Al-Khwarizmi Engineering Journal, Vol. 18, No. 2, June, (2022)
P. P. 1- 12

Al-Khwarizmi Engineering Journal

# Estimate and Analysis the Availability of Generator in Electric Power Plant Using ANN

**Asmaa J. Awad*　　Ahmed A. Ahmed**　　Osamah F. Abdulateef *****

**,***Department of Automated Manufacturing Engineering/Al-Khwarizmi College of Engineering/ University of Baghdad, Al-Jadriayh/ Baghdad/Iraq*

***Department of Mechanical Engineering/ University of Baghdad/ Al-Jadriayh/Baghdad/ Iraq*

*Email: asmaa_jamal_1992@yahoo.com

**Email: aa.alkhafaji@yahoo.com

***Email: drosamah@kecbu.uobaghdad.edu.iq

(Received 27 December 2021; Accepted 20 April 2022)

https://doi.org/10.22153/kej.2022.04.001

## Abstract

The large number of failure in electrical power plant leads to the sudden stopping of work. In some cases, the necessary reserve materials are not available for maintenance which leads to interrupt of power generation in the electrical power plant unit. The present study, deals with the determination of availability aspects of generator in unit 5 of Al-Dourra electric power plant. In order to evaluate this generator's availability performance, a wide range of studies have been conducted to gather accurate information at the level of detail considered suitable to achieve the availability analysis aim. The Weibull Distribution is used to perform the reliability analysis via Minitab 17, and Artificial Neural Networks (ANNs) by approaching of Feed-Forward, Back-Propagation. Operating data from the years 2015–2017 were used to calculate the availability by traditional method (Weibull distribution) and train the ANNs, while data from the year 2018 of operation were used to verify the model. The study implies that the ANN may be able to forecast the availability of the generator with a correlation coefficient (R) 0.99874 and a Mean Square Error (MSE) 5.6937E-06 between the availability predicted by ANN and Weibull distribution output.

***Keywords:*** *Back-Propagation, Failure analysis, Feed-Forward, Weibull distribution.*

## 1. Introduction

Estimation theory is a field of statistics concerned with estimating parameter values based on empirical data containing a random component that has been measured. The parameters represent an underlying physical setup in such a way that the distribution of the measured data is affected by their value [1].The maintenance besides repairs are the problems that cost a large part of the budget, The high costs occur because of parts failure, therefore by improving the availability and reliability that will lead to decrease costs, in order reducing system maintenance. In this sense, availability, which is a combination of maintainability and dependability, has become widely employed as a metric for determining the success of a system's maintenance. Availability is defined as the chance that the system will operate properly under specified conditions at any point in time, or as the ratio of uptime to total time, while the reliability concept is the probability that the item may work to fulfill a certain work for a span of time until the breakdown has occurred, so the behavior of the complex repairable systems can be studied in terms of their availability [2].

Availability analysis techniques have been gradually accepted as standard tools for the planning and operation of complex thermal power plants. de Oliveira, et al, [3] presented a Monte Carlo Simulation to project the availability of hydroelectric plants. The proposed methodology addresses operational and regulatory aspects, where the plant's availability is evaluated through the measured hours of interruptions due to scheduled and forced maintenance. The proposed model was successfully implemented using real data, achieving the goal of estimating the risk of regulatory penalties for the hydroelectric plant. In addition, the proposed methodology is applicable to other hydroelectric power plants. Hanumant Jagtap, et al, [4] presents availability based simulation modeling of the boiler–furnace system of thermal power plant with capacity (500MW). The Markov based simulation model of the system is developed for performance analysis. The differential equations are derived from a transition diagram representing various states with full working capacity, reduced capacity, and failed state. The availability of the boiler–furnace system is optimized using particle swarm optimization method by varying the number of particles. The study results revealed that the maximum system availability level of 99.9845% is obtained. In addition, the optimized failure rate and repair rate parameters of the subsystem are used for suggesting an appropriate maintenance strategy for the boiler–furnace system of the plant. Zouhair Issa Ahmed, et al, [5] suggested a methodology for availability estimation of the caustic pump by using Artificial Neural Network (ANN), training pairs (time, availability), to determine availability at every ten working hours, for the real times of failures MATLAB codes were used, by front feed type of multilayer type of network for each parts for the caustic pump study. The proposed method was more precise and closer to reality, the mode and steps of the methodology in predicting by using ANNs, enables its implication on any part and equipment for mechanical or electrical system. Hanumant P. Jagtap, [6] presented reliability, availability, and maintainability (RAM) analysis framework for assessing the achievement of a circulation system of water (WCS) used in a coal-fired power plant (CFPP). The achievement of WCS is estimated utilizing a reliability block diagram (RBD), fault tree analysis (FTA), and Markov birth–death probabilistic approach. The system under consideration composed of five subsystems connected in series and parallel structure. The reliability block diagram (RBD) and fault tree approach (FTA) have been used for the achievement evaluation of WCS. The availability of the system was optimized utilizing the particle swarm optimization method. The optimized failure rate and repair rate parameters of the subsystem are utilized to proposed an acceptable maintenance strategy for the water circulation system of the thermal power plant. Ling Wang, et al, [7] developed an improved delay time model (DTM) with imperfect maintenance at inspection on the basis of the assumption of imperfect inspection maintenance and perfect failure maintenance. The model of the long-run availability for the improved DTM is fixed. Numerical simulations are done to study the effect of imperfect maintenance on the long-run availability and to verify the credibility of the parameters estimation method. The results revealed that imperfect maintenance reduces the long-run availability. P.S. Rajpal, et al, [8] utilized neural network approach to analyze the reliability, availability and maintainability of a complex repairable system a helicopter transportation facility, The operational characteristics of the helicopter facility have been discovered, measured, visually shown and modeled using recent past data of the system. The insights received from outcomes of simulation are important in designing strategies for optimal operation of the system. Manmath Kumar Bhuyan ,et al, [9] presented a novel technique for software reliability estimation utilizing feed forward neural network with back-propagation. Most of the predictive criteria are considered. An experimental evidence showed that feed forward network with back propagation yields accurate result corresponding to other methods, and that this approach is computationally practicable and can considerably decrease the cost of testing the software by estimating software reliability. Małgorzata Kutyłowska [10], predicted the availability indicator of water mains, distribution pipes, and house connections by means of an ANN model. Operating data for a period 1999–2005 were utilized to train the ANNs while data from the next seven years of operation were utilized to prove the model. Thus ANNs are fairly simple to carry out and utilize when functions of many variables are to be approximated.

