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Reliability-Based Scheduled Maintenance (SM) for Mining Equipment with Artificial Neural Network (ANN) Model

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Abstract: Prompt and proper maintenance management helps extend the operation lifespan of workplace equipment to achieve production targets without interrupting the production process. In this connection, accurate prediction of the reliability-based scheduled maintenance (SM) time intervals of equipment is essential. The current research aimed to develop a reliability-based model to forecast the maintenance time intervals specifically for Load-Haul-Dumper (LHD) underground mining equipment. The series configuration system of the Reliability Block Diagram (RBD) model was adopted to evaluate the overall system reliability for each LHD machine. The reliability percentage of each sub-system was ascertained through a reliability analysis of a complex repairable system. To build the required Artificial Neural Network (ANN) model for analysis, the "Isograph Reliability Workbench 13.0" software was adopted to estimate the input layers of reliability (R) and the best-fit distribution parameters, such as the scale parameter (η), shape parameter (β), and location parameter (γ). The ANN model created was trained using the Levenberg-Marquardt (LM) learning algorithm. The predicted SM values were extremely close to the calculated values as indicated by the optimal R^2 value of 0.9998. The outcome demonstrated that the ANN model could improve the performance of the equipment with a major impact on the initial weight optimization. Suggestions were made for the industry practitioners to enhance the dependability of the equipment with planned maintenance procedures designed by the proposed ANN, with possible potential to be explored by other equipment users.

Keywords: LHD; Maintenance; Reliability; Reliability block diagram; Artificial neural network; Performance

1 Introduction

The mining industry is constantly changing to increase productivity, yet the realization of the desired production level fundamentally depends on the efficient use of personnel and machinery [1, 2]. As higher productivity and profitability are the results of using equipment effectively and efficiently, to ensure the dependability of the equipment is crucial for all sectors involved in the production process. Underground mine production in India has not increased to a satisfactory level in recent decades for a number of reasons; among them, one of the most significant factors is the absence of machines in its operating environment. To avoids this situation, it is essential to maintain a high level of equipment dependability through meticulously planned maintenance procedures [3]. A maintenance management program that could minimize unplanned downtime, reduce unexpected breakdowns, and lower annual maintenance costs is considered to be indispensable [4–6], yet could be accomplished by assessing the performance of the equipment.

When assessing the functionality of intricate repairable systems, reliability estimation is essential. The reliability of equipment use, the working equipment, the efficiency of maintenance, the operational procedures, and the technical proficiency of operators all have a major impact on the performance of the equipment. Reliability forecasting facilitates the planning of operational and maintenance tasks [7]. Optimizing the available resources such as labor, supplies, tools, and testing apparatuses, is part of the maintenance. The main goal of maintenance is to economically assist an organization in profit making and mission implementation [8]. Maintaining a minimum number of maintenance staff to support production and plant availability optimization while guaranteeing safety lays the foundation of facility maintenance philosophy [9]. To realize this philosophy, reliability-centered maintenance, condition-based maintenance, total productive maintenance, corrective maintenance, and preventive or scheduled maintenance are some strategies that could be successfully applied if used in the right combinations [10, 11]. Controlling the inventory of spare parts and implementing a preventive maintenance program constitute crucial components of a comprehensive quality maintenance program. Historical soft computing approaches like genetic algorithms, are appropriate ways to investigate the effect of an efficient maintenance program on the productive operation of industrial machinery [12].

In addition, there is an urgent demand for the creation of new knowledge to tackle the difficulties in condition monitoring and diagnostics of intricate modern machinery applications that have not yet been recognized [13, 14]. Along with the rapid advancement of intelligent information, sensing, data security, and intelligent signal processing techniques, continuous development of Artificial Intelligence (AI) tools is feasible [15]. Fuzzy interface systems (FIS), support vector machines (SVM), Artificial Neural Networks (ANN), and genetic algorithms (GA) are examples of artificial intelligence techniques that have been widely used in the engineering field. In comparison to traditional fault diagnostic methods, AI systems are effective techniques that can quantitatively enhance event detection. In addition to boosting performance, these methods could be readily adapted and expanded by incorporating new information or data [16, 17].

