Maintenance Assessment of an Industrial System Using Artificial Intelligence

Wasan M. Ahmed, Abbas F. M. Aldoory, Najah M. Ahmed

Department of Refrigeration and Air Conditioning, University of Dijlah, Baghdad, Iraq

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ABSTRACT

In the (electricity plants, water desalination plants) whose parts are connected in a row, there are no fixed maintenance procedures for them because of the happening of faults at different times. To fulfill the research aims is developed a predictive maintenance program, using A.I. techniques. Al-fifth Dora's unit data. Two stages of research were conducted. First, missing data without temporal sequences were processed. The data was filled using time series hour after hour and consideration filling times as system working hours, making the volume of data relatively high for 2015-2016-2017, and 2018 was utilized as a test year to assess the modelling work and validate experimental results. In the second step, the artificial neural networks approach employed the python program as an A.I., and the affinity ratio to real data using the performance measurement (Root Mean Square Error) R.M.S.E (0.507). 2019-2030 showed the program's long-term predictability.

Corresponding Author: Abbas F. M. Aldoory

Department of Mechanical Engineering, University of Dijlah

Almasafi street, Baghdad, Iraq Email: abbas.aldoory@duc.edu.iq

1. INTRODUCTION

Maintenance ensures equipment and machinery run correctly.. The maintenance strategy goal is to reduce losses by reduction of cost and implement perfect operating conditions. The strategy must consider the overall optimized cost [1]. The Maintenance is categorized by the nature, purpose, and job as preventative, predictive, failure-finding, and corrective [2]. Maintenance that is scheduled in advance to avoid unexpected breakdowns or failures of a functional system is known as preventative Maintenance. Equipment failure can be avoided, its functionality can be preserved, and its lifespan can be increased by preventative Maintenance. In most cases, the expected lifetime of the equipment will determine how frequently it needs to be maintained [3]. Preventive Maintenance is a program of planned maintenance procedures to prevent equipment failures. After a certain number of hours, jet engines are lubricated and their lightning arresters replaced. This increases equipment reliability by replacing worn parts before they fail [4,5]. Predictive maintenance (PdM) or Condition-Based Maintenance (C.B.M.) can be performed after collecting and analyzing sufficient physical data, such as temperature, vibration, or oil particle matter. To establish a maintenance plan, data evaluation is performed [4]. Infrared, acoustic (partial discharge and airborne ultrasonic), corona detection, vibration analysis, sound level measurements, oil analysis, and others are among the detection methods [5]. Failure-Finding maintenance Comprises evaluating a (quiescent) system portion. This is a fairly frequent occurrence for defensive subsystems. When numerous safety system components fail simultaneously, the consequences might be devastating. Inspections uncover issues previously unknown (also called dormant failures). While the element is being inspected, no maintenance is performed unless the component fails the examination, in which case corrective Maintenance is conducted [5]. Corrective Maintenance addresses malfunctioning equipment or systems. This Maintenance involves either the replacement or repair of the faulty component. Because the failure duration of a component is unclear, Corrective Maintenance is performed at irregular intervals. After repairs or Maintenance, equipment becomes operational.