The aim of this study is to construct a model by artificial neural network methods to estimate the availability of the generator in unit 5 of Al Dora electric power plant.

## 2. Case Description

Al- Doura Power Station shown in figure 1 is electric steam-powered station located in Baghdad near the Tigris River. It consists six units working to generate electricity for the capital Baghdad with a production capacity estimated at (400MW) per unit and all unit connected by parallel to compensation in the event of a malfunction in any of the units to perform the required function and increase efficiency, unit 5 was taken for the purpose of the study.


**Fig. 1. Al- Doura Power Station.**

Unit 5 consists of four main subsystems linked together in series; these subsystems are boiler, turbine, generator, and condenser as shown in Figure 2. The failure in any subsystem leads to stop of the unit and make it out of work.

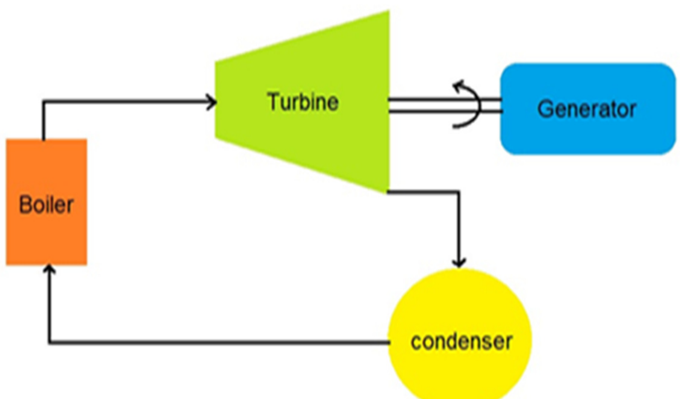


**Fig. 2. Parts of Unit 5.**

## 3. Methodology

The proposed methodology to estimate the availability of "Generator" in unit 5 of Al- Doura Power Station is divided in three stages as summarized in figure 3.The first stage included the description of the system under study and its sub-systems, as well as the collection of raw data, classification and organization of data to suit the required study. The second stage contained the application of the traditional methodology in determining the availability of the system and subsystems. The third and final stage is the application of artificial intelligence networks.