When it comes to solving complex problems, the analytical and statistical methods of machine performance analysis typically take longer time than software-based methods [18]. In order to address a variety of non-linear problems, researchers have recently shown a great deal of interest in soft computing techniques. Many traditional problems for these kinds of analyses cannot be solved, without using basic equations, conventional correlations, or trial-and-error methods to develop novel strategies from experimental data [19]. The Artificial Neural Network (ANN) technique, differed from traditional methods, has been applied to resolve a variety of complex problems and difficulties in various domains by processing data accurately and efficiently. As is frequently the case with the majority of conventionally statistical methods, ANN could model both linear and non-linear systems without assumptions [20], hence applicable in different engineering fields.

2 Case Study

The suggested analysis was conducted via a case study carried out in one of the underground mines run by Messrs The Singareni Coal Colleries Company Limited (SCCL). A fleet of five load-haul-dump (LHD) machines was the subject of the analysis. Transporting coal from mined areas to main crushing locations is facilitated by LHDs, which are the main workhorses in underground mining operations. The Emico Elicon Company Limited is the manufacturer of the LHD machines, with bucket capacities ranging from 2.5 to 3 cubic meters, used in this case study. Figure 1 shows an example of a typical LHD machine in its operating environment.

Figure 1. A typical LHD machine in an operating environment

2.1 Data Collection and Classification

To classify different modes of breakdown, the LHD machine, a complex repairable system, was split into multiple sub-systems before the analysis. LHD1, LHD2, LHD3, LHD4, and LHD5 are the designations for each LHD in this study, which treats them as separate systems. Each LHD system was divided into eight subsystems, including the Sub-System of Engine (SSE), Sub-System of Braking (SSBr), Sub-System of Blank Off (SSBo), Sub-System of Tyre (SSTy), Sub-System of Hydraulics (SSH), Sub-System of Electrical (SSEl), Sub-System of Transmission (SSTr), and Sub-System of Mechanical (SSM). For every LHD subsystem, the data gathered on Time between Failures (TBF), Time to Repair (TTR), and Failure Frequency (FF) are shown in Table 1. The Mean Time between Failures (MTBF) and the Mean Time to Repair (MTTR) calculated values from the field failure data are displayed in Table 2.

Table 1. Failure and repair data of LHDs from the field investigation

Machine ID	Parameter	SSE	SSBr	SSBo	SSTy	SSH	SSEl	SSTr	SSM
	FF (No/.)	10	4	5	12	16	24	10	28
LHD1	TBF (Hours)	321.8	807.7	646.4	261.5	192.1	127.1	323.2	100.7
	TTR (Hours)	372.7	807.7	742.6	317.2	241.87	162.2	371.3	147.3
	FF (No/.)	8	6	10	4	12	16	11	24
LHD2	TBF (Hours)	442.1	3585	3585	890.5	1788	220.6	3583	65.79
	TTR (Hours)	147.8	1135	1135	289.5	572	74.31	1137	130.8
	FF (No/.)	10	5	5	12	12	16	9	26
LHD3	TBF (Hours)	348.7	703.8	701.8	286.4	289.7	211.8	391.4	103.6
	TTR (Hours)	351.4	696.4	698.4	297	293.6	225.7	386.4	165.6
	FF (No/.)	10	5	6	12	12	26	9	30
LHD4	TBF (Hours)	323.3	647.2	538.6	261.7	263.4	122.4	359.6	101.2
	TTR (Hours)	375.9	751.2	626.6	320.9	319.2	146.5	417.2	131.8
	FF (No/.)	9	9	7	12	14	26	10	34
LHD5	TBF (Hours)	357.7	356.6	458	262	220.6	117.8	320	81.97
	TTR (Hours)	419.1	420.2	540.8	320.6	278.78	151.1	379.2	123.6

Table 2. Computed MTBF and MTTR of LHDs

Machine ID	FF	MTBF (Hours)	MTTR (Hours)
LHD1	109	395.35	197.56
LHD2	91	349.57	162.89
LHD3	95	389.31	179.65
LHD4	110	386.16	178.72
LHD5	121	329.17	137.83

3 Estimation of Performance Characteristics

3.1 Kolmogorov-Smirnov (K-S) Test

The best-fit analysis was conducted using the Kolmogorov-Smirnov (K-S) method for the TBF datasets. The underlying principle is to determine the extent of deviation between the chosen distribution and the actual dataset, or in other words, the effectiveness of the selected distribution in representing the observed distribution. Four statistical probability distribution functions, including Exponential, Weibull 1-Parameter, Weibull 2-Parameter, and Weibull 3-Parameter functions, were assessed for optimal fit. The parameters for these distributions were estimated employing the Maximum Likelihood Estimate (MLE) technique. Both tests were performed using the software of "Isograph Reliability Workbench 13.0". The best-fit distributions derived from the K-S test and MLE parameters are presented in Table 3.