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2. LITERATURE REVIEW

Maintenance in production facilities is a very recent topic as the global interest in equipment maintenance leads to lower operating costs, both Maintenance and production. It also leads to an overall reduction in production equipment failures and an increase in production potential and efficiency. Preventive Maintenance (PM) in the production industry is one of the most critical measures to eliminate accidental machinery malfunctions by replacing/repairing damaged machinery or parts. The decision to perform preventive Maintenance is not accessible due to the complex and random nature of the industry where PM is performed. This studies emphasizes previous research that deals with different maintenance techniques. It has been divided into two parts: Previous research about its traditional maintenance techniques and research related to modern maintenance techniques. Many studies specialize in the situation. The following are the most important studies on the proposed system in Omur & Orhan (2009)[6]. Deal with designated preventive Maintenance to reduce repair costs and improve device deterioration availability. Per periodic system, checks revealed that deterioration cases occur in the system.in Naser M. (2010) [7]. Deal with the use of two different methods preventive Maintenance and scheduling method. The selected methods calculated the optimum time for supported equipment reliability of optimum time. The result of maintenance time for both cases is identical but preferred the scheduling method over reliability despite the same effects.in Moghaddam K. (2010) [8]. Defined two different maintenance methods preventive maintenance and replacement schedule. This thesis results in two methods for improving system reliability and availability to reduce maintenance costs. This thesis develops optimization models for PM schedules. The genetic algorithm was used to solve nonlinear mixed models.in Abdulsamat H et al. (2013)[9]. referred to reducing tools' scheduled downtime by analyzing and enhancing the checklist preventive downtime by analyzing and enhancing the checklist preventive maintenance. It implemented the benefit of having a checklist for elements, smoothed the technicians' work and reduced the time of stopping the factory in Badi I. & Shetwan A. (2016) [10]. Deal pointed out the significance of indicators for measuring maintenance performance by calculating twelve indicators of maintainability to measure the efficiency of maintenance performance. The final paper results showed a low rate of Accessibility to manufacturing actual lines and lower preventive maintenance rates than corrective Maintenance. Adulghafour & Abdulwahad I. (2018)[11] aims to create a maintenance plan by applying statistical data to generate a probability-of-failure distribution model using the built-in approach to the effect failure pattern critical analysis and fault tree analysis. The researchers concluded that applying the proposed R.C.M. methodology based on preventive maintenance planning will reduce the total value of the maintenance cost of labor signification by reducing the time required for repair in Dawood L et al. (2018) [12] deals with two inductors' values, the through point and performance indicator values. This paper uses preventive Maintenance with M.M.S. in carrying out maintenance actions for all factories. The preventive Maintenance with M.M.S. recycled to choose greatly affects improving quality and reliability in the manufacturing works, reducing the product cost by increasing the factory production. In Ran U et. al. (2019) [13], refers to the literature on predictive Maintenance with a focus on the purposes and approaches in the industry, as this study showed that any unplanned shutdown of machines or systems would lead to the deterioration of the company's basic business and thus cause great losses. The study showed that traditional maintenance methods suffer from many defects, such as high repair costs, affecting the reputation of companies. Therefore, researchers worked on introducing the artificial intelligence method for Maintenance, as they formed a model of maintenance models capable of predicting faults before they occur, which reduces the loss of time and money, thus achieving goals for Maintenance. In Mohmmed A et al. (2020) [14] dealt with using a dump truck system to discover the components with the lowest reliability and estimate the system failures time. This study developed a preventive maintenance strategy to improve reliability and decrease mountainous costs. The current level of reliability is not convincing. It can be conducted and improved by focusing on some components, as well as the study suggested that technicians report any errors or outages to avoid any damage. High safety and good operation solved the problem and gave perfect solutions that affected factory systems' failure rate and existence. In Moghaddam S. (2010) [15], This study improves the parameter models that reduce the new non-linear function's life. By studying the active life of factory systems, the paper developed a practical method to determine the effect of preventive Maintenance on failure rate. The improved models include a basic trade-off between maintenance replacement costs and failure rate savings. Maintenance schedules have been implemented to balance individual operation costs and non-linear optimization models. Genetic algorithms have been used to build optimization models, saving designers and analysis time and effort in reaching a final solution. In Mansour & Makhoul (2012)[16], deals with reaching a high-reliability electrical system that protects electrical power's permanence. Different method was presented for service continuity in electricity distribution networks through the use of genetic algorithms raised reliable and improved performance have been the data used in the algorithm calculation. The proposed models reduce high-cost, decreasing the time of