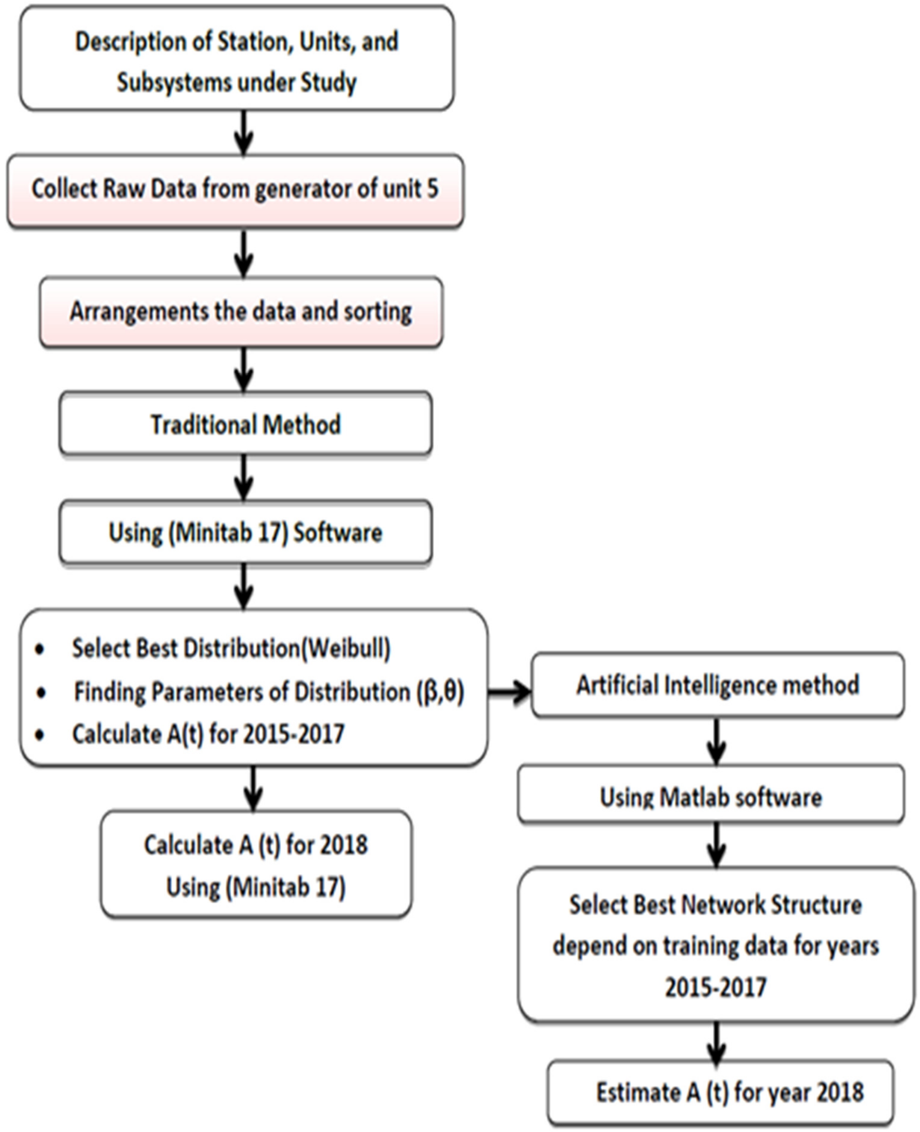


**Fig. 3. The Stages and Steps of Proposed Methodology.**

The data collected from the generator of unit 5 for the years 2015 to 2018 are classified and arranged as shown in Table 1, year 2015 was considered to be the zero hour, or the beginning of operation, and this is not the reality, due to the lack of real data for the operation of the system, the stop time or the maintenance and replacement time (TTR) is added in each case, which is the starting time for the unit to operate after performing maintenance on it in a cumulative aggregate, the types of failure is also shown in the last column of the Table.

**Table 1,**
**Data collected of the generator and type of failure.**

| | Operation Time | Stopping Time | From [hr.] | To [hr.] | TTR [hr.] | Type of failure |
|---|---|---|---|---|---|---|
| **1** | 01/01/2015 00:00 | 16/07/2015 16:30 | 0.00 | 4720.50 | 1.5 | Electrical |
| **2** | 16/07/2015 18:00 | 19/07/2015 13:45 | 4722.00 | 4789.75 | 0.75 | Electrical |
| **3** | 19/07/2015 14:30 | 27/08/2015 11:45 | 4790.50 | 5723.75 | 1.5 | Electrical |
| **4** | 27/08/2015 13:15 | 06/09/2015 15:30 | 5725.25 | 5967.50 | 2.5 | Electrical |
| **5** | 06/09/2015 18:00 | 27/12/2015 12:00 | 5970.00 | 8652.00 | 2.25 | Electrical |
| **6** | 27/12/2015 14:15 | 06/06/2016 10:30 | 8654.25 | 12538.50 | 1 | Electrical |
| **7** | 06/06/2016 11:30 | 16/08/2016 08:45 | 12539.50 | 14240.75 | 0.75 | Electrical |
| **8** | 16/08/2016 09:30 | 09/09/2016 08:30 | 14241.50 | 14816.50 | 1 | Mechanical |
| **9** | 09/09/2016 09:30 | 30/09/2016 22:00 | 14817.50 | 15334.00 | 28.5 | Mechanical |
| **10** | 02/10/2016 02:30 | 05/10/2016 16:30 | 15362.50 | 15448.50 | 0.75 | Mechanical |
| **11** | 05/10/2016 17:15 | 29/10/2016 23:30 | 15449.25 | 16031.50 | 8.5 | Mechanical |
| **12** | 30/10/2016 08:00 | 23/11/2016 15:15 | 16040.00 | 16623.25 | 1 | Mechanical |
| **13** | 23/11/2016 16:15 | 27/11/2016 10:00 | 16624.25 | 16714.00 | 2.75 | Mechanical |
| **14** | 27/11/2016 12:45 | 12/12/2016 14:00 | 16716.75 | 17078.00 | 29.75 | Mechanical |
| **15** | 13/12/2016 19:45 | 10/05/2017 17:00 | 17107.75 | 20657.00 | 11.25 | Electrical |
| **16** | 11/05/2017 04:15 | 11/05/2017 16:45 | 20668.25 | 20680.75 | 0.75 | Mechanical |
| **17** | 11/05/2017 17:30 | 14/06/2017 17:30 | 20681.50 | 21497.50 | 2 | Mechanical |
| **18** | 14/06/2017 19:30 | 14/06/2017 20:15 | 21499.50 | 21500.25 | 1 | Mechanical |
| **19** | 14/06/2017 21:15 | 10/08/2017 14:30 | 21501.25 | 22862.50 | 1 | Mechanical |
| **20** | 10/08/2017 15:30 | 10/08/2017 16:30 | 22863.50 | 22864.50 | 1.75 | Mechanical |
| **21** | 10/08/2017 18:15 | 13/08/2017 00:45 | 22866.25 | 22920.75 | 60.5 | Mechanical |
| **22** | 15/08/2017 13:15 | 22/10/2017 17:45 | 22981.25 | 24617.75 | 2 | Mechanical |
| **23** | 22/10/2017 19:45 | 18/11/2017 13:00 | 24619.75 | 25261.00 | 0.5 | Control |
| **24** | 18/11/2017 13:30 | 14/02/2018 22:00 | 25261.50 | 27382.00 | 1 | Mechanical |
| **25** | 14/02/2018 23:00 | 12/05/2018 21:30 | 27383.00 | 29469.50 | 104.5 | Electrical |
| **26** | 17/05/2018 06:00 | 12/06/2018 11:45 | 29574.00 | 30203.75 | 7.75 | Electrical |
| **27** | 12/06/2018 19:30 | 03/08/2018 18:00 | 30211.50 | 31458.00 | 1.25 | Mechanical |
| **28** | 03/08/2018 19:15 | 11/08/2018 04:45 | 31459.25 | 31636.75 | 17.25 | Mechanical |
| **29** | 11/08/2018 22:00 | 23/09/2018 13:30 | 31654.00 | 32677.50 | 1.75 | Electrical |
| **30** | 23/09/2018 15:15 | 30/09/2018 05:00 | 32679.25 | 32837.00 | 71.25 | Mechanical |
| **31** | 03/10/2018 04:15 | 13/10/2018 05:30 | 32908.25 | 33149.50 | 4 | Mechanical |
| **32** | 13/10/2018 09:30 | 16/10/2018 04:45 | 33153.50 | 33220.75 | 24 | Mechanical |
| **33** | 17/10/2018 04:45 | 24/10/2018 23:00 | 33244.75 | 33431.00 | 17.75 | Mechanical |
| **34** | 25/10/2018 16:45 | 01/01/2019 00:00 | 33448.75 | 35064.00 | 0 | No Failure |