3.2 Estimation of Availability Percentage

Availability is an important performance indicator in performance assessment; it is measured in downtime losses, which refer to any events that stop production for a significant period of time, including the breakdown time and idle time caused by machine malfunctions, shortages of spare parts, and changeover time. It may not be possible to eliminate the changeover time completely, but in many cases, it can be minimized. The remaining time is called operating or working time [10]. These figures were calculated in Table 4 in accordance with Eq. (1). The availability percentage decreased to 70.48% due to maintenance and operational problems.

$$\text{Availability} = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \tag{1}$$

Table 3. Results of the K-S test and MLE parameters of LHDs

Machine ID	K-S Statistics Maximum Difference				MLE Parameters			Best Fit Model
	Exponential	Weibull 1-Parameter	Weibull 2-Parameter	Weibull 3-Parameter	η	B	Γ	
LHD1	0.1641	0.1451	0.0553	0.0534	351.8	1.779	54.47	Weibull 3P
LHD2	0.0846	0.0814	0.0764	0.0687	539	0.706	54.84	Weibull 3P
LHD3	0.1965	0.1759	0.0529	0.0438	251.4	1.261	223.7	Weibull 3P
LHD4	0.1306	0.11	0.0688	0.0568	975	3.209	-366.3	Weibull 3P
LHD5	0.1487	0.1289	0.0852	0.0672	791.8	48.66	-748.1	Weibull 3P

Table 4. Computed results of availability

Machine ID	FF	MTBF (Hours)	MTTR (Hours)	Availability (%)
LHD1	109	395.35	197.56	66.67
LHD2	91	349.57	162.89	68.21
LHD3	95	389.31	179.65	68.42
LHD4	110	386.16	178.72	68.36
LHD5	121	329.17	137.83	70.48

3.3 Estimation of Reliability

Reliability is defined as the probability that a machine or its parts perform their intended functions successfully before failures under given operating conditions [20]. The optimal distribution parameters and the MTBF values can be used to evaluate the equipment proportion. Comparing the reliability of the various units, the analysis of the results in Table 5 showed that the lowest reliability was 49.76% (LHD5), while the highest reliability was 70.28% (LHD1). Together with lower TBFs, the frequent occurrence of failures is a major factor in the remarkable decline in reliability.

Table 5. Results of the K-S test and MLE parameters of LHDs

Machine ID	MTBF (Hours)	MLE Parameters			Reliability R(t) (%)
		η	B	Γ	
LHD1	395.35	351.8	1.779	54.47	76.20
LHD2	349.57	539	0.706	54.84	58.16
LHD3	389.31	251.4	1.261	223.7	66.88
LHD4	386.16	975	3.209	-366.3	64.94
LHD5	329.17	791.8	48.66	-748.1	49.76

4 Neural Network Modelling

The mining industry uses Artificial Intelligence (AI) tools extensively and in a variety of ways. With the many computer-based applications in routine mining operations, knowledge-based and expert systems are among the most popular AI tools. Another potent AI tool, the Artificial Neural Network (ANN), is created by these artificial intelligence frameworks, in conjunction with a growing number of intricate and custom software programs.

ANN, the Matrix Laboratory (MATLAB) simulation tool, is intended to mimic processes that are similar to those of human brains. An advanced information processing framework made up of interconnected segmental processing units, neurons, is called an Artificial Neural Network (ANN). These neurons generate final outputs as yield after extracting information from multiple sources and usually applying a non-linear operation to the results. A MATLAB program called Neural Network Toolbox was used to model and prepare the system model. There are two stages in the Artificial Neural Network (ANN); the first is training the system model and the second is validating the system model using fresh data that was not used for training. A hidden layer for processing, an output layer for results, and an input layer for data entry make up the ANN architecture.

