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Article

Determining the Availability of Continuous Systems in Open Pits Using ANFIS and a Simulation Model

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Abstract: This paper presents a model for determining the availability of continuous systems at open pits using the neuro-fuzzy system. The concept of availability is divided into partial indicators (synthetic indicators and sub-indicators). The presented model in relation to already existing models for determining availability uses a combination of the advantages of artificial neural networks and fuzzy logic. The case study addressed the I ECC (bucket wheel excavator–conveyors–crushing plant) system of the open pit Drmno, Kostolac. In this paper, in addition to the ANFIS model for determining the availability of continuous systems, a simulation model was developed. The obtained results of the ANFIS model were verified with the help of a simulation model that uses certain assumptions about the distribution of failures. This paper was created as a result of several years of field and theoretical research into the availability of continuous systems in open pits, and completes a cycle that consists of several published articles on the subject of modeling the behavior of these systems in real time using a time picture of the state, expert assessment, simulation and AI models, while respecting the multidisciplinarity of the problem (mining technological, mechanical, and information technological aspects). The developed ANFIS model is a key instrument for improving operational efficiency and resource management in the mining sector. Its ability to accurately predict the availability of the ECC system brings not only operational benefits through reduced downtime and optimized maintenance, but also a potential reduction in overall costs at coal open pits. Such an innovative model marks a significant step forward in the mining industry, especially when it comes to continuous systems in coal open pits.

Keywords: coal; ECC system; open pits; availability; ANFIS; simulation

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1. Introduction

The surface exploitation of coal deposits is carried out in difficult and complex conditions. The operation of continuous systems and their availability is of great importance for the stability of the energy system of the Republic of Serbia, because the largest part of the coal needed for the operation of the power plant is obtained precisely by exploitation with continuous systems. About 70 percent of the electricity in the Republic of Serbia comes from coal.

Continuous surface mining systems are systems where the flow of material is continuous. The mechanization that is applied is very complex and made according to special requirements, because these systems must be adapted to specific working conditions. The basic function of these systems when it comes to surface coal mine is to excavate, transport and deposit coal, which can be uniquely described as coal production.

The application of expert systems based on fuzzy logic and neural networks has played an increasing role in mining. Given that mining as an industrial sector has a major role in global economic development, many authors have tried to improve the operations applied in mining, increase efficiency, and reduce risks to people and the environment by applying expert systems. In the following chapter, an overview of articles concerning the application of expert systems in mining is given.

2. Literature Review

Expert systems based on fuzzy logic and neural networks use the knowledge and rules of experts from a specific domain to make decisions or solve problems. In mining, expert systems can have different applications, intended to improve efficiency, safety and productivity, to optimize the planning and execution of mining operations, to increase the safety of the operations themselves, and to enable the more efficient management of resources while reducing costs.

By implementing expert systems, it is also possible to see equipment's conditions, predict equipment availability, predict maintenance needs, and provide recommendations for the repair or replacement of parts, which would directly affect downtime reduction and increase equipment efficiency.

In the paper "Adaptive neuro-fuzzy prediction of operation of the bucket wheel drive based on wear of cutting elements" [1], Miletic et al. define an ANFIS model that aims to determine how the wear of cutting elements affects the operation of a bucket wheel excavator.

In the paper "A Fuzzy Expert Model for Availability Evaluation" [2], Ivezic and others define the concept of the availability of auxiliary machinery, such as bulldozers. The formed expert fuzzy model analyzes and integrates the partial indicators of the availability of bulldozers working at surface mines (open pits) of the Electric Power Company of Serbia (Beograd, Serbia).

Petrović and others, in the paper "Fuzzy Model for Risk Assessment of Machinery Failures" [3], present a model for the implementation of negative risk parameters in the synthetic risk assessment model of the Lokotrack LT 1213S mobile crusher operating at the open pit Ladna Voda. The model shows that there is a high level of risk and that it is necessary to introduce the concept of risk-based maintenance.

In the paper entitled "Applying the Fuzzy Inference Model in Maintenance Centered to Safety: Case Study—Bucket Wheel Excavator", Jovančić et al. [4] use the Fuzzy Inference Model to promote safety-centered maintenance, which has undergone online adaptation to work conditions. The model was tested on a case study of two SRs 1200 and SchRs 630 bucket wheel excavators.

Monjezi M. and others, in the paper entitled "Evaluation of effect of blast design parameters on flyrock using artificial neural networks" [5], applied the method of artificial neural networks to predict the flying of fragments during blasting at the Sungun copper mine (Sungun), Iran. Several ANN (artificial neural networks) models were run, and it was observed that a model trained with a back-propagation algorithm with a 9-5-2-1 architecture gave the best results. The flight of pieces was calculated side by side on the basis of available empirical models. Statistical modeling was also performed to compare the predictive ability of the artificial neural network against other methods. The comparison of the results showed the absolute superiority of the artificial neural network.

In the article by Qin J. and colleagues entitled "SVNN-ANFIS approach for stability evaluation of open-pit mine slopes" [6], an analysis of the stability of open pit mine slopes was conducted. The study utilized the SVNN-ANFIS model with a singular value for slope stability assessment. The findings from the applied methodology indicate a training accuracy of 99.20% and a testing accuracy of 97.62%.

The article "Predictive Model of Rock Fragmentation Using the Neuro-Fuzzy Inference System (ANFIS) and Particle Swarm Optimization (PSO) to Estimate Fragmentation Size in Open Pit Mining" [7] by Betty Vergara and others describes a predictive model used to estimate rock fragmentation size using the ANFIS in combination with Particle Swarm Optimization (PSO). Utilizing statistical measures such as the correlation coefficient (R2) and mean square error (RMSE), the study determined that the ANFIS-PSO model, with an

R2 value of 0.85 and an RMSE value of 0.78, can be considered a dependable and satisfactory model for predicting rock fragmentation in the field.

In the article “Lost production costs of the overburden excavation system caused by rubber belt failure” [8], Bugarić and others examines the average costs incurred due to malfunctions (resulting in lost production) in the overburden excavation system at the Tamnava-east field open pit mine. The focus is on failures of rubber belts in the belt conveyor system, which operates on a bucket wheel excavator, belt wagon, and spreader. The study determines the unit cost of system malfunctions per hour of belt conveyor operation over the belt’s lifetime. The analysis is based on a proposed methodology that considers the working time to failure of rubber belts. This methodology accounts for sudden failures (tear, breakthrough), described by an exponential distribution, and gradual failures, described by a normal distribution. This approach aids in planning for malfunctions, determining spare rubber belt requirements, reducing operational costs, and suggesting optimal maintenance strategies.

In the article entitled “Reliability of rubber conveyor belts as a part of the overburden removal system-case study: Tamnava-east field open cast mine” [9], Bugaric U. and co-authors define the reliability function for belt conveyors in an ECS system (comprising bucket wheel excavator, belt conveyors, and spreader) at the Tamnava-East field open pit mine in Kolubara. The reliability function is established based on the length of conveyor belts and working hours. The methodology for determining the reliability function involves analyzing the operational time until the failure of belt conveyors. This operational time is characterized by a combination of exponential distribution (representing time until sudden failures) and normal distribution (representing time until gradual failures). Additionally, the study notes a linear relationship between the length of belt conveyors and the mean operational time until gradual failures.

In the paper “Safety Analysis and Synthesis Using Fuzzy Sets and Evidential Reasoning” [10], Wang J., Yang JB., and Sen P. introduce a distinctive approach to analyzing the safety of intricate technical systems. The authors advocate breaking down the system structure into hierarchical levels for a comprehensive assessment. Fuzzy logic is employed to characterize individual failures, and the information is synthesized using fuzzy inference, providing a nuanced understanding of system safety.

In the paper entitled “Reliability of Hydraulic Installation of Auxiliary Mechanization Machines—Applying the Theory of Fuzzy Sets and Factual Reasoning” [11], Tanasijević M. and colleagues conduct a reliability analysis of a technical system. They utilize fuzzy sets theory and integrate the obtained information through factual reasoning. Beyond the conventional quantitative assessment represented by a reliability function, the authors also consider the experiences and insights of maintenance and operational personnel. This approach provides a more realistic depiction of the reliability of the examined technical system.

In the paper entitled “Performance Evaluation of Hybrid FFA-ANFIS and GA-ANFIS Models to Predict Particle Size Distribution of a Muck-pile After Blasting” [12], Zhou J. and collaborators employed an ANFIS model to predict the particle size distribution resulting from the blasting process. The key contribution of the paper lies in optimizing the parameters of the ANFIS model, both initial and consequential, using the Firefly Algorithm (FFA) and Genetic Algorithm (GA).

The authors of the article “Predicting the Risk of Fault-Induced Water Inrush Using the Adaptive Neuro-Fuzzy Inference System” [13] developed a method for forecasting the likelihood of fault-induced water inrush in underground engineering. They utilized the Adaptive Neuro-Fuzzy Inference System (ANFIS) and identified six key parameters related to the aquifer, the water-resisting properties of the aquifuge, and mining-induced stresses. The ANFIS model was trained using twenty documented cases of fault-induced water inrush, and its predictive performance was tested with five additional cases. The conclusive outcomes demonstrated perfect alignment between the predicted results and the actual occurrences for the five test cases.

In the article "Study on ANFIS Application in Coal Mining Stray Current Security Prediction" [14], the authors introduced an Adaptive Neuro-Fuzzy Inference System model specifically tailored for predicting stray current security in coal mining workfaces. This model is capable of predicting workface stray current security using easily measurable parameters from non-production fields. If the stray current surpasses the defined standard, the system issues timely alarms. Additionally, the study compared the accuracy rates of security predictions using different membership functions. The findings reveal that ANFIS, based on subtractive clustering, achieves the highest prediction accuracy and faster computational speed.