All these data are entered to Minitab17 software to select the appropriate functional distribution matching the data. The software can able to analysis (11) probability distributions, best four probability distribution graphs shown in Figure 4, Weibull, Loglogestic, Log Normal, and Exponential. Weibull distribution is approved depends on the lowest value of Anderson darling and highest value of correlation coefficient as shown in figure 5.

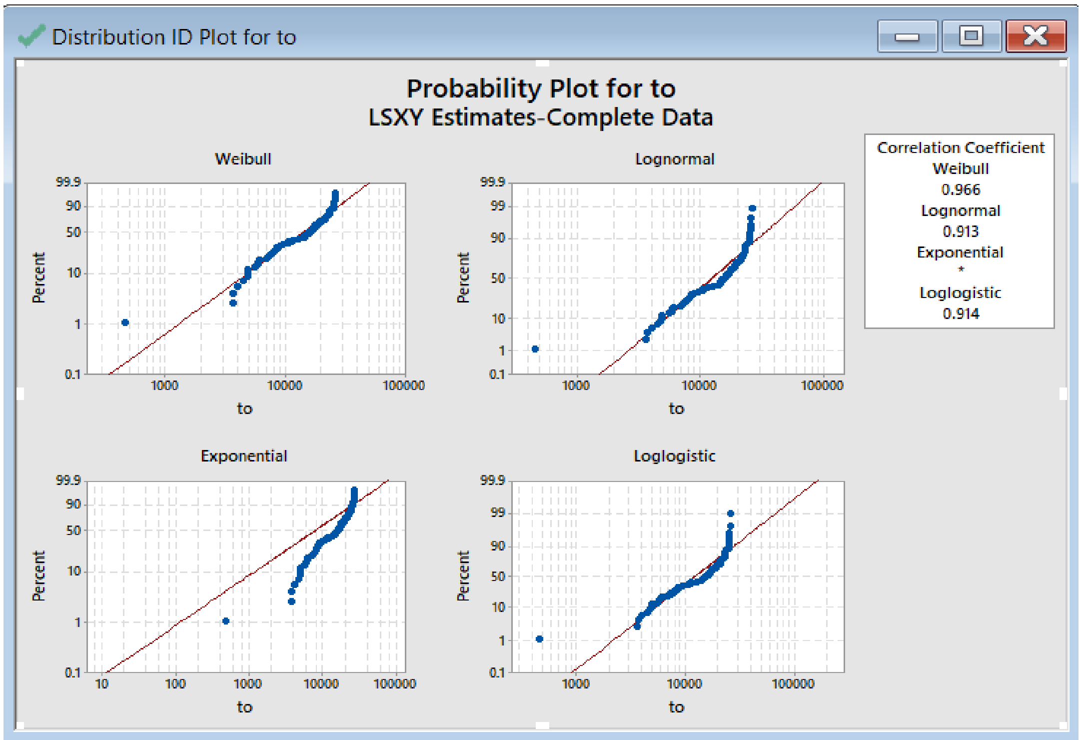


**Fig. 4. Graph of Best Distribution.**

Session

| Distribution | Anderson-Darling (adj) | Correlation Coefficient |
|---|---|---|
| Weibull | 1.211 | 0.966 |
| Lognormal | 2.304 | 0.913 |
| Exponential | 14.232 | * |
| Loglogistic | 2.602 | 0.914 |
| 3-Parameter Weibull | 1.200 | 0.982 |
| 3-Parameter Lognormal | 1.407 | 0.975 |
| 2-Parameter Exponential | 13.397 | * |
| 3-Parameter Loglogistic | 2.071 | 0.960 |
| Smallest Extreme Value | 2.683 | 0.950 |
| Normal | 1.399 | 0.975 |
| Logistic | 2.059 | 0.960 |