electrical failure and Maintenance. In Rami Al-Hadithi et al. (2012) [17] proposed implementing a preventive maintenance scheduling system based on an intelligent fuzzy logical algorithm. The proposed models proved that time scheduling has many disadvantages that are difficult to include in the information system. Therefore, the practical application of theoretical research was developed to optimum variable scheduling time and mounting planning systems to deliver Maintenance to customers. The proposed Fuzzy Replacement System is an advanced and practical solving problem of providing reliable schedules through the Enterprise Material Planning Unit and confirmed the success of applying fuzzy logic to solve the scheduling problem. In Krenek J et. al. (2016) [18]. Deal with different techniques for Maintenance with artificial neural networks in the automotive industry chain. The studies proved that neural networks have a strong potential in maintenance tasks. It proposed methods effect evaluating the risks of faults and early analysis to discover errors. This feature delivers the option of prevention. The new method gives high operative in equipment failure and increases performance results. In Javanmard H.& Koraeizadeh A. (2016) [19]. Deal with expecting the activities necessary for preventive Maintenance by studying equipment's optimum costs and reliability. The paper methodology was applied by extracting some data from the equipment and maintenance department. The lingering data required through the application of a genetic algorithm predicted downtime, costs and reliability in a predetermined period. The proposed methods applied the extracted feature to all manufactured and non-manufactured equipment. In Gregor M et al. (2016) [20] deal with explaining a new generation of industrial automation, intelligent production, and development towards the industry. This system statement in organizations the role of increasing the performance system about the costs experienced. This paper discusses integrating a reconfigurable maintenance system into the system's production. It deals with adversative production conditions and confirms reliability for production configurations. In Alhamad k et al. (2016) [21]. Deal with reliability, a key decision tool that improves maintenance scheduling for cogeneration plants. The paper's 4 points are better than 2 points for each electricity and water concentration. The numerical analysis used for genetic algorithms may improve diagnostic mathematics solutions. The works' goal can be expanded to include Maintenance and production costs of optimal units. The paper method was used to create all possible schedules with the optimal cost solution. In Montiel A et. al. (2017) [22] progress the preventive maintenance procedures used by the medium-voltage electricity distribution companies, especially on times and cost. The improvement is based on the real data of the station implemented for the genetic algorithm to have an optimum solution. The proposed methods were theoretically done by simulation for a whole year of station results. The model can use this approach to improve the process of performing preventive Maintenance significantly. In Vannucci M et. al. (2018) [23]. This paper proposes a new type of genetic algorithm for industrial optimization. This method used a genetic algorithm with a fuzzy inference system approach that controls the search strategies of the algorithm. This method calls the FAR method. The prevent optimization from attaining the minimum level instead of the overall level; the fars relies on controlling genetic algorithm recombination rates by takeout features that define the stage of development. The proposed methods enhanced the performance of industrial Maintenance. Its ability to troubleshoot faults with high efficiency, avoid lower limits, and reduce the time required for improvement.in Bampoula X et. al. (2021) [24]. deal with an approach to qualifying the change from preventive Maintenance with a deep learning algorithm for planning maintenance events to the equipment's actual operating condition. In this paper study, real data was calculated to form training and testing of the prototype model executed in python language. The proposed method reduced the cost of Maintenance and redundant downtime.

3. PROPOSED SYSTEM

A proposed system with different stages and steps; the first stage includes describing the system under study and its subsystems, the dataset collection, categorization, and creation of the enhancement data to suit the required research. The second stage contained the application of the proposed model by designing the ANN. Figure (1) shows the two stages and steps necessary to implement the proposed methodology.

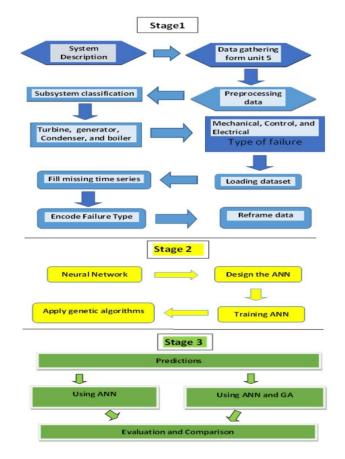


Fig.(1): Stages and steps proposed methodology.

3.1 First stage

System Description Al-Doura Power Station is a steam-powered electric power station located in Baghdad near the Tigris River. It consists of six units, the first and second units out of service because of the war conditions, and the branches (3,4,5 and 6) currently working to generate electricity for the capital Baghdad with a production capacity estimated at (400 MW) per Unit and all units connected. Figure (2) shows the subsystems (the main parts) of the generating units of the station. Each Unit consists of four main parts linked together respectively. The failure in any part leads to the stop the parts, which are (Boiler, Turbine, Generator, and Condenser). Unit 5 was chosen as a case study of race methodology; the data was collected for four years (2015-2018).