In the article titled "Prediction of backbreak in open pit blasting by adaptive neuro-fuzzy inference system (ANFIS) model" [15] authored by Bazzazi A.A. and colleagues, the application of the ANFIS model was explored for predicting cracks, an undesirable outcome of the blasting process. The assessment of the ANFIS model's performance relied on metrics such as the root mean squared error (RMSE), variance accounted for (VAF), and correlation coefficient (R2). The results presented in this study demonstrate the model's outstanding predictive capabilities, indicating its excellent performance in predicting the occurrence of cracks during the blasting process.

The authors of the article [16] introduce a novel approach to enhance the efficiency of ANFIS by utilizing the Mine Blast Algorithm (MBA) for optimization. This marks the first instance of applying MBA to ANFIS learning. The optimized ANFIS, achieved through MBA, is then utilized for predicting the strength of Malaysian small and medium enterprises (SMEs). The findings demonstrate that the ANFIS rule-base optimized by MBA outperforms Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in terms of efficiency in parameter training and overall accuracy.

The idea for the ANFIS model shown in this article, in addition to the mentioned works, came from articles published in the previous period related to this model [17–19].

In the article "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" [17], authored by Bugaric U. and others, a model is presented for analytically determining the availability of the rotary excavator SchRs 800.15/1.5 within the ECC system at the Drmno surface mine. Utilizing this methodology enables the efficient identification of key operational factors over time. Through the application of statistical methods and modeling the work process as a function of time, the study defines functional relationships for parameters like availability, duration of failure, and work duration. The statistical analysis of parameter values provides insights into the current operational stage of the rotary excavator. In this specific instance, the excavator SchRs 800.15/1.5, based on the Bathtub curve, is identified to be in the exploitation phase, mirroring the actual operational context. The determined parameters play a vital role in assessing the availability of the rotary excavator.

In the paper entitled "Determining the Availability of Continuous Systems at Open Pits Applying Fuzzy Logic" [18], Gomilanovic M. and others present a model for determining the availability of continuous systems at open pits using fuzzy logic. The used model was constructed by synthesizing independent partial indicators of availability. This model relies on an expert system to assess the availability of continuous mining systems. The availability of the system, as a complex state parameter, is broken down into partial indicators, i.e., reliability and maintainability, and the fuzzy compositions used for the integration of partial indicators are max–min and min–max compositions. The advantage of this model compared to conventional models is that it takes into account the influence of partial indicators of availability, and it does not require long-term monitoring and records to yield a snapshot of the system's state.

In the paper entitled "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" [19], Gomilanovic M. and others present a model for determining the fuzzy ratings of partial indicators of the availability of continuous systems in surface coal mines using a neuro-fuzzy inference system. The key advantage of this model lies in the fact that it relies on historical data of the specific system (I ECC system of the Drmno surface mine), instead of the general experience of experts and the usual assumed values for fuzzy ratings of partial indicators. As a result, the model can more accurately predict the availability of continuous systems based on expert ratings in a certain period of time. Another advantage of this model is that availability is estimated on a quarterly basis, thus providing a more accurate picture because it focuses on a smaller time period with similar characteristics, thus including certain external influences related to quarterly meteorological conditions. Based on the displayed values of MAE and RMSE statistics, we conclude that the model using the Gaussian function has better prediction capabilities compared to the other displayed models using the Sigmoid and Bell functions.

This article was created as a synthesis of the three mentioned works. In the first paper [17], the availability of one part of the system (the bucket wheel excavator) was calculated using assumptions about the distribution of time in failure and time in operation, which served to create a simulation model that uses theoretical assumptions about the distribution of time of the system, itself composed of four parts (excavator, beltwagon, conveyors and crushing plant). In the second paper, a further composition of the concept of availability was created based on several partial indicators, with the creation of a certain hierarchy between them. This is the availability decomposition used in the development of this ANFIS model. The advantage of the new model compared to the model in paper [18] is that it does not use pre-defined stages of assessment for the mentioned partial sub-indicators, but rather, their form is developed based on historical data of system availability. In the third paper, it is shown how, on the basis of historical data on the availability calculated on a quarterly level, the parameters of the fuzzy assessment of partial indicators can be estimated. The advantage of the new model compared to [19] is that the set of partial indicators has been expanded, and a hierarchical structure has been introduced among them with the application of the IF-THEN rule.

For more detailed information on new modern techniques, and learning expert systems based on fuzzy logic and neural networks, see [20–33].

3. Case Study: I ECC System

The evaluation of the model in this article was performed by focusing on the I ECC system of the Drmno open pit. Continuous surface mining systems usually consist of a bucket wheel excavator, multiple conveyor systems and a stacker or crushing plant.

The I ECC system of the Drmno open pit consists of a bucket wheel excavator (SRs 400.14/1.5), a beltwagon (BRs 2400), conveyors and a crushing plant. Figure 1 shows the Drmno open pit.

Figure 2 shows part I of the ECC system at the Drmno open pit. A more detailed description of the I ECC system is given below in Figure 2.

The bucket wheel excavator SRs 400.14/1.5 is a compact excavator with a relatively short boom in relation to the diameter of the rotor. It can perform selective excavation with a maximum digging height of 14 m. The theoretical capacity of the excavator is 2800 m^3/h. The beltwagon BRs 2400 comprises the connection between the excavator and the conveyor. It allows coal blocks that are further away from the conveyor position to be mined. Its capacity is slightly higher than the capacity of the excavator, 3000 m^3/h.

The transport system consists of seven belt conveyors. Five belt conveyors have a belt width of 1800 mm, with a conveying speed of 5.2 m/s and capacity of 7200 m^3/h. The last two conveyors have a belt width of 2000 mm. The crushing plant is located at the end of the last conveyor. In it, coal is crushed using hammer crushers to a size below 30 mm, suitable for the needs of the thermal power plant.

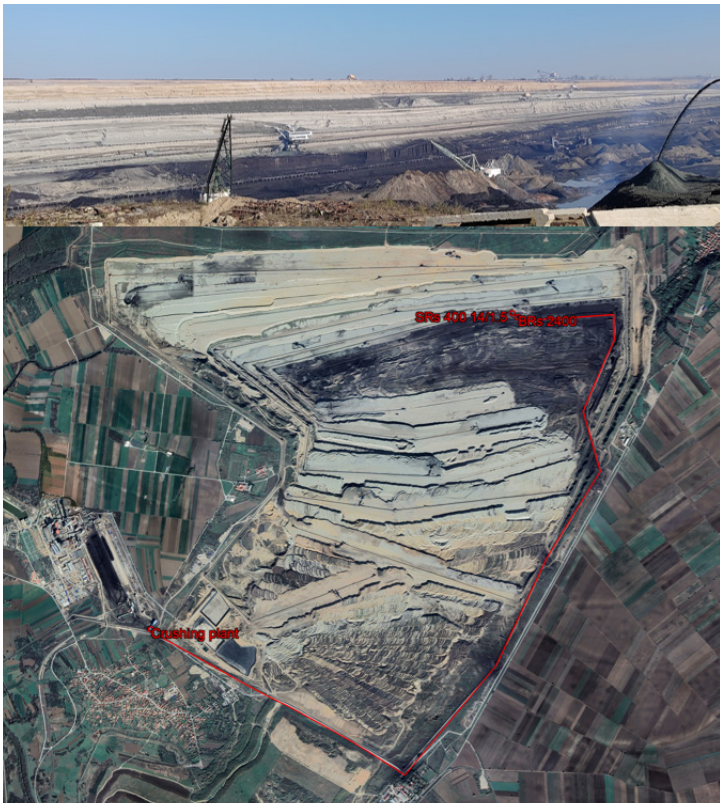

Figure 1. Drmno open pit with the plotted position of the I ECC system (first photo photographed by M.G., second photo: source—Google Earth).

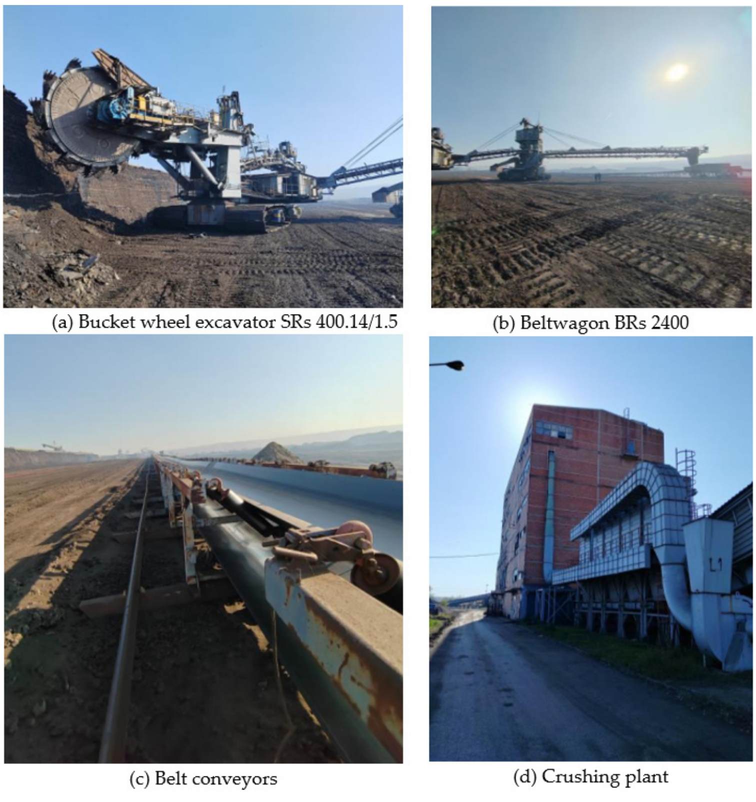

Figure 2. I ECC system at the open pit Drmno with parts of system—(**a**) Bucket wheel excavator, (**b**) Beltwagon BRs 2400, (**c**) Belt conveyors, (**d**) Crushing plant (photographed by M.G.).

