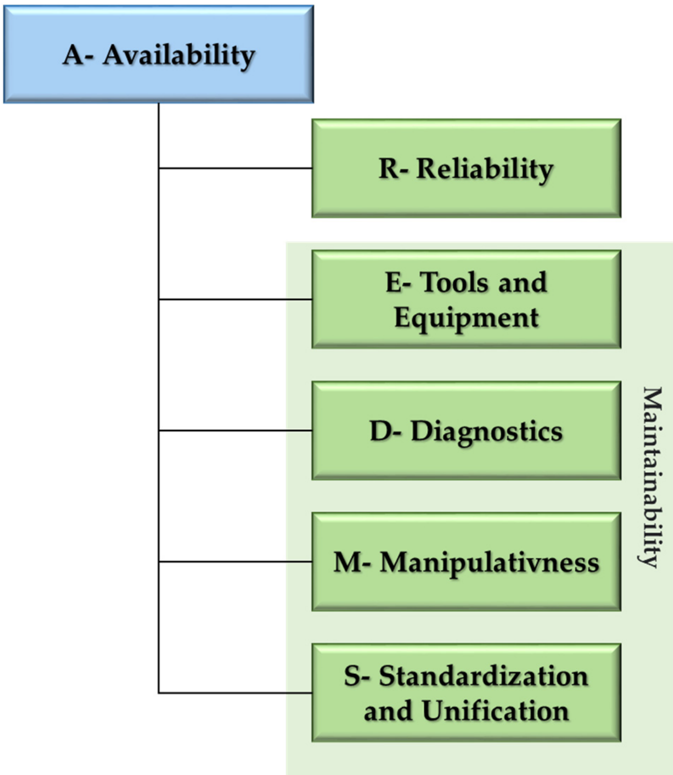

Figure 10. Partial indicators of the availability of continuous systems.

The partial indicators were described in detail in the questionnaire. A total of five experts with long experience in surface mines with a continuous system were included. The expert evaluations referred to the mentioned partial indicators of availability in a certain quarter and cover the period from 2016 to 2018. In the questionnaire, the experts offered ratings ranging from 1 (the worst rating) to 10 (the best rating). The layout of the survey for one partial indicator (R-reliability for 1 Quarter) is shown in Figure 11.

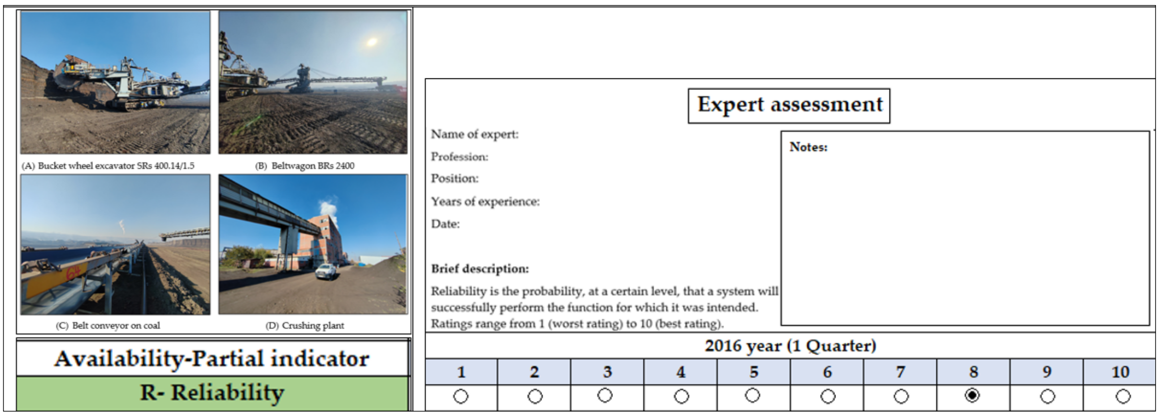

Figure 11. Survey layout for one partial indicator (R-reliability for 1 Quarter).

Table 1 gives the expert evaluations for partial indicators of system availability in the period from 2016–2018.