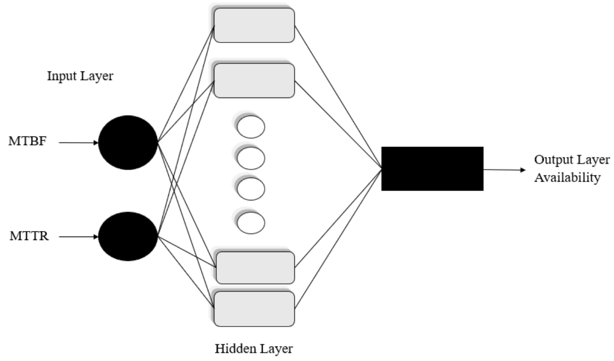

Figure 2. ANN model for availability

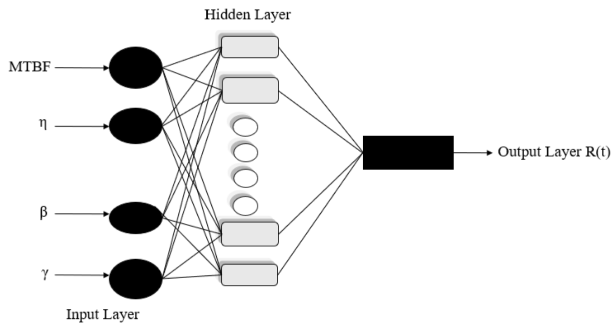

Figure 3. ANN model for reliability

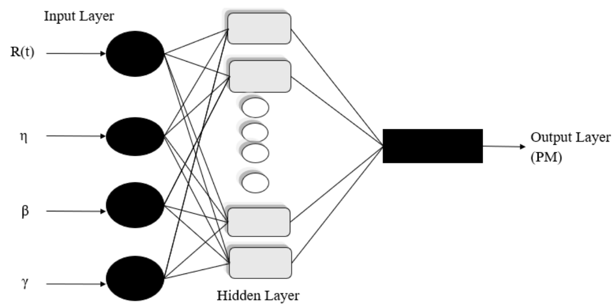

Figure 4. ANN model for PM

In the current ANN architecture, as shown in Eq. (2) [12], the input data for each component, together with the assigned weights, is sent to a summation junction where it is combined with the bias neurons until it reaches the desired threshold value.

$$X = \left(\sum_{i=1}^{n} W_{ij} a_i \right) + b_j = (W_{11}a_1 + W_{21}a_1 \ldots\ldots + W_{n1}a_n) + b_j \tag{2}$$

where, the total number of input data are denoted as n, W_{ij} be the interconnecting weights of input data (a_i) and the bias for the neurons was denoted as b_j.

The value of X then passes through transfer function (F) of the model, referred to in Eq. (3):

$$F(X) = u_i = \left(\sum_{i=1}^{n} W_{ij} a_i \right) + b_j \tag{3}$$

The hyperbolic tangent sigmoid function (TANSIG) and the log-sigmoid transfer function (LOGSIG) are commonly used transfer functions for hidden layers. When the output response lies between 0 to 1 SIGMOD, non-linear activation function Eq. (4) has been used.

$$F(X) = \frac{1}{1+e^{-x}} \tag{4}$$

The TANSIG transfer function has been utilized when there is an existence of any negative values in the output response and is referred to in Eq. (5):

$$F(X) = \frac{1-e^{-2x}}{1+e^{2x}} \tag{5}$$

The representation of the performance index for various training algorithms was made based on the mean square error (MSE) and is represented in Eq. (6):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Xa_i - Xb_i)^2 \tag{6}$$

In this study, the availability, reliability, and PM parameters of five LHDs were forecasted using the ANN tool (refers to in Figures 2-4).

4.1 Development of ANN Simulation Model for Reliability

The ANN model was developed for reliability using the MTBF and MTTR metrics. Training was conducted using the TRAINLM learning function. The learning function that was chosen after the completion of the training function was the Gradient Descent with Momentum Weight and Bias Learning Function (LEARNGDM). The TANSIG transfer function was selected for the hidden layer, and the output function was given the linear transfer function, PURELIN. For optimal outcome, the model was tested using a range of 4 to 10 neurons and trained for up to 1,000 iterations. To find the optimal value of R^2, use the Root Mean sq\. RMSE error in (Table 6). Figure 5 displays the network model designed for dependability. The results in Table 6 indicated that R^2, of 0.9972 was the best value for LM-8 at 0.0104 Root Mean sq\. Error (RMSE).