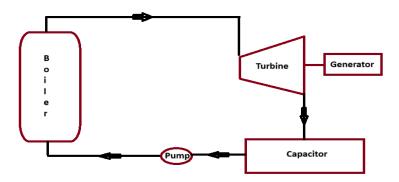


Fig.(2): Parts of Unit[42].

Filling missing dataset, the dataset collected from previous studies suffers from random time jumps and missing values. A significant variation in the standard periods. This fluctuation leads to an effect on practical training, which

means the results will be completely inaccurate. To solve this issue, process the dataset and convert it to a time series dataset; then new dataset treats periodically within the standard period difference. And coding failure and reasons. Unit 5 has four parts (Boiler, Turbine, Generator, and Condenser) as shown in figure 3, plural this kind of failure as a system in one column labelled BTGC. Write a python program to code the type of failure depending on the first letter of failure type as an abbreviation for the initials of the components, for example, B for Boiler, T for Turbine, G for Generator, and C for Condenser. Table(1) includes the encoding failure and failure reason specifically.

Code value	BTGC	Failure type
0	Low vacuum	Mechanical
1	Check vibration	Mechanical
2	Electrical hydraulic suddenly open	Control
3	Shutdown	Mechanical
4	Signal under voltage	Electrical
6	High temp in room exciter	Electrical
7	Control room	Mechanical
8	Reply valve 5 NM28 safety	Mechanical
9	The trip by signal drum level high	Mechanical
10	Over Current	Electrical
11	Push button fire protection	Mechanical
12	The trip by signal I.P.S logic	Control
13	A trip by signal loss of both (F.D.F G.R.F)	Mechanical
14	High pressure	Mechanical
15	Vacuum low	Mechanical
16	Steam leakage in the control valve	Mechanical
17	High vibration in all bearing	Mechanical

Table (1): Coding failure and reason

3.2 Second Stage

Artificial Neural Network (ANN) was utilized, the data that's enhancement going to be an input of the ANN network, then the output is the prediction of failure type and time further. Most importantly, the model can predict till 2030. Design the ANNThe fully connected ANN was created with 15 neurons of 2 hidden layers and two outputs; Figure (3) shows the structure of the ANN. Where w is the weight to be trained and b is the bias used to adjust the output along the weighted sum. The activation function is the sigmoid function used to scale the work.

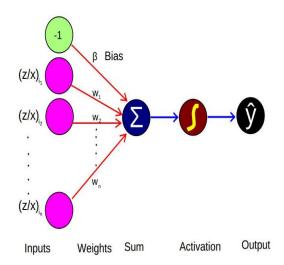


Fig.(3): ANN network Structural.

Training and testing are neural network processing phases. Use 80% of the data for training and 20% for testing. Training involves adjusting weights and biases to produce accurate results. Supervised training is most general. Backpropagation trains and modifies the network to reduce output error. Adjusting initial random weights and biases begins network training. Forward-propagation of intermediate results produces the output vector. The difference between target and network outputs equals error. Back-propagating network error modifies weights and biases to reduce cycle prediction error. During testing, the network's structure doesn't change. Using (genetic algorithm) with (ANN) G.A. generates several potential solutions to the issue and then refines them throughout several generations. Every answer contains all of the parameters that could contribute to improving the findings. When applied to ANN, weights in each layer contribute to the great accuracy that can be achieved. Because of this, a single solution in G.A. will include all the weights.

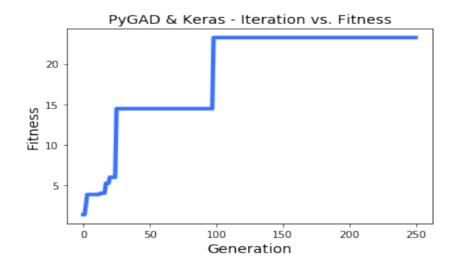


Fig. (4): Genetic algorithm to adjust the weight.