Table 1. Expert evaluations for partial indicators of system availability in the period from 2016–2018.

Year	Quarter	R	E	D	M	S	Experts	Year	Quarter	R	E	D	M	S	Experts	Year	Quarter	R	E	D	M	S	Experts
2016	1	8	4	6	9	10	1	2017	1	6	5	7	9	10	1	2018	1	5	6	7	8	8	1
		8	4	6	8	10	2			5	6	8	10	9	2			6	8	6	7	8	2
		8	5	7	8	9	3			5	6	8	9	9	3			5	8	7	8	8	3
		9	5	7	8	9	4			4	6	8	9	10	4			6	7	6	7	9	4
		9	4	7	10	8	5			6	5	6	9	10	5			4	7	6	9	9	5
	2	8	5	7	10	10	1		2	4	6	8	9	9	1		2	6	7	6	8	8	1
		9	5	7	9	10	2			5	5	7	8	9	2			5	7	6	8	9	2
		9	4	7	9	10	3			5	4	8	9	10	3			5	7	6	8	8	3
		8	5	7	10	9	4			6	5	7	9	9	4			4	6	7	8	9	4
		9	4	6	9	10	5			5	6	7	8	9	5			5	6	7	9	8	5
	3	8	4	7	8	10	1		3	5	4	8	9	9	1		3	3	6	6	7	8	1
		6	5	7	9	9	2			5	4	9	9	9	2			4	6	6	6	7	2
		8	4	7	9	10	3			4	5	7	8	9	3			4	6	6	7	8	3
		8	4	8	7	10	4			4	3	8	9	10	4			3	7	7	6	7	4
		7	5	6	9	9	5			5	5	7	9	9	5			3	6	7	6	8	5
	4	6	4	7	9	8	1		4	3	5	9	8	8	1		4	6	4	7	9	9	1
		7	5	6	9	8	2			3	5	8	8	8	2			7	5	6	9	8	2
		7	5	6	9	9	3			5	4	6	9	9	3			7	5	6	9	9	3
		6	4	7	9	10	4			3	7	7	7	9	4			6	5	7	8	10	4
		6	5	8	8	9	5			4	6	8	7	8	5			6	4	8	9	8	5

Before conducting analysis, a database was created related to the duration of the mechanical, electrical and other failures and ECC system performance over a period of three years (2016, 2017, 2018). Data from this database were used to determine the availability and to compare it with the results obtained based on the ANFIS model. Table 2 shows a part of the database. The data was taken from the Electric Power Company of Serbia and contained 85,698 pieces of information about failures in the specified time period.

Table 2. Database form (a part of database).

Date	Months	Year	System	Object	Failure	Start of Failure	End of Failure	Downtime	Total Downtime in Minutes	Notes	Shift
1.1.2016	January	2016	I ECC	BWE SRs-400	Electrical	10:00:00	10:50:00	00:50	50	/	1
1.1.2016	January	2016	I ECC	Crushing Plant	Other	13:00:00	14:30:00	01:30	90	/	1
1.1.2016	January	2016	I ECC	BWE SRs-400	Electrical	19:00:00	19:10:00	00:10	10	/	2

Based on the available data, the system availability was determined on a quarterly basis; the obtained values are shown in the next table. Table 3 contains the obtained values for the system availability.

Table 3. Obtained values for the system availability.

Year	Quarter	Availability	Year	Quarter	Availability	Year	Quarter	Availability
2016	1	0.76747	2017	1	0.74064	2018	1	0.69444
	2	0.79212		2	0.71587		2	0.69151
	3	0.76305		3	0.68101		3	0.59121
	4	0.71043		4	0.65674		4	0.70301

Table 4 shows the evaluation parameters for the Gaussian function and Table 5 shows the evaluation parameters for the bell-shaped function. Table 6 shows the evaluation parameters for the sigmoid function.

Table 4. Evaluation parameters of partial indicators for the Gaussian function.