Table 6. Computed results of availability

Sl. No	Number of Neurons	R^2	RMSE
1	4	0.9199	0.0216
2	5	0.8532	0.0424
3	6	0.8934	0.0224
4	7	0.8019	0.0468
5	8	0.9972	0.0104
6	9	0.9868	0.0126
7	10	0.9816	0.0121

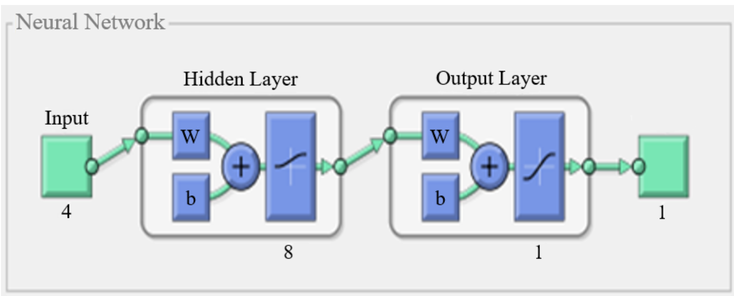

Figure 5. An optimum network model for reliability

4.2 Development of ANN Simulation Model for Availability

MTBF, scale parameter (η), shape parameter (β), and location parameter (γ) metrics were used to build the ANN model for availability. Similar to the established reliability model, this model used the same functions for learning, training, testing, transfer, and output. In order to get the best results, the availability model was trained for up to 1,000 iterations in which the number of neurons varied from 2 to 9. A value for the Root Mean square Error (RMSE) was used to determine the ideal R^2 value. Figure 6 shows the network model that was created for reliability. Based on the results, it was found that the RMSE for LM-6 was 0.0091, which was the same as the optimal R^2 at 0.9999. Table 7, subsequently documents the expected values linked to the optimal R^2 for additional verification.

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

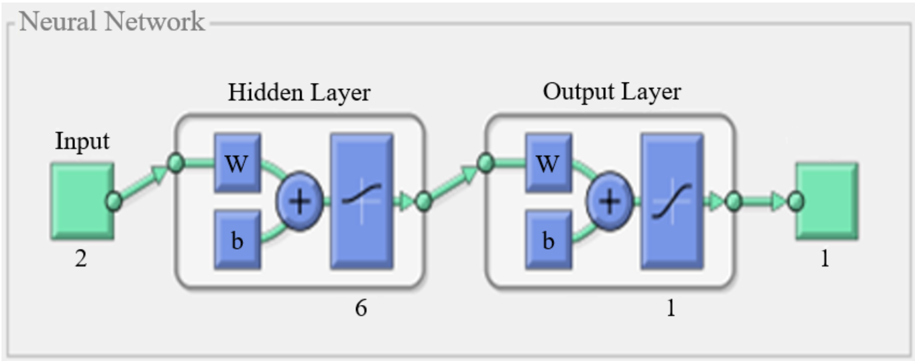

Figure 6. Developed an optimum network model for availability

Table 7. Trained results of availability for various neurons

Sl. No	Number of Neurons	R^2	RMSE
1	2	0.8517	0.0169
2	3	0.9894	0.0097
3	4	0.7813	0.0114
4	5	0.9987	0.0096
5	6	0.9999	0.0091
6	7	0.9816	0.0097
7	8	0.8910	0.0198
8	9	0.9010	0.0199

4.3 Development of ANN Simulation Model for Preventive Maintenance (PM)

Scale (η), shape (β), location (γ), and reliability percentage (R) metrics were used to build the ANN model for availability. This model used exactly the same functions for learning, training, testing, transfer, and output as the well-known reliability model. Neuron counts between 2 and 9 was chosen to assess the availability model, which was trained for up to 1,000 iterations to produce the best results. The RMSE value served as the basis for calculating the ideal R^2 value. Figure 7 shows the network model that was created for reliability. At an RMSE of 0.00916 for LM-6, the results showed that the optimal R^2 at 0.9999 was reached. Table 8 documents the expected values corresponding to the optimal R^2 for additional validation.