4. Availability

Availability is a frequently employed term in maintenance engineering, indicating the service quality of an engineering system, such as machines. It involves the examination of vulnerable areas and asset management, and plays a crucial role in decision-making throughout the lifecycle management process [18].

On the basis of the time state picture [34], wherein the times in the correct state alternate with the times in failure, the availability can be displayed and calculated [34]. The time during which the technical system is operational (in working order) is divided into:

- Time while the technical system waits to be put into operation (t_{11});
- Time when the technical system is in operation (t_{12}).

When the technical system is down, the time is divided into:

- Organizational time (t_{21});
- Logistic time (t_{22});
- Active repair time (t_{23}) (time for corrective repairs (t_{231}) and time for preventive repairs (t_{232})).

Outage times t_{21} and t_{22} refer to breakdown, interventions, the procurement of spare parts, tools, trained workforce and administrative work, etc. Active repair time includes the processes of repair, assembly, disassembly, replacement, etc. [19,34].

Availability can be calculated using Equation (1). The equation is presented as the quotient of the total time during which the technical system is in a correct state (operational) and the total time consisting of the time in the correct state and the time in failure [19,34]:

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

5. Methods and Material

5.1. Development of ANFIS Model

The ANFIS model shown and described below was developed in the Python programming language in the PyCharm 2023.2.1 editor (Community Edition, Jet Brains), which is open to user access.

ANFIS systems exhibit a synergy of artificial neural networks and fuzzy logic (fuzzy inference system). The advantage of these systems is reflected in the combinations of their positive features, namely, the ability to learn with artificial neural networks and the use of expert knowledge with fuzzy logic.

The architecture of the ANFIS system bears resemblance to that of artificial neural networks, where, based on the set of input–output data, a corresponding fuzzy inference system is formed, and the parameters of the membership functions that transform the input data are calculated. The general structure of the ANFIS model consists of five layers (Figure 3). Below is a brief description of the layers.

In the first layer, the input data are transformed into a system of appropriate fuzzy sets:

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

where x is the input argument of the first layer, and $\mu_{d,i}$ is the membership function of the corresponding linguistic variable d.

In the second layer of the ANFIS model, the output parameters from various variables in the preceding layer are integrated. The determination of output data involves:

$$O_{2,d_1,d_2,i,j} = \omega_{2,d_1,d_2,i,j} = \mu_{d_1,i}(x) \cdot \mu_{d_2,j}(y), i, j = 1, 2, \tag{3}$$

where d_1 and d_2 are two different variables.

In the third layer, the values derived from the second layer undergo a normalization process. The normalization procedure is conducted in the following manner:

$$O_{3,d_1,d_2,i,j} = \overline{\omega_{d_1,d_2,i,j}} = \frac{\omega_{d_1,d_2,i,j}}{\sum_{d_1,d_2} \omega_{d_1,d_2,i,j}}, i,j = 1,2. \tag{4}$$

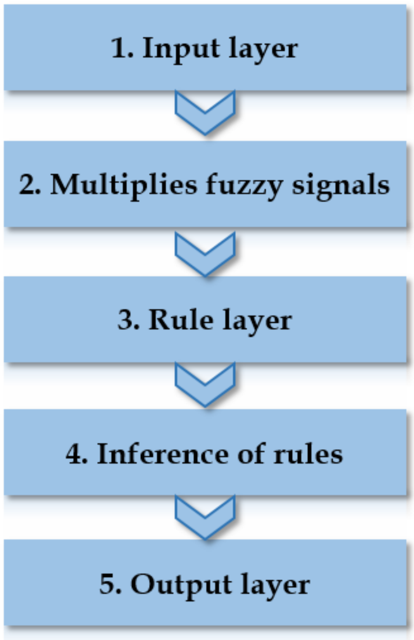

Figure 3. ANFIS layers [19,35].

The following layer involves the amalgamation of normalized values from the preceding layer with first-order polynomials:

$$O_{4,d_1,d_2,i,j} = \overline{\omega_{d_1,d_2,i,j}} f_{d_1,d_2,i,j} = \overline{\omega}_{d_1,d_2,i,j}\left(p_{d_1,d_2,i,j}x + q_{d_1,d_2,i,j}y + r_{d_1,d_2,i,j}\right), i,j = 1,2. \tag{5}$$

where $p_{d_1,d_2,i,j}$, $q_{d_1,d_2,i,j}$ and $r_{d_1,d_2,i,j}$ are the parameters of the fourth layer model.

In the fifth and final layer, the normalized values from the preceding layer are summed using the following formula:

$$O_{5d_1,d_2,i,j} = \sum_{i,j,d_1,d_2,} \overline{\omega_{d_1,d_2,i,j}} f_{d_1,d_2,i,j} = \frac{\sum_{d_1,d_2,i,j} \omega_{d_1,d_2,i,j} f_{d_1,d_2,i,j}}{\sum_{d_1,d_2,i,j} \omega_{d_1,d_2,i,j}} \tag{6}$$

In Figure 4, the general architecture of the ANFIS model described in the previous part is shown.

The training of a neuro-fuzzy system is best done by applying a back-propagation process that uses the $RMSE$ as the error function, defined by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{7}$$

where $y_1, y_2, \ldots, y_n$ are actual values, and $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are values predicted by the ANFIS model.

When the input membership function parameters are set, the output from the ANFIS model is calculated as follows:

$$f = \frac{w_1}{w_1 + w_2} \cdot f_1 + \frac{w_2}{w_1 + w_2} \cdot f_2 = \overline{w_1} \cdot f_1 + \overline{w_2} \cdot f_2 \tag{8}$$

Using $f_1 = x \cdot p_1 + y \cdot q_1 + r_1$ and $f_2 = x \cdot p_2 + y \cdot q_2 + r_2$, the following equality is obtained:

$$f = (\overline{w_1} \cdot x) \cdot p_1 + (\overline{w_1} \cdot y) \cdot q_1 + (\overline{w_1}) \cdot r_1 + (\overline{w_2} \cdot x) \cdot p_2 + (\overline{w_2} \cdot y) \cdot q_2 + (\overline{w_2}) \cdot r_2 \quad (9)$$

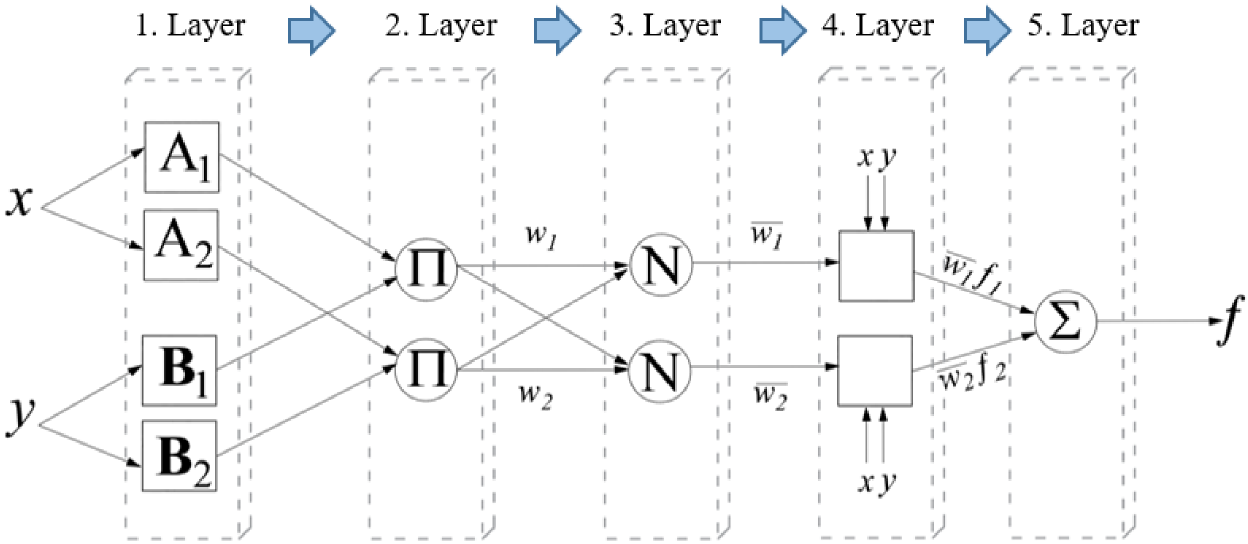

Figure 4. ANFIS model architecture [13].

The training process, referred to as model training, centers around adjusting parameter values based on the provided training data. Essential to this process is the utilization of the back-propagation method, an algorithm designed to minimize the error between the network's output and the desired output.

The determination of the availability of continuous systems and its partial indicators was processed using the results obtained through questionnaires related to the expert assessment of partial indicators of availability, and to historical data on downtime and work, which include the time period from 2016 to 2019.

The ECC system's availability is contingent on specific factors, commonly classified into two groups: partial indicators, such as reliability and maintainability. These synthetic indicators further rely on a multitude of independent parameters (sub-indicators) (Figure 5), all treated as variables within the context of this ANFIS model.