Gaussian Function			
Partial Availability Indicators		***a***	***b***
R—reliability	A_{11}	2.0005	1.0010
	A_{12}	5.0951	1.0900
	A_{13}	8.9980	1.0018
E—tools and equipment	A_{21}	0.0000	0.9999
	A_{22}	4.9873	1.0296
	A_{23}	9.0000	0.9999
D—diagnostics	A_{31}	1.9999	0.9999
	A_{32}	4.9929	0.9930
	A_{33}	9.0001	1.0000
M—manipulativeness	A_{41}	2.0000	1.0000
	A_{42}	5.0000	1.0000
	A_{43}	8.9963	1.0036
S—standardization and unification	A_{51}	2.0000	1.0000
	A_{52}	5.0000	0.9999
	A_{53}	9.0000	1.0000

Table 5. Evaluation parameters of partial indicators for the bell-shaped function.

Bell-Shaped Function			
Partial Availability Indicators		***a***	***b***
R—reliability	A_{11}	2.0000	1.0000
	A_{12}	5.0000	1.0000
	A_{13}	8.8131	1.0000
E—tools and equipment	A_{21}	2.7494	1.0000
	A_{22}	5.0000	1.0000
	A_{23}	8.9996	1.0000
D—diagnostics	A_{31}	2.0000	1.0000
	A_{32}	5.0000	1.0000
	A_{33}	8.9941	1.0000
M—manipulativeness	A_{41}	2.0000	1.0000
	A_{42}	5.0000	1.0000
	A_{43}	9.0030	1.0000
S—standardization and unification	A_{51}	2.0000	1.0000
	A_{52}	5.0000	1.0000
	A_{53}	9.0000	1.0000

Table 6. Evaluation parameters of partial indicators for the Sigmf function.

Sigmf Function			
Partial Availability Indicators		***a***	***b***
R—reliability	A_{11}	2.0000	1.0000
	A_{12}	5.0000	1.0000
	A_{13}	8.8199	1.0000
E—tools and equipment	A_{21}	0.0000	1.0000
	A_{22}	5.0000	1.0000
	A_{23}	8.9995	1.0000
D—diagnostics	A_{31}	2.0000	1.0000
	A_{32}	5.0000	1.0000
	A_{33}	8.9937	1.0000
M—manipulativeness	A_{41}	2.0000	1.0000
	A_{42}	5.0000	1.0000
	A_{43}	9.0013	1.0000
S—standardization and unification	A_{51}	2.0000	1.0000
	A_{52}	5.0000	1.0000
	A_{53}	8.9953	1.0000

A summary of the considered models for predicting the evaluation of partial system availability indicators is given in Table 7.

Table 7. Summary of the considered models for predicting the evaluation of partial indicators of availability.

ANFIS Parameter Type	ANFIS (1)	ANFIS (2)	ANFIS (3)
Number of Inputs	5	5	5
Membership Functions Type	Gaussian function	Bell-shaped function	Sigmf function
Number of Membership Functions	$3 \times 3 \times 3 \times 3 \times 3$	$3 \times 3 \times 3 \times 3 \times 3$	$3 \times 3 \times 3 \times 3 \times 3$
Training Data Set	60	60	60
Epoch Number	20	20	20
Number of Fuzzy Rules	243	243	243
RMSE	0.0013	0.0020	0.00159
MAE	0.0058	0.0127	0.0127

Figures 12–14 show the actual values compared to the values predicted by the ANFIS model.