| 106 | 34857.0 | 35064.00 | 35064. |
|---|---|---|---|

Worksheet 17 ***

| ↓ | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| | from | to | | | | | |
| 1 | 0.0 | 448.00 | | | | | |
| 2 | 449.0 | 3592.50 | | | | | |
| 3 | 3604.5 | 3610.50 | | | | | |
| 4 | 3613.5 | 3947.00 | | | | | |

**Fig. 5. Anderson-Darling and Correlation Coefficient Values.**

## 3.1 Traditional Method (Weibull Distribution)

It is one of the most distributions that are used to evaluate the reliability of the system, it is a flexible distribution and gives a clearer and more realistic view of the life of the system, and it uses two number parameters in determining the behavior of the system [11]. This type of probability distributions is governed by two parameters; the first is the shape parameter (β), where it affects the approach or the distribution away from the main axis and the equation governing it. The second parameter is scale parameter (θ), who influenced the probability value when guessing the times. The reliability R (t) and availability A(t) functions for Weibull distribution are given as:

$$R(t) = e^{-(\frac{t}{\theta})^{\wedge}\beta} \qquad t>0 \qquad \ldots(1)$$

$$A(t) = 1 - e^{-(t/\theta)^{\wedge}\beta} \qquad t>0,\ \beta>0 \qquad \ldots(2)$$

The availability for the years (2015-2017) was calculated for the generator using equations 1 and 2 in Minitab17 software as shown in Table 2.

**Table 2,**
**Availability of Generator for the years (2015-2017) by Minitab17 software.**

| | years | From [hr.] | To [hr.] | TTR [hr.] | A(t) Weibull |
|---|---|---|---|---|---|
| **1** | 2015 | 0.00 | 4720.50 | 1.5 | 0.95731 |
| **2** | 2015 | 4722.00 | 4789.75 | 0.75 | 0.955881 |
| **3** | 2015 | 4790.50 | 5723.75 | 1.5 | 0.934159 |
| **4** | 2015 | 5725.25 | 5967.50 | 2.5 | 0.927744 |
| **5** | 2015 | 5970.00 | 8652.00 | 2.25 | 0.837799 |
| **6** | 2016 | 8654.25 | 12538.50 | 1 | 0.658902 |
| **7** | 2016 | 12539.50 | 14240.75 | 0.75 | 0.57127 |
| **8** | 2016 | 14241.50 | 14816.50 | 1 | 0.541396 |
| **9** | 2016 | 14817.50 | 15334.00 | 28.5 | 0.514646 |
| **10** | 2016 | 15362.50 | 15448.50 | 0.75 | 0.508751 |
| **11** | 2016 | 15449.25 | 16031.50 | 8.5 | 0.478928 |
| **12** | 2016 | 16040.00 | 16623.25 | 1 | 0.449088 |
| **13** | 2016 | 16624.25 | 16714.00 | 2.75 | 0.444558 |
| **14** | 2017 | 16716.75 | 17078.00 | 29.75 | 0.426534 |
| **15** | 2017 | 17107.75 | 20657.00 | 11.25 | 0.266425 |
| **16** | 2017 | 20668.25 | 20680.75 | 0.75 | 0.26549 |
| **17** | 2017 | 20681.50 | 21497.50 | 2 | 0.234482 |
| **18** | 2017 | 21499.50 | 21500.25 | 1 | 0.234381 |
| **19** | 2017 | 21501.25 | 22862.50 | 1 | 0.187844 |
| **20** | 2017 | 22863.50 | 22864.50 | 1.75 | 0.18778 |
| **21** | 2017 | 22866.25 | 22920.75 | 60.5 | 0.186 |
| **22** | 2017 | 22981.25 | 24617.75 | 2 | 0.137531 |
| **23** | 2017 | 24619.75 | 25261.00 | 0.5 | 0.121751 |
| **24** | 2017 | 25261.50 | 26304.00 | 0 | No failure until end 2017 |
| | | | **Weibull $\beta$ = 2.31123, $\theta$= 18302.9** | | |

## 3.2 Non Traditional Method (Artificial Neural Network (ANN))

Artificial neural network (ANN) is one of the most important artificial intelligence techniques; the working concept is based on the artificial neurons which are the processing components. It can deal with noisy data or incomplete information, and it can be very efficient, especially in situations where it is impossible to describe the steps or rules that lead to the solution of the problem, and it can model the system using only samples, so it can be used to predict availability with a reliable and fast process. The network input layer has 2 neurons which related to time of generator working and the output layer houses the response factor in 1 neuron. The input-output gathering of data was divided into two groups: the training data group consist of the availability data obtained from the Weibull traditional method for the years (2015-2017) and the test data containing the availability data obtained from the Weibull traditional method for the year 2018. There are 24 training models considered for ANN availability modeling.