Within this model, availability decomposes into partial sub-indicators that are assessed by experts via a questionnaire. Each component of the I ECC system, including the bucket wheel excavator, beltwagon, belt conveyors, and crushing plant, undergoes evaluation.

In the expert evaluation, 10 experts specializing in continuous systems within surface mining were interviewed. They offered assessments for the sub-indicators of availability during specific quarters, encompassing the timeframe from 2016 to 2019, for each component of the ECC system.

Data from 2016–2018 were used to train the ANFIS model (480 data points—training data set), while data from 2019 (160 data points—test data set) were used to test the obtained model. The experts gave grades in the questionnaire ranging from F (the worst grade) to A (the best grade). The layout of the questionnaire is shown in Figure 6; in this questionnaire, the expert was required to make assessments at the quarterly level in a predetermined period of time for each part I of the ECC system. The scores obtained in this way have been used as input data for this model.

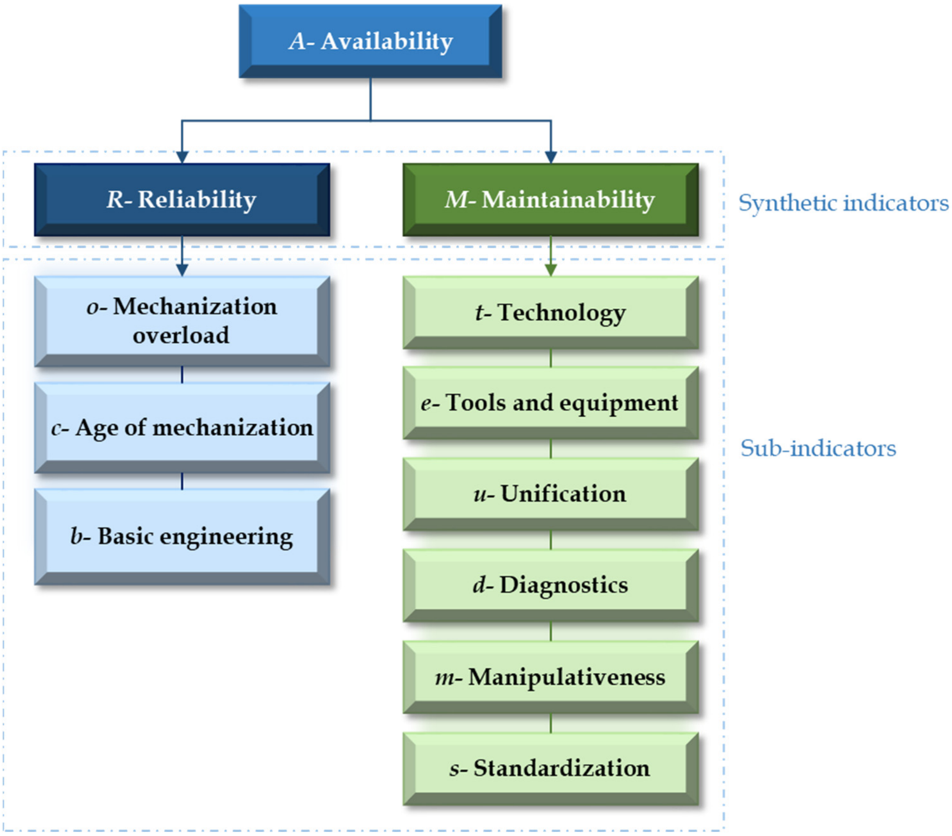

Figure 5. Presentation of partial availability indicators [18] (synthetic indicators, sub-indicators).

I ECC system	Questionnaire						
Part of the system:	Note:						
Expert:							
Year:	Quarter:	Marks					
Description of sub-indicators:	Sub-indicators	F	E	D	C	B	A
o - Mechanization overload	*o*						
c - Age of mechanization	*c*						
b - Basic engineering	*b*						
t - Technology	*t*						
e - Tools and equipment	*e*						
u - Unification	*u*						
d - Diagnostics	*d*						
m - Manipulativeness	*m*						
s - Standardization	*s*						

Figure 6. Layout of the questionnaire.

Prior to model development, a database was established concerning the durations of mechanical, electrical, and other failures within the ECC system spanning four years (2016, 2017, 2018, 2019). Information from this database is employed for calculating historical availability on a quarterly basis, serving as the output data for the ANFIS model. The availability for each quarter was computed using the Formula (1).

In Table 1, part of the database is shown. The data were taken from the Electric Power Company of Serbia and contain information about downtimes on the specific system in the specified time period.

Table 1. Presentation of part of the database on downtimes of the I ECC system.

Date	Month	Year	System	Object	Failure	Start of Failure	End of Failure	Downtime	Total Downtime (min.)	Note	Shift
1 January 2016	January	2016	I ECC	BWE SRs-400	Electrical	10:00:00	10:50:00	00:50	50	/	1
1 January 2016	January	2016	I ECC	Crush. plant	Other	13:00:00	14:30:00	01:30	90	/	1
1 January 2016	January	2016	I ECC	BWE SRs-400	Electrical	19:00:00	19:10:00	00:10	10	/	2

The system's availability was assessed on a quarterly basis (based on the available data), and the resulting values are presented in Table 2.

Table 2. Obtained results for the availability of the I ECC system.

Year	**Quarter**	**Availability**	**Year**	**Quarter**	**Availability**
2016	1	0.8300	2018	1	0.8039
	2	0.8203		2	0.8425
	3	0.8018		3	0.8365
	4	0.8008		4	0.7790
Year	Quarter	Availability	Year	Quarter	Availability
2017	1	0.8079	2019	1	0.8100
	2	0.7825		2	0.7500
	3	0.8370		3	0.7831
	4	0.8177		4	0.7758

The resulting ANFIS model was given the survey results for all nine partial sub-indicators for each part of the I ECC system as input parameters, while the output represents the corresponding availability in the quarter to which the survey results refer, which was obtained based on historical data taken from the Electric Power Company of Serbia.

In the first step of the model, fuzzification was performed, which represents the transformation of partial indicator scores, using membership functions, into the corresponding j-scale for j = 10. Predefined fuzzy sets are not used for probability functions, but membership functions are used instead, the parameters of which are estimated within the model training process. The utilized membership functions include the Bell-shaped membership function, the Gaussian membership function, and the Sigmoid membership function.

Using IF-THEN rules that are pre-defined, the synthetic indicator R is determined based on the partial sub-indicators o, c and b, and the synthetic indicator M is determined based on the partial sub-indicators t, e, u, d, m and s.

In the following, we will illustrate the determination of the synthesis indicator R using IF-THEN rules based on sub-indicators o, c and b. Let the IF-THEN rule be defined by IF o_i AND c_j AND b_k THEN R_l, where i, j and k are in the set $\{A, B, C, D, E, F\}$, and l is in the set $\{A,\ B, C, D, E\}$. Then, the fuzzy sets come together:

$$\mu_{o_i}(x) \cdot \mu_{c_j}(y) \cdot \mu_{b_k}(z), \quad (10)$$

where x, y and z are the input values of grades i, j and k, respectively. For partial indicators o, c and b, we assign the value l. The fuzzy set corresponding to the rating l of the indicator

R is the sum of all fuzzy sets assigned the value l. In a similar way, on the basis of sub-indicators t, e, u, d, m and s, the synthesis indicator M is calculated.

In the next step, using the IF-THEN rules, as described in the previous paragraph, the availability indicator A is determined by synthetic indicators R and M. Then, the Euclidean distance of the obtained fuzzy sets from the fuzzy sets assigned to the availability indicator A is determined based on the corresponding membership functions whose parameters we estimate within this ANFIS model. The distances d_1, d_2, d_3, d_4 and d_5 determined in this way can be joined by the normalized reciprocal values of the relative distances, determined by:

$$\mu_i = \frac{\frac{d_{min}}{d_i}}{\frac{d_{min}}{d_1} + \frac{d_{min}}{d_2} + \frac{d_{min}}{d_3} + \frac{d_{min}}{d_4} + \frac{d_{min}}{d_5}}, i \in \{1, 2, 3, 4, 5\}. \tag{11}$$

These values belong to the appropriate set of grades that determine the indicator of availability, i.e.,

$$A = \{(\mu_1, E), (\mu_2, D), (\mu_3, C), (\mu_4, B), (\mu_5, A)\}. \tag{12}$$

Finally, the linguistic description is transformed into a numerical designation:

$$\frac{1\mu_1 + 2\mu_2 + 3\mu_3 + 4\mu_4 + 5\mu_5}{\mu_1 + \mu_2 + \mu_3 + \mu_4 + \mu_5}. \tag{13}$$

Dividing by 5 gives the predicted value of availability, which is compared with the realized value of availability, calculated on a quarterly basis.