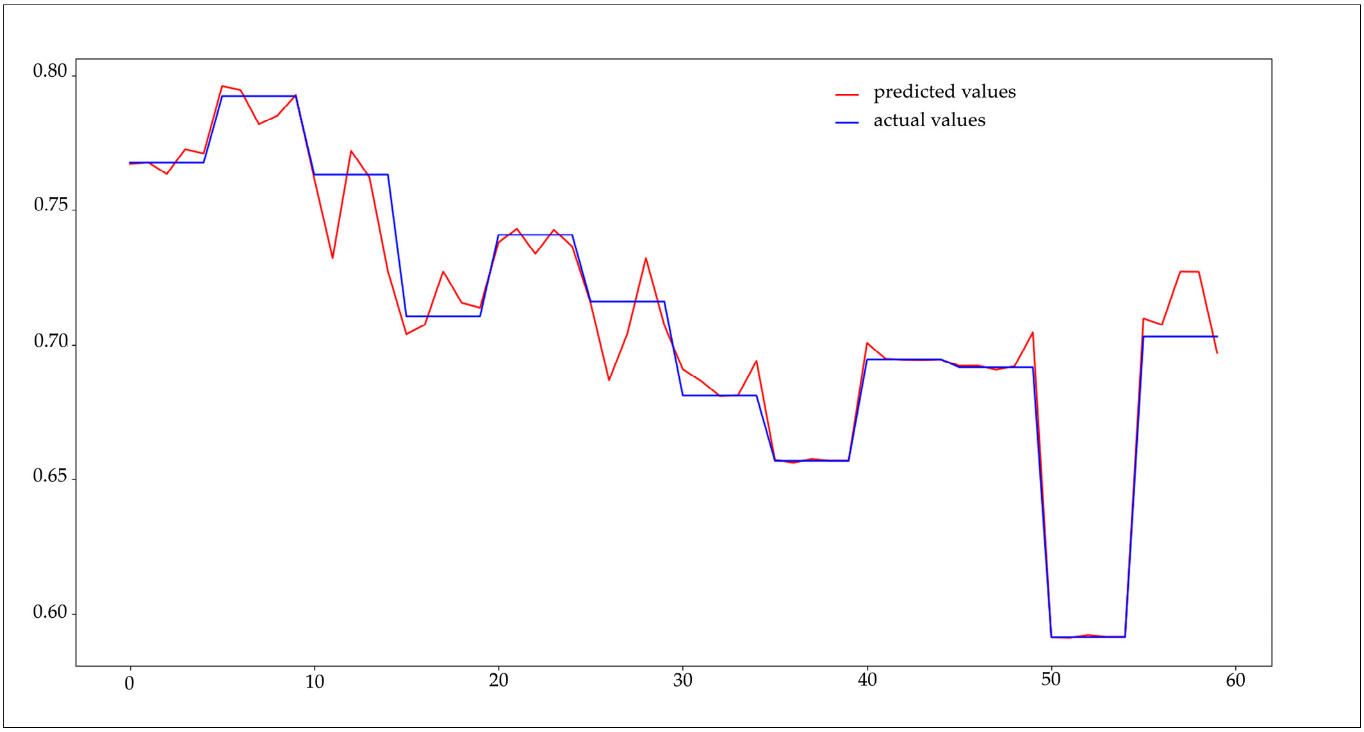

Figure 12. Actual values and values predicted by the ANFIS model—Gaussian function.