A trial and error method was selected to calculate the number of neurons in the hidden layer,. The best approach with a minimal mean squared error is done with eleven hidden layer neurons for availability having a regression model 0.99874, and the mean square error (MSE) calculated using equation 3 was 5.6937E-06. Fig.6 shows the architecture of the neural network that offers the highest predictive accuracy for the purpose of using it to estimate the availability in the future.

$$\textbf{MSE} = \frac{1}{n}\sum_i^n (h_i - h_m)^\wedge 2 \qquad \ldots(3)$$

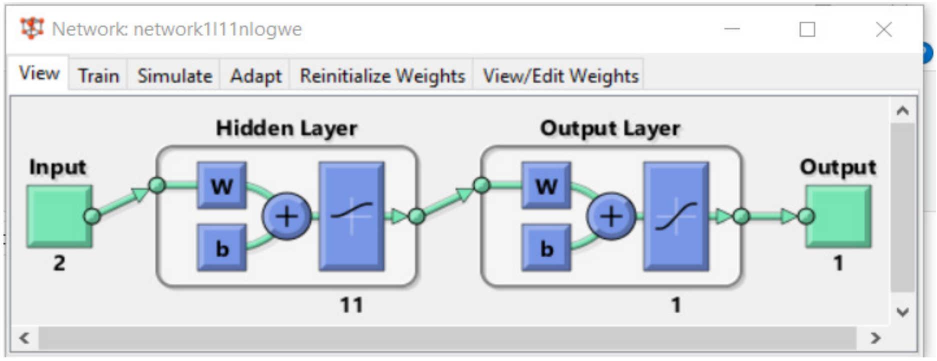


**Fig. 6. Neural Network Structure.**

## 4. Results and Discussions

The weights are fixed once the network has been trained, and the model is checked for accuracy. The model was validated using the verification data chosen as the availability of 2018 as shown in figure 7 to examine the predicted precision of the emerging neural network model. It is clear that there is a difference between the values of availability by Weibull and ANN, that is due to the fact that a real time failures of year 2018 did not used into accounting the parameters of (β) and (θ) in Weibull distribution. This means that the application of neural networks gave better results and is closer to the studied reality of the collected data, because it takes into account any data that enters the network, and based on it, it changes the weights between the network layers to improve the estimation values.

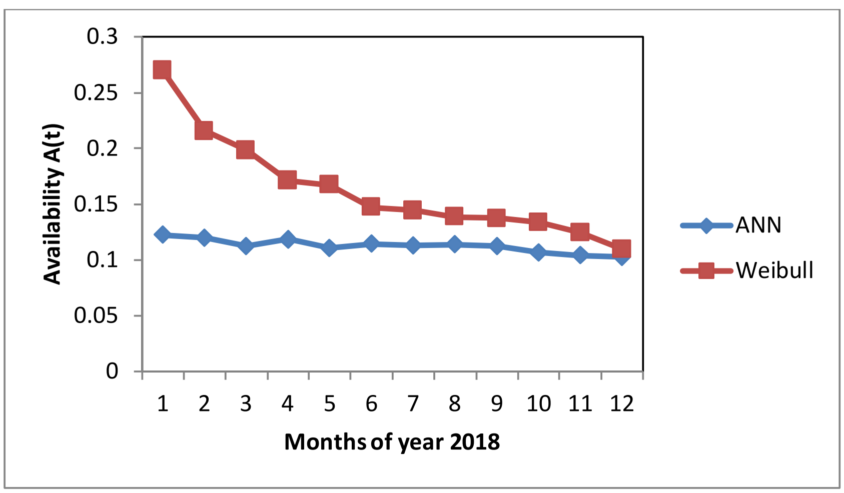


**Fig. 7. A(t) of testing year 2018 by ANN & Weibull .**

Tables 3 shows the estimation results for the availability of the Generator for year 2019 in every 100 working hours obtained by the ANN structure. It is preferable to adopt more hours of operation in the estimated availability, because the (100 hours) operation has given close results.