5 Validation of Computed Results with Predicted Results

Following the successful development and simulation of performance characteristics, namely PM, availability, and reliability, the calculated results were validated using the MATLAB-based predicted values of the ANN as in Table 9 With the highest R^2 value, a comparison showed that the calculated and predicted values of the performance characteristics were satisfactory.

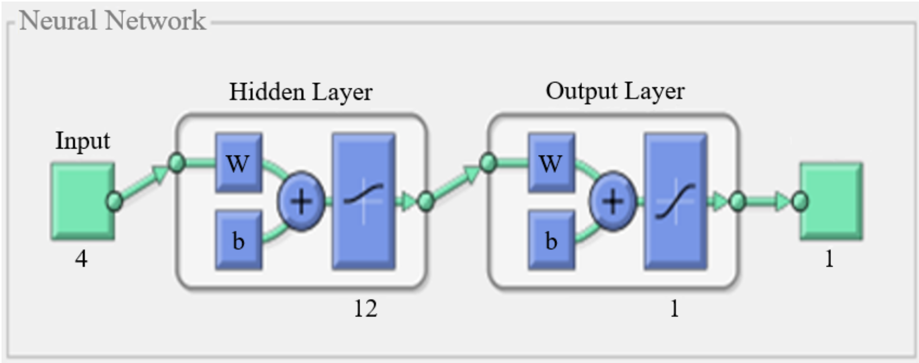

Figure 7. An optimum network model for PM

Table 8. Trained results of PM for various neurons

Sl. No	Number of Neurons	R^2	RMSE
1	4	0.8947	0.2110
2	5	9010	0.2840
3	6	0.9240	0.1672
4	7	0.8874	0.1876
5	8	0.8921	0.2010
6	9	0.7894	0.1957
7	10	0.8916	0.2437
8	11	0.9464	0.2267
9	12	0.9829	0.1521
10	13	0.9164	0.2146
11	14	0.9146	0.2122

Table 9. Validation of computed results with predicted results of the ANN

Sl. No	Machine	Computed values from Isograph Reliability Workbench 13.0			Predicted values from MATLAB based ANN		
		Availability (%)	Reliability (%)	PM (Hours)	Availability (%)	Reliability (%)	PM (Hours)
1	LHD1	66.67	70.28	114.26	66.68	68.57	114.27
2	LHD2	68.21	58.16	172.64	68.21	58.16	172.63
3	LHD3	68.42	66.88	174.64	68.45	66.88	174.63
4	LHD4	68.36	64.94	174.00	68.36	64.94	173.99
5	LHD5	70.48	49.76	184.68	70.48	50.96	185.27

6 Conclusions

Effective planning and implementation of appropriate management techniques could enable the continuous operation of equipment. The analysis done in this paper led to the following conclusions. For the machines, availability is a critical Key Performance Indicator (KPI). When compared LHD5 to the other systems, the availability percentage reaches the highest at 70.48%. The reduced rates of production are the consequences of unavailability and inefficient use. By carefully following preventive maintenance (PM) plans, managing staff and equipment, hiring a qualified operating team, and ensuring effective management of machinery, production could be improved. Reliability estimation is crucial for performance assessment. LHD1 had the highest predicted reliability of 68.57% whereas LHD5 had the lowest predicted reliability of 50.96%. Frequent and unexpected failures are one factor contributing to reduction in reliability. Therefore, it is advised to design optimal maintenance practices to maintain equipment of low efficiency at an adequate level. It has been estimated that reliability-based PM time intervals could forecast early system failures. PM should take place every 114.26 hours if the reliability requirement of LHD1 is set at 90%. Completing PM on time could help reach the anticipated lifespan easily.

The optimal R^2 of 0.9972 for the reliability model of the ANN was determined to be RMSE 0.0104 for LM-8. R^2 of 0.9999 was at its best for the ANN availability model at RMSE 0.0091 for LM-6. Similarly, for LM-12, R^2

of 0.9829 was optimal for the ANN PM model at RMSE 0.1521. When the computed results were compared to the predicted performance characteristics such as availability, reliability, and PM with the highest R^2 values, the results were satisfactory. It is therefore concluded that the ANN could be a useful tool for network analysis.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare that they have no conflicts of interest.

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