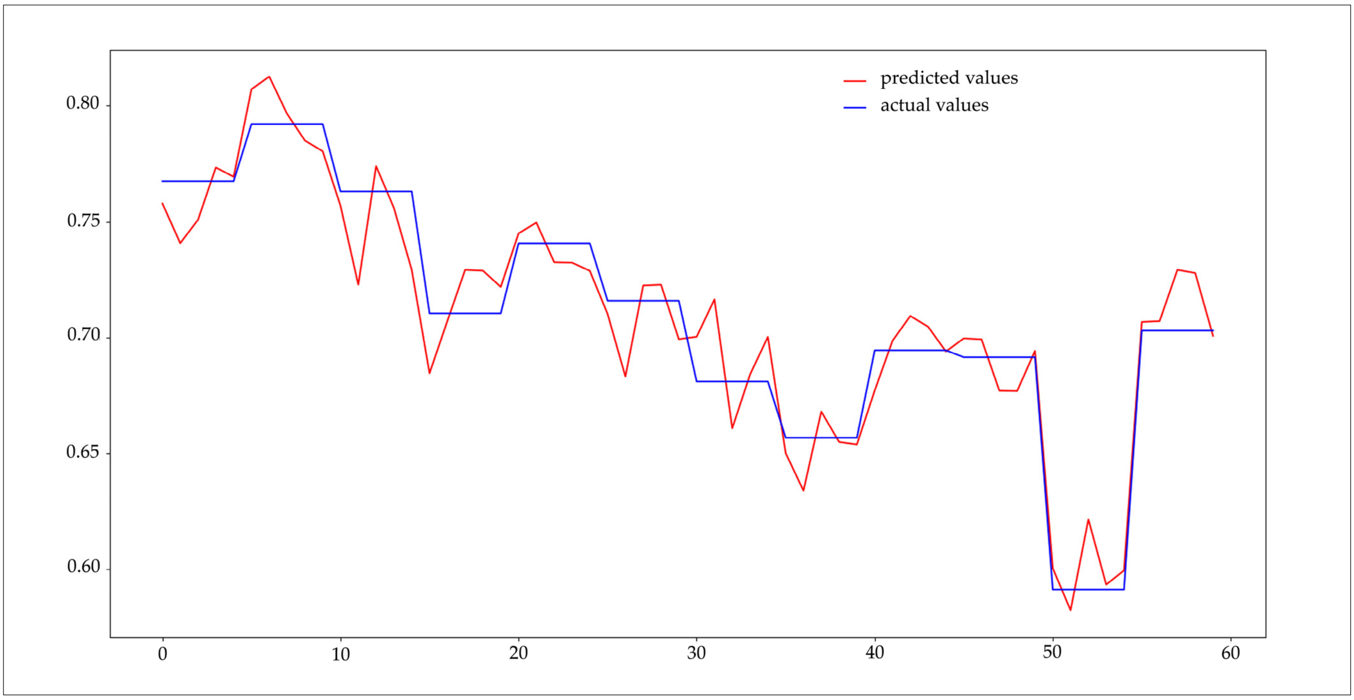

Figure 13. Actual values and values predicted by the ANFIS model—bell-shaped function.