The IF-THEN rules used in this ANFIS model are shown in Tables 3–5. So, for example, the values shown in the first type of this table are interpreted as follows:

Table 3. IF-THEN rules for determining the indicator R—reliability.

o	*c*	*b*	*R*
F	F	F	E
E	E	E	D
D	D	D	C
C	C	C	B
B	B	B	A
B	C	B	A
C	B	C	B
C	B	B	A
B	C	D	B
C	C	B	B
D	C	D	C
E	B	E	C
C	D	B	A
E	E	D	D
C	C	A	A
D	C	B	B
B	B	A	A
B	C	D	B
A	B	A	A
D	B	B	A
D	E	A	B

Table 3. *Cont.*

o	*c*	*b*	*R*
A	*C*	*C*	*A*
A	*C*	*D*	*B*
A	*B*	*B*	*A*
A	*E*	*D*	*B*
A	*B*	*C*	*A*
B	*C*	*E*	*B*
B	*D*	*D*	*B*
B	*E*	*E*	*C*
B	*B*	*A*	*A*
A	*A*	*A*	*A*
F	*E*	*E*	*D*
F	*D*	*D*	*C*
F	*C*	*C*	*B*
F	*A*	*A*	*A*
F	*E*	*D*	*D*
E	*D*	*C*	*C*
D	*C*	*B*	*B*
C	*B*	*A*	*A*

Table 4. IF-THEN rules for determining the indicator *M*—maintainability.

t	*e*	*u*	*d*	*m*	*s*	*M*
F	*F*	*F*	*F*	*F*	*F*	*E*
E	*E*	*E*	*E*	*E*	*E*	*D*
D	*C*	*C*	*C*	*B*	*B*	*B*
D	*C*	*C*	*C*	*C*	*C*	*B*
D	*C*	*A*	*C*	*B*	*B*	*A*
C	*B*	*B*	*B*	*C*	*B*	*A*
B	*C*	*B*	*B*	*B*	*B*	*A*
B	*D*	*D*	*C*	*C*	*C*	*B*
C	*C*	*D*	*B*	*B*	*B*	*B*
D	*C*	*D*	*C*	*D*	*B*	*B*
E	*D*	*C*	*B*	*B*	*C*	*B*
C	*B*	*B*	*B*	*B*	*B*	*A*
B	*D*	*C*	*C*	*B*	*B*	*B*
C	*C*	*B*	*B*	*D*	*C*	*B*
B	*B*	*B*	*B*	*B*	*A*	*A*
B	*A*	*C*	*C*	*C*	*B*	*A*
C	*C*	*B*	*C*	*B*	*B*	*A*
C	*C*	*C*	*C*	*B*	*B*	*B*

Table 4. *Cont.*

t	*e*	*u*	*d*	*m*	*s*	*M*
C	*D*	*C*	*C*	*D*	*C*	*B*
C	*C*	*B*	*B*	*C*	*D*	*B*
C	*A*	*B*	*C*	*D*	*C*	*B*
B	*C*	*D*	*D*	*D*	*B*	*B*
D	*D*	*D*	*D*	*D*	*D*	*C*
C	*C*	*C*	*C*	*C*	*C*	*B*
B	*B*	*B*	*B*	*B*	*B*	*A*
A	*A*	*A*	*A*	*A*	*A*	*A*
E	*E*	*E*	*D*	*D*	*D*	*C*
D	*D*	*D*	*C*	*C*	*C*	*B*
C	*C*	*C*	*B*	*B*	*B*	*A*
B	*B*	*B*	*A*	*A*	*A*	*A*
F	*E*	*D*	*C*	*B*	*A*	*B*
E	*E*	*D*	*C*	*B*	*A*	*B*
D	*E*	*D*	*C*	*B*	*A*	*B*
C	*E*	*D*	*C*	*B*	*A*	*B*
B	*E*	*D*	*C*	*B*	*A*	*A*
A	*E*	*D*	*C*	*B*	*A*	*A*

Table 5. IF-THEN rules for determining *A*—availability.

R	*M*	*A*
D	*D*	*D*
D	*C*	*C*
D	*B*	*C*
D	*A*	*B*
C	*D*	*C*
B	*D*	*C*
C	*C*	*C*
B	*B*	*B*
A	*A*	*A*
E	*D*	*D*
C	*B*	*B*
B	*A*	*A*
C	*A*	*B*

If the partial sub-indicator *o* is *F* (the working environment conditions typically do not align with the requirements for the equipment in use), and if the partial sub-indicator *c* is *F* (write-off machine, very high level of failure) and the partial sub-indicator *b* is *F* (underdeveloped basic engineering), then indicator *R* is unreliable, *E*.

A summary of the models considered for predicting availability is given in Table 6.

Table 6. A summarized overview of the models being examined for predictive availability.

ANFIS Parameters	**1**	**2**	**3**
Inputs (number)	9	9	9
Function type	Gaussian function	Bell-shaped function	Sigmoid function
Number of membership functions	$6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6$	$6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6$	$6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6$
Training data set	480	480	480
Test data set	160	160	160
Number of iterations	10	10	10
Number of fuzzy rules	39 (R) + 36 (M) + 13 (A)	39 (R) + 36 (M) + 13 (A)	39 (R) + 36 (M) + 13 (A)
$RMSE$(Training data set)	0.0000	0.0000	0.0000
$RMSE$(Test data set)	0.0014	0.0015	0.0015

480 data—training data set, given as an attachment to this article (4 parts of the system × 3 years × 4 quarters × 10 experts). 160 data—test data set, given as an attachment to this article (4 parts of the system × 1 year × 4 quarters × 10 experts).

5.2. Development of Simulation Model

During the creation of the simulation model, all failures were classified into one of three types of failure (mechanical, electrical, and others). As in the case of the ANFIS model, the simulation model used data from three years (2016, 2017 and 2018) to obtain results.

In Table 7, the experimental and theoretical frequencies of machine failures by interval are given.

Table 7. Experimental and theoretical frequency of mechanical failures by interval.

No.	**The Lower Bound of the Interval**	**The Upper Bound of the Interval**	**Experimental pdf**	**Experimental cdf**	**Theoretical pdf**	**Theoretical cdf**	**KS Test**
1	5	14	0.2682	0.2682	0.2230	0.2230	0.0452
2	14	22	0.2948	0.5630	0.2890	0.5120	0.0510
3	22	31	0.1607	0.7237	0.1765	0.6885	0.0353
4	31	40	0.0363	0.7601	0.1109	0.7994	0.0393
5	40	48	0.0727	0.8328	0.0706	0.8700	0.0372
6	48	57	0.0372	0.8700	0.0454	0.9153	0.0454
7	57	66	0.0412	0.9111	0.0293	0.9447	0.0335
8	66	74	0.0129	0.9241	0.0191	0.9637	0.0396
9	74	83	0.0145	0.9386	0.0124	0.9761	0.0375
10	83	92	0.0210	0.9596	0.0081	0.9843	0.0247
11	92	100	0.0162	0.9758	0.0053	0.9896	0.0138
12	100	109	0.0040	0.9798	0.0035	0.9931	0.0133
13	109	118	0.0137	0.9935	0.0023	0.9954	0.0019
14	118	126	0.0032	0.9968	0.0015	0.9970	0.0002

The distributions of mechanical failure times, considered in the 96th percentile of the data, conform to the Weibull distribution, with parameters $\gamma = 5$, $\beta = 0.9511$ and $\eta = 18.4311$. More precisely, the empirical distribution function is determined by:

$$F(x) = 1 - \exp\left(-\left(\frac{x-5}{18.4311}\right)^{0.9511}\right) \tag{14}$$

The model was developed based on a total of 1238 instances of mechanical failures.

The testing of the hypothesis regarding the distribution of data was performed with the help of the Kolmogornov–Smirnov test, whose statistic value $\sqrt{n}\, D_n$ is equal to 1.7944, so with a significance level of 0.001 we cannot reject the null hypothesis that claims that the data are in accordance with the Weibull distribution. The Figure 7 shows the experimental and theoretical functions of the distribution of mechanical failures.

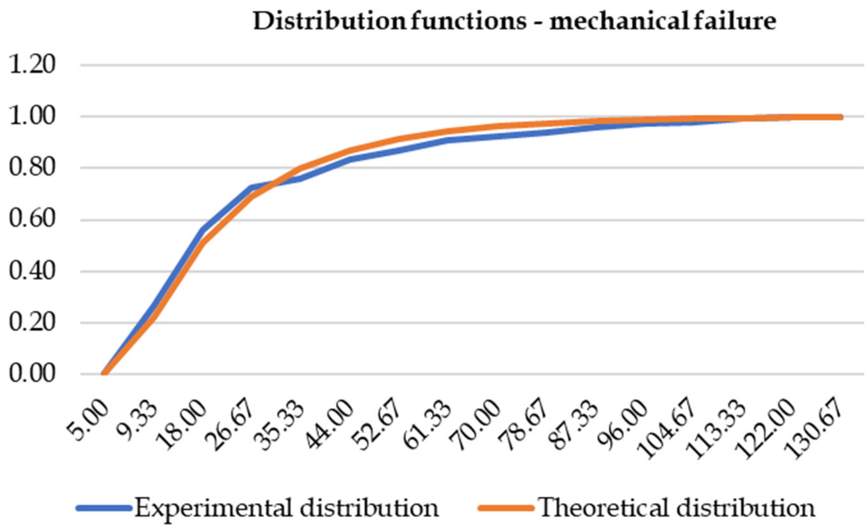

Figure 7. Experimental and theoretical distribution functions of mechanical failures.

In Table 8, experimental and theoretical frequencies of electrical failures by interval are given.

Table 8. Experimental and theoretical frequency of electrical failures by interval.