3.3 Third Stage

Predictions Validation of ANN algorithm in the year (2018) The validation of the (ANN) algorithm by comparing the predicted results of the failure type and its reasons of occurrence with the actual data (2018). Figure (5) shows comparing of the actual data with the predictive data by using ANN, which indicates the actual values of no failure are equal to (7605) hours and in predicted value is (7700)hours. Also can see that the mechanical failure, Equal to (1033) in actual and (1008) in predict, then the number of electrical failure hours in actual and predict is (122 and 50), respectively.

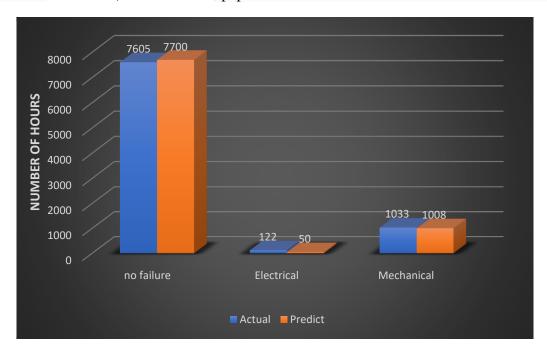


Fig. (5): comparing results using ANN based on failure type in 2018.

Validation of prediction by using (ANN) and (G.A.) in the year (2018)After optimizing the weights of the ANN by using the genetic algorithm. Figure (6) shows comparing of the real data with the predictive data by using ANN with G.A., which indicates the real values of no failure are equal to (7605) hours and in predicted values is (7650)hours. Also can see the mechanical failure. Equal to (1033) in actual and (1018) in predict, then the number of electrical failure hours in actual and predict is (122 and 90), respectively.

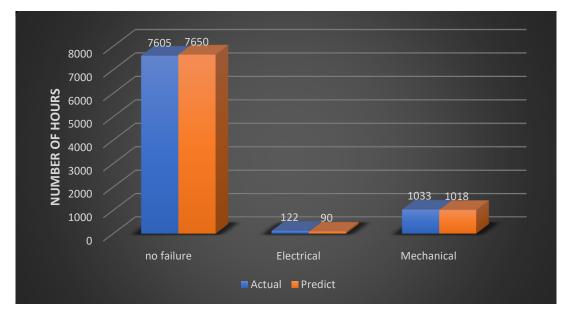


Fig. (6): Comparing results using ANNwith GA based on failure type in 2018.

Evaluation and Comparison, The Comparison between the percentage of hours for each type of failure is shown in figure(7). The predicted rate of the number of hours in no failure using ANN with G.A. is more current than the predicted using ANN alone.

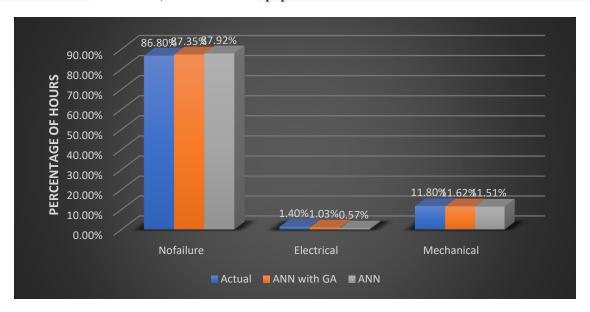


Fig. (7): comparing results between actual and after genetic and before genetic.

4. RESULTS AND DISCUSSION

To show the results clearly, a comparison between the two proposed approaches was carried out for the predictive years 2019 and 2020. AND To verify and compare the two approaches, compare the predictive of failures for 2019 using ANN alone and ANN with G.A., as shown in figure (8). It's clear from this figure that the predictions by using ANN with G.A. are better than using ANN alone, where note that the percentage of continuity of the system work by using ANN alone is (23%), while it increased to (28.6%) by using ANN with G.A. While for mechanical failures, the percentage of predictions by using ANN alone is (59.4%), it decreased by using ANN with G.A. to (56.4%). Also, the rate of electrical failures in ANN alone is (17.6%), while it decreased by using ANN with G.A. to(15%).