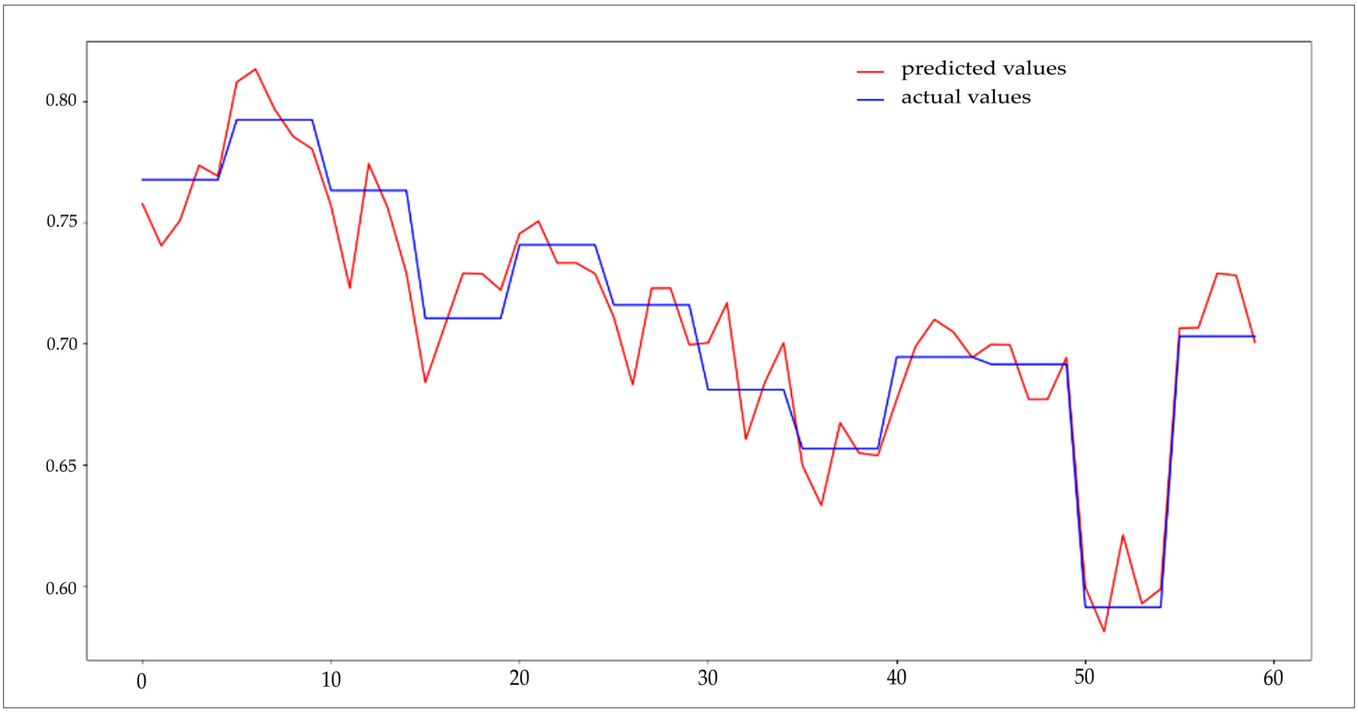

Figure 14. Actual values and values predicted by the ANFIS model—Sigmf (sigmoid) function.

6. Discussion and Conclusions

Bearing in mind the quantity of data on which the model was developed, it is necessary to provide a larger amount of data in the future in order to apply the described technique to them and to further improve the performance of the obtained model. It is necessary to obtain historical data on system downtimes for the period ahead of the period discussed in this paper and, thus, to improve the model itself. Another type of improvement would be increase in the number of experts who, based on their many years of experience, could give estimates for the indicated indicators. By simply increasing the number of observations on which the model was developed, some new indicators could be included, which would create an additional view of the dependence of the availability in relation to indicators for the described model.

Based on the values of the MAE and $RMSE$ statistics shown in Table 7, it is concluded that the model which uses the Gaussian function for partial indicator evaluations provides better prediction ability than the other models which use the Sigmf and bell-shaped functions for the partial indicator evaluations. The advantage of models of this type is that they do not rely on the historical experience of experts and the usual predicted values for the fuzzy evaluation of partial indicators, which are based on the assumption that, in similar systems, similar influences have a similar effect on availability. The evaluation of the fuzzy evaluation of partial indicators is an indicator based on historical data for the specific system for which the model was created. As such, it can more accurately predict the availability of continuous systems based on expert evaluations in the appropriate time period. In this model, the availability is estimated on a quarterly basis giving a more accurate picture because it uses a smaller time period with more similar characteristics, and, thus, includes certain external influences related to the quarterly meteorological conditions. In this model, for the first time, a conditionally consequential connection between the availability and meteorological conditions is provided. The model presented in this paper has an innovative character and represents an overarching framework for previous scientific achievements.

The results of the model can be used in the process of planning, designing and controlling the functioning of continuous systems in surface mines. Based on these, an appropriate maintenance strategy can be developed, with the aim of both increasing the time utilization and reducing maintenance costs. The model is applicable to continuous systems in other areas where appropriate corrections need to be made in accordance with the natural functioning of those systems.