No.	The Lower Bound of the Interval	The Upper Bound of the Interval	Experimental pdf	Experimental cdf	Theoretical pdf	Theoretical cdf	KS Test
1	5	20	0.2996	0.2996	0.2571	0.2571	0.0425
2	20	35	0.2500	0.5496	0.2956	0.5527	0.0031
3	35	50	0.1608	0.7104	0.1688	0.7215	0.0111
4	50	65	0.1145	0.8249	0.1020	0.8235	0.0014
5	65	80	0.0518	0.8767	0.0633	0.8867	0.0101
6	80	95	0.0385	0.9152	0.0399	0.9267	0.0115
7	95	110	0.0165	0.9317	0.0255	0.9522	0.0204
8	110	125	0.0187	0.9504	0.0164	0.9686	0.0182
9	125	140	0.0066	0.9570	0.0107	0.9793	0.0222
10	140	155	0.0110	0.9681	0.0070	0.9863	0.0182
11	155	170	0.0099	0.9780	0.0046	0.9909	0.0129
12	170	185	0.0088	0.9868	0.0030	0.9939	0.0071
13	185	200	0.0055	0.9923	0.0020	0.9959	0.0036
14	200	215	0.0077	1.0000	0.0013	0.9973	0.0027

The distribution of the duration of electrical failures, considered in the 98.5th percentile of the data, is in accordance with the Weibull distribution, with parameters $\gamma = 5$, $\beta = 0.9066$ and $\eta = 28.6022$. More precisely, the empirical distribution function is determined by:

$$F(x) = 1 - \exp\left(-(\frac{x-5}{28.6022})^{0.9066} \right) \tag{15}$$

The number of electrical failures on which this model was developed amounted to 908 failures. The testing of the hypothesis regarding data distribution was performed with the help of the Kolmogornov–Smirnov test, whose statistic value $\sqrt{n}\, D_n$ is equal to 1.2804, so with a significance level of 0.05, we cannot reject the null hypothesis that claims that the data are in accordance with the Weibull distribution. Figure 8 shows the experimental and theoretical distribution functions of electrical failure.

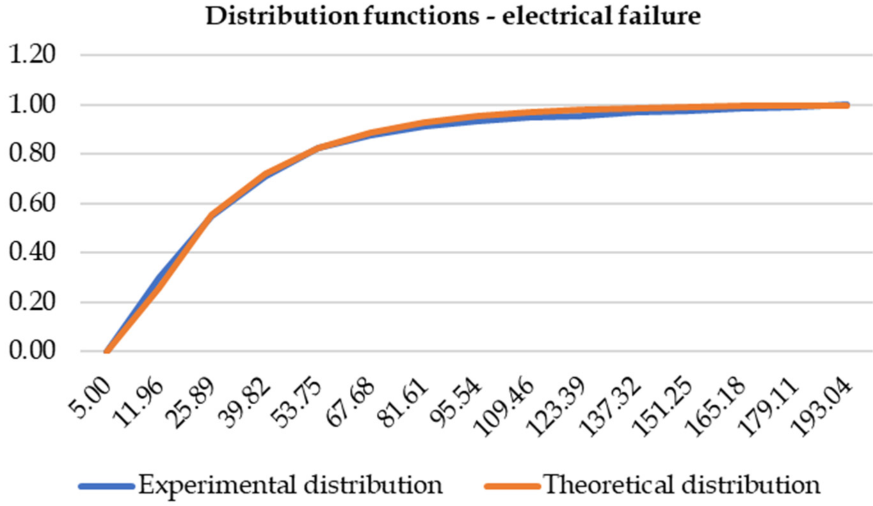

Figure 8. Experimental and theoretical distribution functions of electrical failure.

In Table 9, experimental and theoretical frequencies of other failures by interval are given.

Table 9. Experimental and theoretical frequency of other failures by interval.

No.	The Lower Bound of the Interval	The Upper Bound of the Interval	Experimental pdf	Experimental cdf	Theoretical pdf	Theoretical cdf	KS Test
1	5	53	0.3803	0.3803	0.3910	0.3910	0.0107
2	53	101	0.2837	0.6640	0.2381	0.6291	0.0350
3	101	149	0.1384	0.8025	0.1450	0.7741	0.0284
4	149	198	0.0823	0.8847	0.0883	0.8624	0.0223
5	198	246	0.0433	0.9281	0.0538	0.9162	0.0119
6	246	294	0.0217	0.9498	0.0328	0.9490	0.0008
7	294	342	0.0172	0.9670	0.0200	0.9689	0.0019
8	342	390	0.0069	0.9739	0.0122	0.9811	0.0072
9	390	438	0.0113	0.9852	0.0074	0.9885	0.0032
10	438	486	0.0054	0.9906	0.0045	0.9930	0.0023
11	486	534	0.0015	0.9921	0.0027	0.9957	0.0036
12	534	583	0.0015	0.9936	0.0017	0.9974	0.0038
13	583	631	0.0015	0.9951	0.0010	0.9984	0.0033
14	631	679	0.0020	0.9970	0.0006	0.9990	0.0020
15	679	727	0.0020	0.9990	0.0004	0.9994	0.0004
16	727	775	0.0010	1.0000	0.0002	0.9996	0.0004

The distribution of the durations of other failures, considered in the 100th percentile of the data, is in accordance with the exponential distribution, with parameters $\gamma = 5$ and $\lambda = 0.0103$. More precisely, the empirical distribution function is determined by:

$$F(x) = 1 - \exp(-0.0103 \cdot (x - 5)) \quad (16)$$

The number of other failures on which this model was developed amounted to 2030 failures. The testing of the hypothesis regarding data distribution was performed with the help of the Kolmogornov–Smirnov test whose value of the statistic $\sqrt{n}\, D_n$ is equal to 1.5761, so with a significance level of 0.01, we cannot reject the null hypothesis, which claims that the data are in accordance with the exponential distribution. Figure 9 shows the experimental and theoretical distribution functions of other failures.

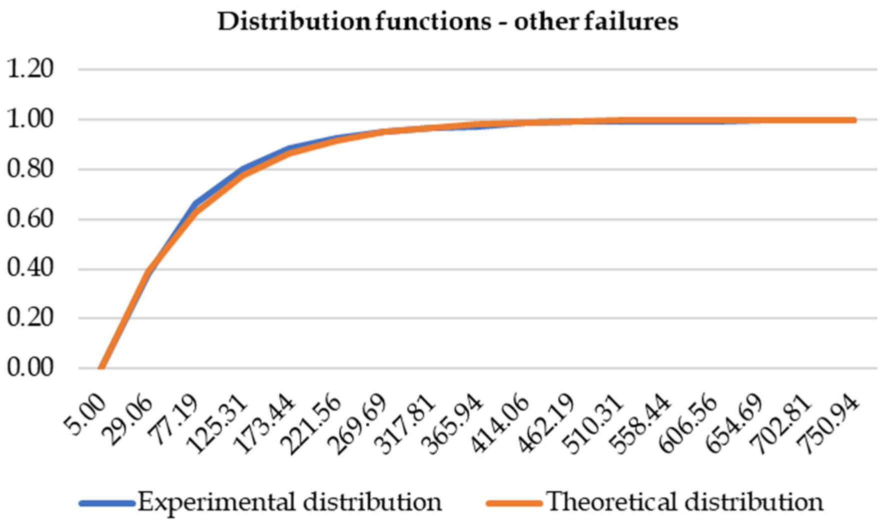

Figure 9. Experimental and theoretical distribution functions of other failures.

In Table 10, the experimental and theoretical frequencies of duration between failures by interval are given.

Table 10. Experimental and theoretical frequencies of duration between failures by interval.

No.	The Lower Bound of the Interval	The Upper Bound of the Interval	Experimental pdf	Experimental cdf	Theoretical pdf	Theoretical cdf	KS Test
1	20	102	0.0819	0.0819	0.0780	0.0780	0.0040
2	102	184	0.1556	0.2375	0.1560	0.2339	0.0036
3	184	266	0.1765	0.4140	0.1660	0.3999	0.0141
4	266	348	0.1450	0.5591	0.1476	0.5475	0.0116
5	348	430	0.1061	0.6652	0.1202	0.6677	0.0025
6	430	512	0.0967	0.7619	0.0930	0.7607	0.0012
7	512	594	0.0670	0.8289	0.0696	0.8302	0.0014
8	594	676	0.0524	0.8812	0.0508	0.8810	0.0002
9	676	758	0.0351	0.9163	0.0364	0.9174	0.0011
10	758	839	0.0198	0.9361	0.0257	0.9431	0.0070
11	839	921	0.0211	0.9572	0.0180	0.9611	0.0039
12	921	1003	0.0140	0.9712	0.0124	0.9735	0.0023
13	1003	1085	0.0092	0.9804	0.0086	0.9821	0.0017
14	1085	1167	0.0054	0.9858	0.0058	0.9879	0.0021
15	1167	1249	0.0048	0.9906	0.0040	0.9919	0.0013
16	1249	1331	0.0052	0.9958	0.0027	0.9946	0.0012
17	1331	1413	0.0023	0.9981	0.0018	0.9964	0.0017
18	1413	1495	0.0019	1.0000	0.0012	0.9976	0.0024

The distribution of the durations between failures, considered in the 95th percentile of the data, is in accordance with the Erlang distribution, with parameters $\gamma = 20$, $k = 2$ and $\lambda = 0.0057$. More precisely, the empirical distribution function is determined by:

$$F(x) = 1 - (1 + 0.0057 \cdot (x - 20)) \exp(-0.0057 \cdot (x - 20)) \quad (17)$$

The number of times between failures on which this model was developed was 5212. The testing of the hypothesis regarding the distribution of data was carried out with the help of the Kolmogornov–Smirnov test, whose value for the statistic $\sqrt{n}\, D_n$ is equal to 1.0192, so with a significance level of 0.2 we cannot reject the null hypothesis that claims that the data are in accordance with the Erlang distribution. Figure 10 shows the experimental and theoretical time distribution functions between failures.