**Table 3,**
**Estimate Availability by (ANN) for Year (2019)/Generator**

| | Operation Time From [hr.] | Stopping Time To [hr.] | Estimating Availability by ANN A(t) |
|---|---|---|---|
| **1** | 35000 | 35064 | 0.111788 |
| **2** | 35064 | 35164 | 0.111783 |
| **3** | 35164 | 35264 | 0.111776 |
| **4** | 35264 | 35364 | 0.111769 |
| **5** | 35364 | 35464 | 0.111763 |
| **6** | 35464 | 35564 | 0.111756 |
| **7** | 35564 | 35664 | 0.11175 |
| **8** | 35664 | 35764 | 0.111745 |
| **9** | 35764 | 35864 | 0.111739 |
| **10** | 35864 | 35964 | 0.111734 |
| **11** | 35964 | 36064 | 0.111729 |
| **12** | 36064 | 36164 | 0.111724 |
| **13** | 36164 | 36264 | 0.111719 |
| **14** | 36264 | 36364 | 0.111715 |
| **15** | 36364 | 36464 | 0.11171 |
| **16** | 36464 | 36564 | 0.111706 |
| **17** | 36564 | 36664 | 0.111702 |
| **18** | 36664 | 36764 | 0.111698 |
| **19** | 36764 | 36864 | 0.111695 |
| **20** | 36864 | 36964 | 0.111691 |
| **21** | 36964 | 37064 | 0.111688 |
| **22** | 37064 | 37164 | 0.111685 |
| **23** | 37164 | 37264 | 0.111681 |
| **24** | 37264 | 37364 | 0.111679 |
| **25** | 37364 | 37464 | 0.111676 |
| **26** | 37464 | 37564 | 0.111673 |
| **27** | 37564 | 37664 | 0.11167 |
| **28** | 37664 | 37764 | 0.111668 |
| **29** | 37764 | 37864 | 0.111665 |
| **30** | 37864 | 37964 | 0.111663 |
| **31** | 37964 | 38064 | 0.111661 |
| **32** | 38064 | 38164 | 0.111659 |
| **33** | 38164 | 38264 | 0.111657 |
| **34** | 38264 | 38364 | 0.111655 |
| **35** | 38364 | 38464 | 0.111653 |
| **36** | 38464 | 38564 | 0.111651 |
| **37** | 38564 | 38664 | 0.111649 |
| **38** | 38664 | 38764 | 0.111647 |
| **39** | 38764 | 38864 | 0.111646 |
| **40** | 38864 | 38964 | 0.111644 |
| **41** | 38964 | 39064 | 0.111643 |
| **42** | 39064 | 39164 | 0.111641 |
| **43** | 39164 | 39264 | 0.11164 |
| **44** | 39264 | 39364 | 0.111639 |
| **45** | 39364 | 39464 | 0.111637 |
| **46** | 39464 | 39564 | 0.111636 |
| **47** | 39564 | 39664 | 0.111635 |
| **48** | 39664 | 39764 | 0.111634 |
| **49** | 39764 | 39864 | 0.111633 |
| **50** | 39864 | 39964 | 0.111632 |
| **51** | 39964 | 40064 | 0.111631 |
| **52** | 40064 | 40164 | 0.11163 |
| **53** | 40164 | 40264 | 0.111629 |
| **54** | 40264 | 40364 | 0.111628 |
| **55** | 40364 | 40464 | 0.111627 |
| **56** | 40464 | 40564 | 0.111627 |
| **57** | 40564 | 40664 | 0.111626 |

| | | | |
|---|---|---|---|
| **58** | 40664 | 40764 | 0.111625 |
| **59** | 40764 | 40864 | 0.111624 |
| **60** | 40864 | 40964 | 0.111624 |
| **61** | 40964 | 41064 | 0.111623 |
| **62** | 41064 | 41164 | 0.111622 |
| **63** | 41164 | 41264 | 0.111622 |
| **64** | 41264 | 41364 | 0.111621 |
| **65** | 41364 | 41464 | 0.111621 |
| **66** | 41464 | 41564 | 0.11162 |
| **67** | 41564 | 41664 | 0.11162 |
| **68** | 41664 | 41764 | 0.111619 |
| **69** | 41764 | 41864 | 0.111619 |
| **70** | 41864 | 41964 | 0.111618 |
| **71** | 41964 | 42064 | 0.111618 |
| **72** | 42064 | 42164 | 0.111617 |
| **73** | 42164 | 42264 | 0.111617 |
| **74** | 42264 | 42364 | 0.111617 |
| **75** | 42364 | 42464 | 0.111616 |
| **76** | 42464 | 42564 | 0.111616 |
| **77** | 42564 | 42664 | 0.111615 |
| **78** | 42664 | 42764 | 0.111615 |
| **79** | 42764 | 42864 | 0.111615 |
| **80** | 42864 | 42964 | 0.111615 |
| **81** | 42964 | 43064 | 0.111614 |
| **82** | 43064 | 43164 | 0.111614 |
| **83** | 43164 | 43264 | 0.111614 |
| **84** | 43264 | 43364 | 0.111613 |
| **85** | 43364 | 43464 | 0.111613 |
| **86** | 43464 | 43564 | 0.111613 |
| **87** | 43564 | 43664 | 0.111613 |
| **88** | 43664 | 43764 | 0.111613 |
| **89** | 43764 | 43824 | 0.111612 |

## 5. Conclusions

In this study an ANN model was developed to predict the availability aspects of generator in unit 5 of Al-Dourra electric power plant. The developed ANN model is used to analyze the effect of process parameters at the time of failure and operating time of the system during three years (2015-2017), and the year 2018 was used as a test year to check the modeling work, and validate experimental results before developing a model. The primary conclusions of the investigation are given below:

- It is possible to take advantage of the methods of artificial intelligence represented by the artificial neural network for the purpose of building an intelligent model that can be used to guess the availability of an industrial system based on the scheduling of data of previous years.
- The (ANN) gives a better estimate of the same cumulative operating time.
- The fact that the data used are few, and that this data was taken during the past four years only (2015-2018), not since the system began operating more than 30 years ago requires more effort to train the network and reach the best network structure to give results closer to reality.
- It is possible through which to build a preventive maintenance schedule and specify the date for the availability of the necessary spare parts, as well as the management of workers.
- The larger the data, the greater the accuracy envisaged, so it is preferable to always update the data by adding data over the years, to update the layer weights.