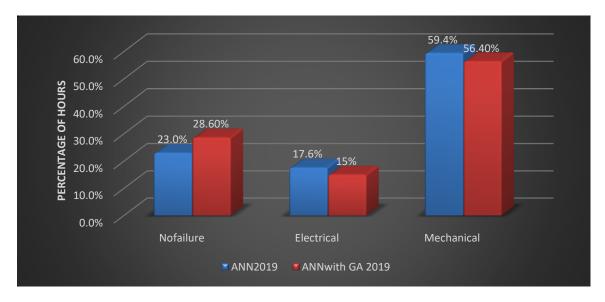


Fig. (8): The general percentage of failure type by using ANN and ANN with GA in 2019.

To verify and compare the two approaches, compare the predictive of failures for 2020 using ANN alone and ANN with G.A., as shown in figure(9). It's clear from this figure that the predictions by using ANN with G.A. are better than using ANN alone, where note that the percentage of continuity of the system work by using ANN with G.A. is

(30%), while it decreased to (27%) by using ANN alone. While for mechanical failure, the percentage of predictions by using ANN with G.A. is (41%), while it increased by using ANN alone to (43%). Also, the rate of electrical failure in ANN with G.A. is (27.5%), while it increased by using ANN alone to (30%). It was concluded by comparing the predictions for 2020 that the use of ANN with G.A. is the best option in improving the accuracy of predictions, as well as for the years 2018 and 2019, which indicates that the use of ANN with G.A. represents the best model for obtaining more accuracy of predictions.

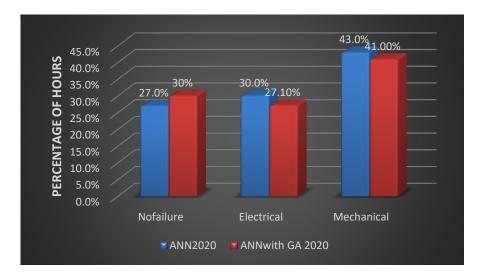


Fig. (9): percentage of failure type in general by using ANN and ANN with GA in 2020.

Designed a failure prediction program that predicts from 2018 till 2030; the user can enter the by using the application system after completing the registration and enter the data including year, month, day and hours to predicate the failure time and type, solution for long-range time predication can estimate the failure time and type till 2030 as explained in figures(10)

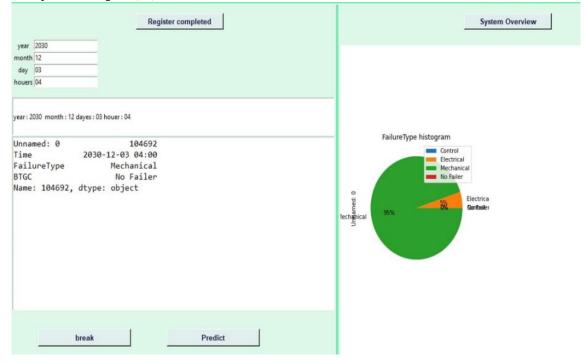


Fig. (10): predicate of 2030

5. CONCLUSIONS

ANN can be used extensively in prediction and modelling, especially in solving problems with a non-linear pattern that changes with time, which causes difficulty in modelling the relationship between input and output. G.A. was used to determine and select the initial weights and basis for the backpropagation neural network to avoid convergence in the optimal solutions. The results showed that the developed network performed much better than others. Time series helps to find future states through reading and inference from the current results available to monitor the system's condition at a future time. The possibility and accuracy of the prediction depend on the amount of information available about the system's working mechanism., The methodology proposed in this thesis can be applied to all systems operating in the maintenance systems, and it gives an excellent indication to the different departments on developing appropriate action plans and what is expected. Thus, it will reduce the internal and external costs of such systems. The ability of the applied program(Python) can be used to integrate other capabilities through the availability of accurate data. As sources for raw materials, costs and others. And The Future Works for this research are Building a new fuzzy neural network model in determining costs and demand time for the type and size of replacement parts and using another neural network of different structures such as Jordan and another web to deal with the data series used and compare the results. And Forecasting faults for intermittent production systems using artificial intelligence methods and finally, Building an integrative program by predicting subsystem failures and comparing it with the main system program.

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