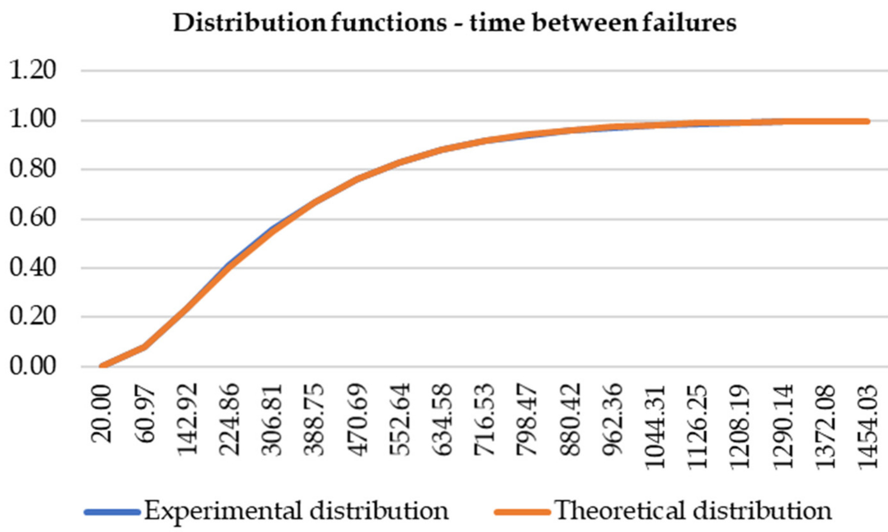

Figure 10. Experimental and theoretical time distribution functions between failures.

During the duration of mechanical and electrical failures, the parameter (β) of the Weibull distribution is close to unity, but less than 1, which indicates that the equipment, parts, etc., both mechanical and electrical, have an approximately constant intensity of maintenance, which is already the case with other failures (exponential distribution), which means that the total intensity of maintenance of the ECC system is approximately constant when $t \to \infty$, that is, it can be considered a function of the convenience of keeping (maintainability) the entire ECC system roughly exponential, and it represents Poisson's recovery process. Below (Figure 11), we show the maintainability function for different types of failures.

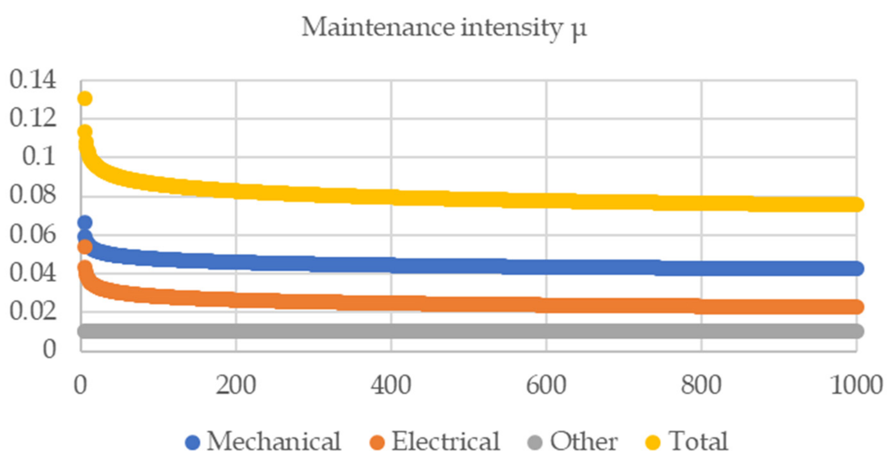

Figure 11. Maintainability functions for different types of failures.

The obtained distribution of times between failures, of Erlang order $k = 2$, indicates that with time, the intensity of failure increases (which is shown in the Figure 12) i.e., the ECC system is at the end of the "exploitation" period and the beginning of the "obsolescence" period (periods II and III of the "bathtub" curve). For $k = 1$ (exponential distribution), the system is in period II of "exploitation". The following figure (Figure 12) shows the intensity of the failure.

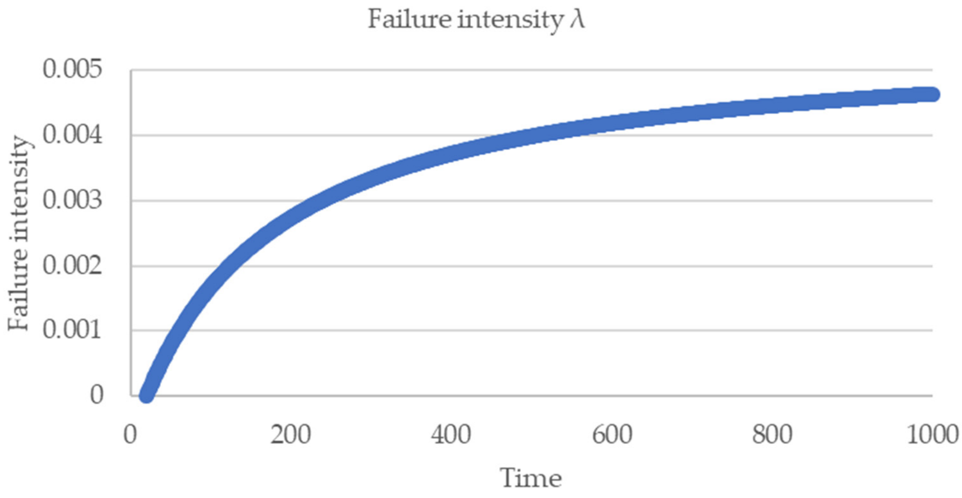

Figure 12. Failure intensity.

Figure 13 shows the frequency distributions of the considered failure types.

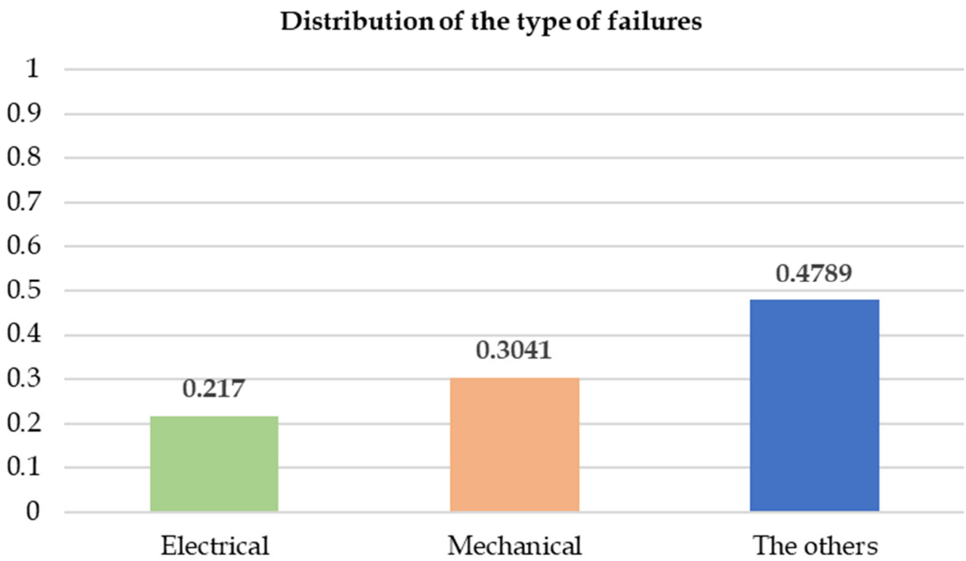

Figure 13. Frequency distribution of the considered failure types.

The algorithm of the developed simulation model is shown in Figure 14. The theoretical distributions obtained using the K-S test are used for generating failure duration times and times between failures in the following way. For mechanical and electrical failures, Weibull distribution is used (Figures 7 and 8), while exponential distribution is used for other failures (Figure 9). For generating the types of failures, empirical distribution, shown in Figure 13, is used. Times between failures are generated using Erlang distribution, as shown in Figure 10.

The simulation experiment is performed for a time period of one year (t_{sim}), while the simulation time (t) is calculated in seconds. The number of simulation (No_{sim}) experiments is one hundred.

At the beginning, for t = 0, the initial state of the system is defined as the state of the ECC system "running" (State = "1"). At this point, the time (t_{bf}) and type (VR_{flr}) of first failure are also generated.