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References

1. Bugarić, U.; Tanasijević, M.; Gomilanović, M.; Petrović, A.; Ilić, M. Analytical determination of the availability of a rotary excavator as a part of coal mining system: Case study: Rotary excavator SchRs 800.15/1.5 of the Drmno open pit. *Min. Metall. Eng. Bor* **2020**, *3–4*, 25–36. [CrossRef]
2. Djenadic, S.; Ignjatovic, D.; Tanasijevic, M.; Bugaric, U.; Jankovic, I.; Subaranovic, T. Development of the Availability Concept by Using Fuzzy Theory with AHP Correction, a Case Study: Bulldozers in the Open-Pit Lignite Mine. *Energies* **2019**, *12*, 4044. [CrossRef]
3. Stanić, N.; Gomilanović, M.; Stepanović, S.; Milijanović, A. Overview of application the Soft Computing methods in the field of mining in our country and in the world. *Min. Met. Eng. Bor* **2022**, *2*, 43–50. [CrossRef]
4. Qin, J.; Du, S.; Ye, J.; Yong, R. SVNN-ANFIS approach for stability evaluation of open-pit mine slopes. *Expert Syst. Appl.* **2022**, *198*, 116816. [CrossRef]
5. Zhou, J.; Li, C.; Arslan, C.A.; Hasanipanah, M.; Amnieh, H.B. Performance evaluation of hybrid FFA-ANFIS and GA-ANFIS models to predict particle size distribution of a muck-pile after blasting. *Eng. Comput.* **2019**, *37*, 265–274. [CrossRef]
6. Bazzazi, A.A.; Esmaeili, M. Prediction of backbreak in open pit blasting by adaptive neuro-fuzzy inference system (anfis) model. *Arch. Min. Sci.* **2012**, *57*, 865–876.
7. AlRassas, A.M.; Al-Qaness, M.A.A.; Ewees, A.A.; Ren, S.; Abd Elaziz, M.; Damaševičius, R.; Krilavičius, T. Optimized ANFIS Model Using Aquila Optimizer for Oil Production Forecasting. *Processes* **2021**, *9*, 1194. [CrossRef]
8. Gomilanovic, M.; Tanasijevic, M.; Stepanovic, S. Determining the Availability of Continuous Systems at Open Pits Applying Fuzzy Logic. *Energies* **2022**, *15*, 6786. [CrossRef]
9. Ivezic, D.; Tanasijevic, M.; Jovancic, P.; Djuric, R. A Fuzzy Expert Model for Availability Evaluation. In Proceedings of the 20th International Carpathian Control Conference (ICCC), Kraków-Wieliczka, Poland, 26–29 May 2019; ISBN 978-1-7281-0701-1.
10. Tanasijević, M.; Ivezić, D.; Jovančić, P.; Ćatić, D.; Zlatanović, D. Study of Dependability Evaluation for Multi-hierarchical Systems Based on Max-Min Composition. *Qual. Reliab. Eng. Int.* **2012**, *29*, 317–326. [CrossRef]
11. Miletić, F.; Jovančić, P.; Milovančević, M.; Ignjatović, D. Adaptive neuro-fuzzy prediction of operation of the bucket wheel drive based on wear of cutting elements. *Adv. Eng. Softw.* **2020**, *146*, 102824. [CrossRef]
12. Gomilanovic, M.; Stanic, N.; Milijanovic, D.; Stepanovic, S.; Milijanovic, A. Predicting the availability of continuous mining systems using LSTM neural network. *Adv. Mech. Eng.* **2022**, *14*, 1–19. [CrossRef]
13. DeLilla, E. Continous surface mining equipment: How to achieve success. *Int. J. Rock Mech. Min. Sci. Geomech. Abstr.* **1995**, *171A*.
14. Banković, M. Optimization of Loading and Transport Systems in the Function of Surface Mining Planning. Ph.D. Thesis, Faculty of Mining and Geology, University of Belgrade, Beograd, Serbia, 2018.
15. Jang, J.-S.R. Fuzzy Modeling Using Generalized Neural Networks and Kalman Filter Algorithm. In Proceedings of the 9th National Conference on Artificial Intelligence, Anaheim, CA, USA, 14–19 July 1991; Volume 2, pp. 762–767.
16. Jang, J.-S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
17. Jovanovic, B. Performance Management of Queues in Postal Traffic. Ph.D. Thesis, University in Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia, 2015.

18. Milovancevic, M.; Denić, N.; Ćirković, B.; Nešić, Z.; Paunović, M.; Stojanović, J. Prediction of shear debonding strength of concrete structure with high-performance fiber reinforced concrete. *Structures* **2021**, *33*, 4475–4480. [CrossRef]
19. Jovančić, P. *Maintenance of Mining Machines*; Faculty of Mining and Geology, University of Belgrade: Belgrade, Serbia, 2014; ISBN 978-86-7352-250-0.

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