## 6. References

[1] G. S. Sampaio, A. R. de Aguiar, L. S. da Silva, and L. A. da Silva, " Prediction of Motor Failure Time Using An Artificial Neural Network," *Sensors*, vol. 19, no. 4342, pp. 1-17, 2019. https://doi.org/10.3390/s19194342

[2] E. Walter and L. Pronzato, Identification of Parametric Models from Experimental Data.

Communications and Control Engineering, 1997th edition, Springer, 1997.

[3] M. T. de Oliveira, P. S. Silva, E. Oliveira, A. M. Marcato, G. S. Junqueira, " Availability Projections of Hydroelectric Power Plants through Monte Carlo Simulation, " Energies, vol. 14, no. 8398, 2021. https://doi.org/10.3390/en14248398

[4] H. Jagtap, A. Bewoor, R. Kumar, M. Ahmadi, G. Lorenzini, " Markov-based performance evaluation and availability optimization of the boiler–furnace system in coal-fired thermal power plant using PSO, " Energy Reports, vol. 6, pp. 1124-1134, 2020. https://doi.org/10.1016/j.egyr.2020.04.028

[5] Z. I. Ahmed, B. I. Kazem, A. R. Al-khafaji, "Availability Estimation of Caustic Pump by Using Artificial Neural Network, " The 6th Engineering Conference: College of Engineering, vol. 3: Mechanical and Nuclear Engineering, 2009.

[6] H. P. Jagtap , A. K. Bewoor , R. Kumar, M. H. Ahmadi, M. E. Assad, and M. Sharifpur, "RAM analysis and availability optimization of thermal power plant water circulation system using PSO," *Energy Reports*, vol. 7, pp. 1133-1153, 2021. https://doi.org/10.1016/j.egyr.2020.12.025

[7] L. Wang, H. Hu, Y. Wang, W. Wu, and P. He, " The availability model and parameters estimation method for the delay time model with imperfect maintenance at inspection, " *Applied Mathematical Modelling*, vol. 35, pp. 2855-2863, 2011. doi:10.1016/j.apm.2010.11.070

[8] P. S. Rajpal, K. S. Shishodia, and G. S. Sekhon, "An artificial neural network for modeling reliability, availability and maintainability of a repairable system, " *Reliability Engineering & System Safety*, vol. 91, no. 7, pp. 809-819, 2006. doi:10.1016/j.ress.2005.08.004

[9] M. K. Bhuyan, D. P. Mohapatra, and S. Sethi, "Software Reliability Assessment using Neural Networks of Computational Intelligence Based on Software Failure Data, " *Baltic Journal of Modern Computing*, vol. 4, no. 4, pp. 1016-1037, 2016. http://dx.doi.org/10.22364/bjmc.2016.4.4.26

[10] M. Kutyłowska, "Neural network approach for availability indicator prediction, "*Periodica Polytechnica Civil Engineering*, vol. 61, no. 4 , pp. 873-881 ,2017. https://doi.org/10.3311/PPci.10429

[11] [S. Mehmet, "Availability analysis of a power plant by computer simulation, " *International Journal of Energy and Power Engineering.*, vol. 9, no.4, pp. 495-498, 2015.

# تقدير وتحليل مدى أتاحية المولد في محطة توليد الطاقة الكهربائية باستخدام ANN

أسماء جمال عواد* أحمد عبد الرسول أحمد** أسامة فاضل عبد اللطيف***

*،*** قسم هندسة التصنيع المؤتمت/ كلية الهندسة الخوارزمي/ جامعة بغداد
** قسم الهندسة الميكانيكية/ كلية الهندسة/ جامعة بغداد
*البريد الالكتروني: asmaa_jamal_1992@yahoo.com
**البريد الالكتروني: aa.alkhafaji@yahoo.com
***البريد الالكتروني: drosamah@kecbu.uobaghdad.edu.iq

## الخلاصة

كثرة الأعطال في محطة الطاقة الكهربائية تؤدي إلى التوقف المفاجئ عن العمل. في بعض الحالات، لا تتوفر المواد الاحتياطية اللازمة للصيانة مما يؤدي إلى انقطاع توليد الطاقة في وحدة محطة الطاقة الكهربائية. تناولت الدراسة الحالية تحديد أوجه توافر المولدات في الوحدة الخامسة بمحطة الدورة لتوليد الكهرباء. من أجل تقييم أداء الأتاحية لهذا المولد، تم إجراء مجموعة واسعة من الدراسات لجمع معلومات دقيقة على مستوى التفاصيل التي تعتبر مناسبة لتلبية هدف تحليل الأتاحية. يتم إجراء تحليل الموثوقية باستخدام توزيع Weibull عبرMinitab 17 ، والشبكات العصبية الاصطناعية (ANN) من خلال الاقتراب من التغذية إلى الأمام، والانتشار الخلفي. تم استخدام بيانات التشغيل للأعوام ٢٠١٥-٢٠١٧ لحساب التوافر بالطريقة التقليدية (توزيع Weibull) وتدريب الشبكات العصبية الاصطناعية، بينما تم استخدام البيانات من عام ٢٠١٨ للتحقق من النموذج. تقترح الدراسة أن ANN قد تتنبأ بأتاحية المولد بمعامل ارتباط 0.99874 (R) ومتوسط خطأ مربع 5.6937E-06 (MSE) بين التوافر الذي تنبأ به ANN وإخراج توزيع Weibull.