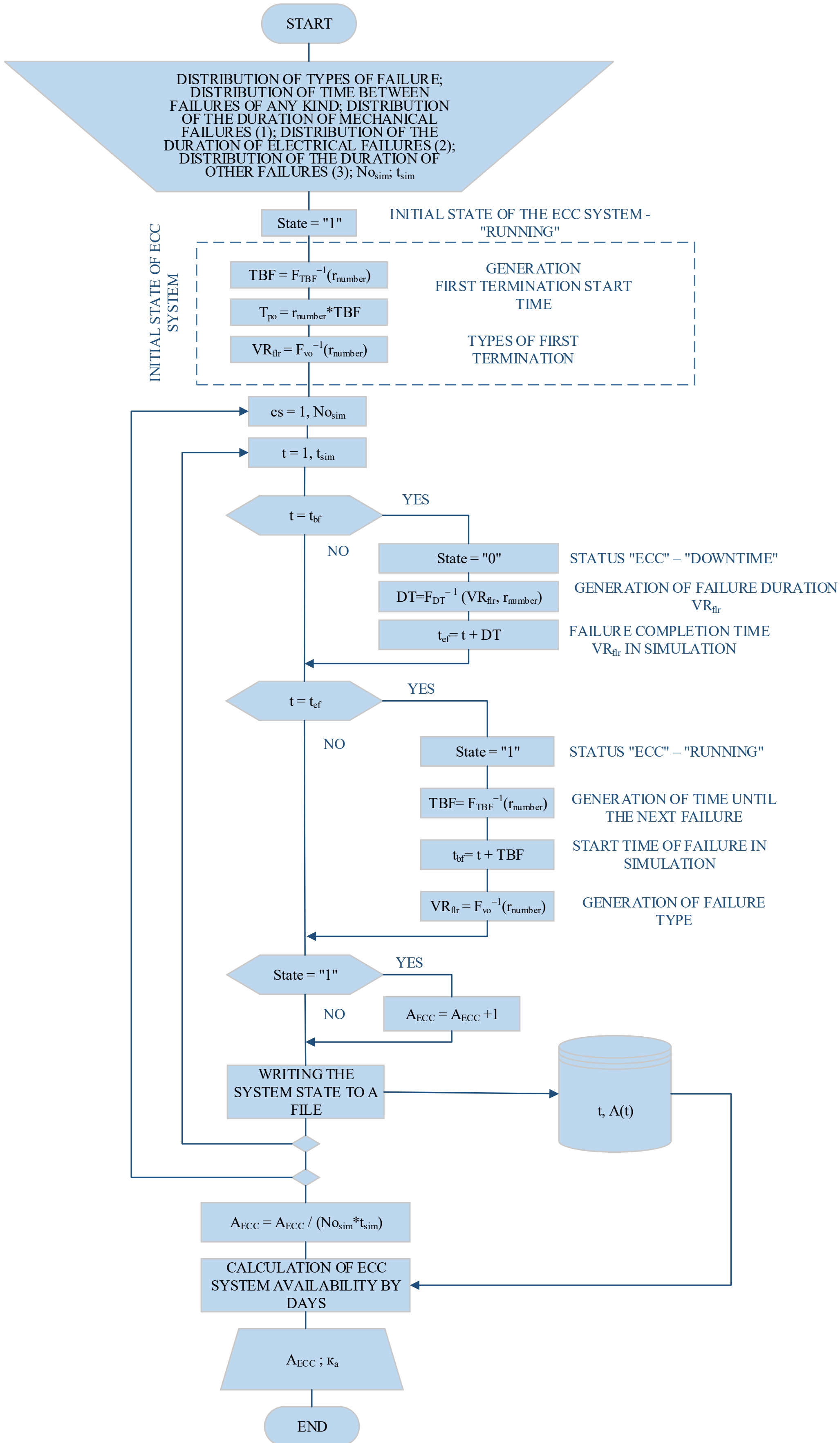

Figure 14. Algorithm of the simulation model.

While the simulation experiment is being performed, the model alternately compares simulation time (t) with the times of failure beginning (t_{bf}) and failure end (t_{ef}).

If the simulation time (t) is equal to the time of failure beginning (t_{bf}), the state of the ECC system is changed to "downtime" (State = "0"), and the time needed for repair is generated according to the current type of failure and the distribution of failure time duration. In other words, the time when failure ends (t_{ef}) is generated.

If the simulation time (t) is equal to the time when the failure ends (t_{ef}), the state of the ECC system is changed to "running" (State = "1"). Also, the type of failure (VR_{flr}) and the time of next failure are generated, meaning that the time of the beginning of the next failure (t_{bf}) is generated.

After that, the availability of the ECC system is checked. If the state of the ECC system is "1" ("running"), then the variable A_{ECC} is increased by one. Also, the current simulation time and appropriate state of the ECC system are written onto a file.

When all Nosim simulation experiments are executed, the average availability of the ECC system A_{ECC} and the stationary value of the ECC system availability k_a are calculated, as are the changes in the ECC system's availability in time.

Glossary:

t_{sim}—duration of the simulation (s);

No_{sim}—number of simulations;

State—state ECC system (1—"running"; 0—"downtime");

r_{number}—random number generated by uniform distribution in the interval [0. . .1];

cs—current simulation;

t_{sim}—simulation time;

TBF—time between failures (current);

DT—downtime failures (current);

t_{ef}—failure completion time (in simulation);

t_{bf}—failure start time (in simulation);

VR_{flr}—type of failure (1—mechanical; 2—electrical; 3—other);

A_{ECC}—system availability—ECC;

A (t)—availability of the system at a given time t;

k_a—stationary availability value.

Figure 15 shows the dependence of availability on time, obtained as a result of the simulation model.

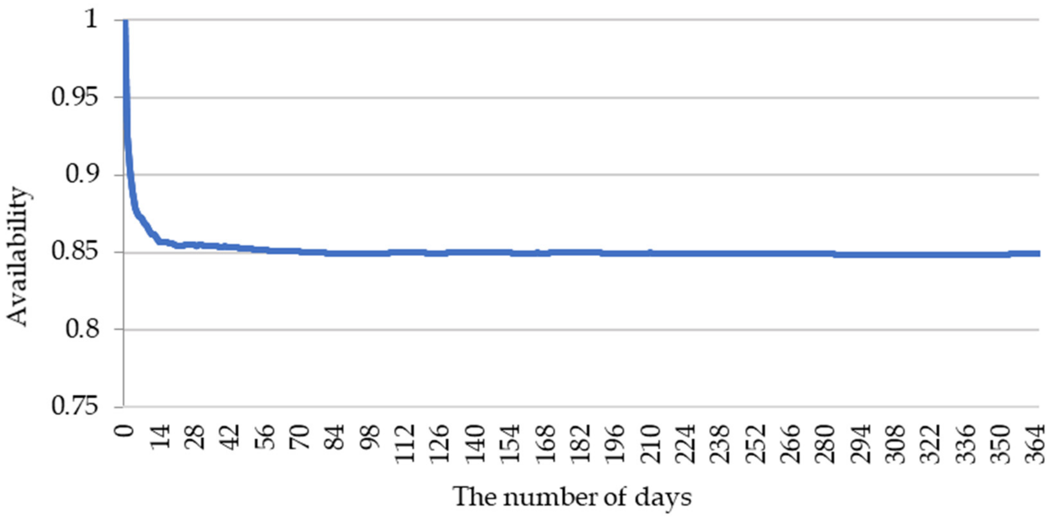

Figure 15. Dependence of availability on time.

Based on the simulation model, the mean availability value is 0.8513, i.e., 85%, and the stationary value is 0.8489, i.e., 85%.

6. Conclusions

Conventional methods are sensitive to the nature of the data, as well as to the presence of noise and outliers. In addition, another problem faced by conventional methods is their behavior in response to unseen data, indicating robustness and adaptability beyond the training set. Machine learning techniques have a tendency to solve these problems, which is shown in this work, where the ANFIS model provides a more accurate prediction of availability compared to the conventional method (simulation model).

Bearing in mind that both in this model and in the model [19] related to the calculation of availability for the forms of fuzzy numbers of partial indicators, those that use the Gaussian function were selected. There is a belief that with the provision of a larger number of data related to different systems, a model could be developed for using transfer learning techniques for specific types of systems.

An ANFIS model that uses a Gaussian function has better predictive power than models that use a Sigmoid or Bell-shaped function.

Using the obtained ANFIS model and the scores of partial sub-indicators provided by the experts for the next time period, the prediction of availability is obtained, which amounts to 0.8090, that is, 81%. Based on the simulation model, the availability value is 0.8513, i.e., 85%. Bearing in mind that the average availability in the time period of three years that was considered within the training of ANFIS and the simulation model is equal to 0.8132, i.e., 81%, while the value of availability for the year 2019 is 0.7797, i.e., 78%, we conclude that the ANFIS model gives a closer picture of the state of availability of the I ECC system. An additional advantage of this model is its simplicity, as it does not include certain assumptions about data distribution. Figure 16 shows the obtained availability values.

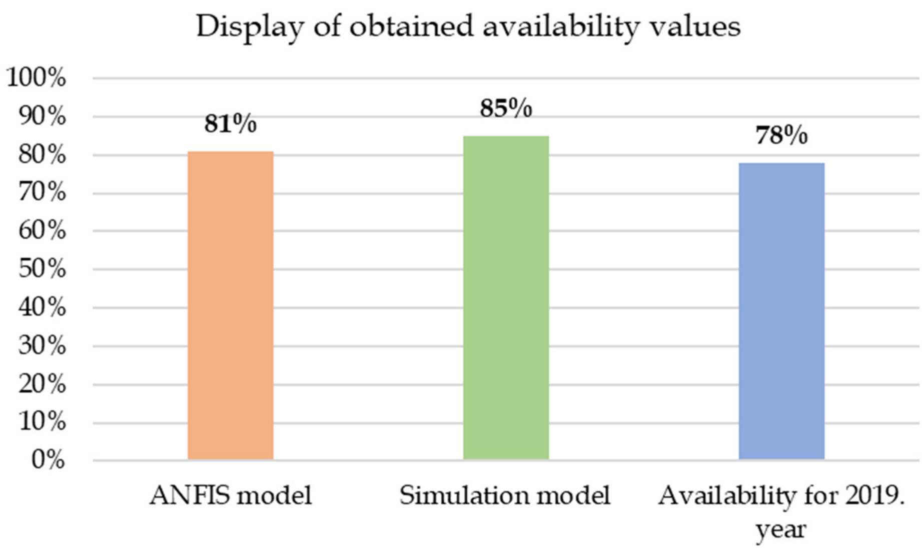

Figure 16. Display of obtained availability values.

The assessment of availability using the ANFIS model gives necessary information related to production planning in surface mines with continuous systems. The obtained availability value represents a limitation regarding the realization of coal mining, as well as transport and storage capacity, and defines the need for possible interventions regarding its increase if there is a demand for it from the aspect of the realization of the projected/required capacity.

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