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A Methodology for Evaluating and Scheduling Preventive Maintenance for a Thermo-Electric Unit Using Artificial Intelligence

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Abstract

Flow-production systems whose pieces are connected in a row may not have maintenance scheduling procedures fixed because problems occur at different times (electricity plants, cement plants, water desalination plants). Contemporary software and artificial intelligence (AI) technologies are used to fulfill the research objectives by developing a predictive maintenance program. The data of the fifth thermal unit of the power station for the electricity of Al Dora/Baghdad are used in this study. Three stages of research were conducted. First, missing data without temporal sequences were processed. The data were filled using time series hour after hour and the times were filled as system working hours, making the volume of the data relatively high for 2015-2016-2017. 2018 was utilized as a test year to assess the modeling work and validate the experimental results. In the second step, the artificial neural networks approach employs the python program as an AI, and the affinity ratio of real data using the performance measurement of the mean absolute error (MAE) was 0.005. To improve and reduce the value of absolute error, the genetic algorithm uses the python program and the convergence ratio became 0.001. It inferred that the algorithm is efficient in improving results. Thus, the genetic algorithm provided better results with fewer errors than the neural network alone. This concludes that the shown network has superior performance over others and the possibility of its long-term predictions for 2030. A Sing time series helped detect future cases by reading and inferring system data. The development of appropriate work plans will lower internal and external expenses of the systems and help integrate other capabilities by giving correct data sources of raw materials, costs, etc. To facilitate prediction for maintenance workers, an interface has been created that facilitates users to apply them using the python program represented by entering the times, an hour, a day, a month, a year, to predict the type and place of failure.

Keywords: *Maintenance, Artificial intelligence (AI), python language.*

1. Introduction

Maintenance ensures that equipment and organisms run correctly. It matches technical interventions to the right opportunities, scope, and technical and legal criteria. The maintenance strategy's goal is to reduce losses by reduction of efficiency and implement perfect operating conditions at the earliest possible delay. The strategy must consider the overall optimized cost [1]. Maintenance is categorized by the nature, purpose, and the frequency of the 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 (CBM) 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 of the evaluation of 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.

2. Literature Review

Maintenance in production facilities is a very recent topic as the global interest in equipment maintenance leads to lower operating costs in 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 in which PM is performed. This study emphasizes previous researches that deal with different maintenance techniques. It has been divided into two parts: previous research about its traditional maintenance techniques and research on modern maintenance techniques. Many studies specialize in the situation. The following are the most important studies on the proposed system. Omur & Orhan (2009) [6] dealt with designated preventive maintenance to reduce repair costs and improve device deterioration availability. Periodic system checks revealed that deterioration cases occur in the system. Naser M. (2010) [7] deals with the use of two different methods, preventive maintenance and the scheduling method. The selected methods calculated the optimal time for supported equipment reliability of optimum time. The result of the maintenance time for both cases is identical but preferred the scheduling method over reliability despite the same effects. Moghaddam K. (2010) [8] defined two different maintenance methods, the preventive maintenance and replacement schedule. This thesis resulted in two methods for improving system reliability and availability to reduce maintenance costs and also developed optimization models for PM schedules. The genetic algorithm was used to solve non-linear mixed models. 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's preventive maintenance. It implemented the benefit of having a checklist for elements, smoothed the technicians' work, and reduced the time of stopping the factory. Badi I. & Shetwan A. (2016) [10] 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] created 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 signified by a reduction in the time required for repair. 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. is recycled to choose what greatly affects the improving quality and reliability in the manufacturing works, reducing the product cost by increasing the factory production. 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 an 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. Mohmmed A et al. (2020) [14] used a dump truck system to discover the components with the lowest reliability and estimate the system failure 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. The study also 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. Moghaddam S. (2010) [15] studied to improve 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 the 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 analysts time and effort in reaching a final solution. Mansour & Makhoul (2012) [16] dealt with reaching a high-reliability electrical system that protects the electrical power's permanence. The 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 the cost, and decrease the time of electrical failure and maintenance. Rami Al-Hadithi et al. (2012) [17] suggested the implementation of 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 with optimal 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. Krenek J et al. (2016) [18] dealt with different techniques for maintenance with artificial neural networks in the automotive industry chain. The studies proved that neural networks have strong potential in maintenance tasks. It proposed methods that 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. Javanmard H. & Koraeizadeh A. (2016) [19] dealt with expecting the activities necessary for preventive maintenance by studying the equipment's optimal costs and reliability. The paper methodology was applied by extracting some data from the equipment and maintenance departments. The lingering data was acquired through the application of a genetic algorithm that predicted downtime, costs, and reliability in a predetermined period. The proposed methods applied the extracted feature to all manufactured and non-manufactured equipment. Gregor M et al. (2016) [20] dealt with explaining a new generation of industrial automation, intelligent production, and development towards the industry. This system statement in organizations takes 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. Alhamad k et al. (2016) [21] dealt 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 the diagnostic mathematic solutions. The works' goal can be expanded to include the maintenance and production costs of optimal units. The paper method was used to create all possible schedules with the optimal cost solution. Montiel A et al. (2017) [22] progressed the preventive maintenance procedures used by the medium-voltage electricity distribution companies, especially on time and cost. The improvement is based on the real data of the station implemented for the genetic algorithm to have the optimal solution. The proposed methods were theoretically done by a simulation for a whole year of station results. The model can use this approach to significantly improve the process of performing preventive maintenance. Vannucci M. et al. (2018) [23] proposed 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 is called the FAR method. This method prevents the optimization from attaining the minimum level instead of the overall level; therefore, relies on controlling genetic algorithm recombination rates by taking out features that define the stage of development. The proposed methods enhanced the performance of industrial maintenance. It has the ability to troubleshoot faults with high efficiency, avoid lower limits, and reduce the time required for improvement. Bampoula X. et al. (2021) [24] dealt 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 the python language. The proposed method reduced the cost of maintenance and redundant downtime.

3. Proposed System

The proposed system has 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 that suits the required research. The second stage contains the application of the proposed model by designing the ANN and then integrating the genetic algorithm with the ANN. The third and final stage is predicting the results. Figure 1 shows the three stages and steps necessary to implement the proposed methodology.

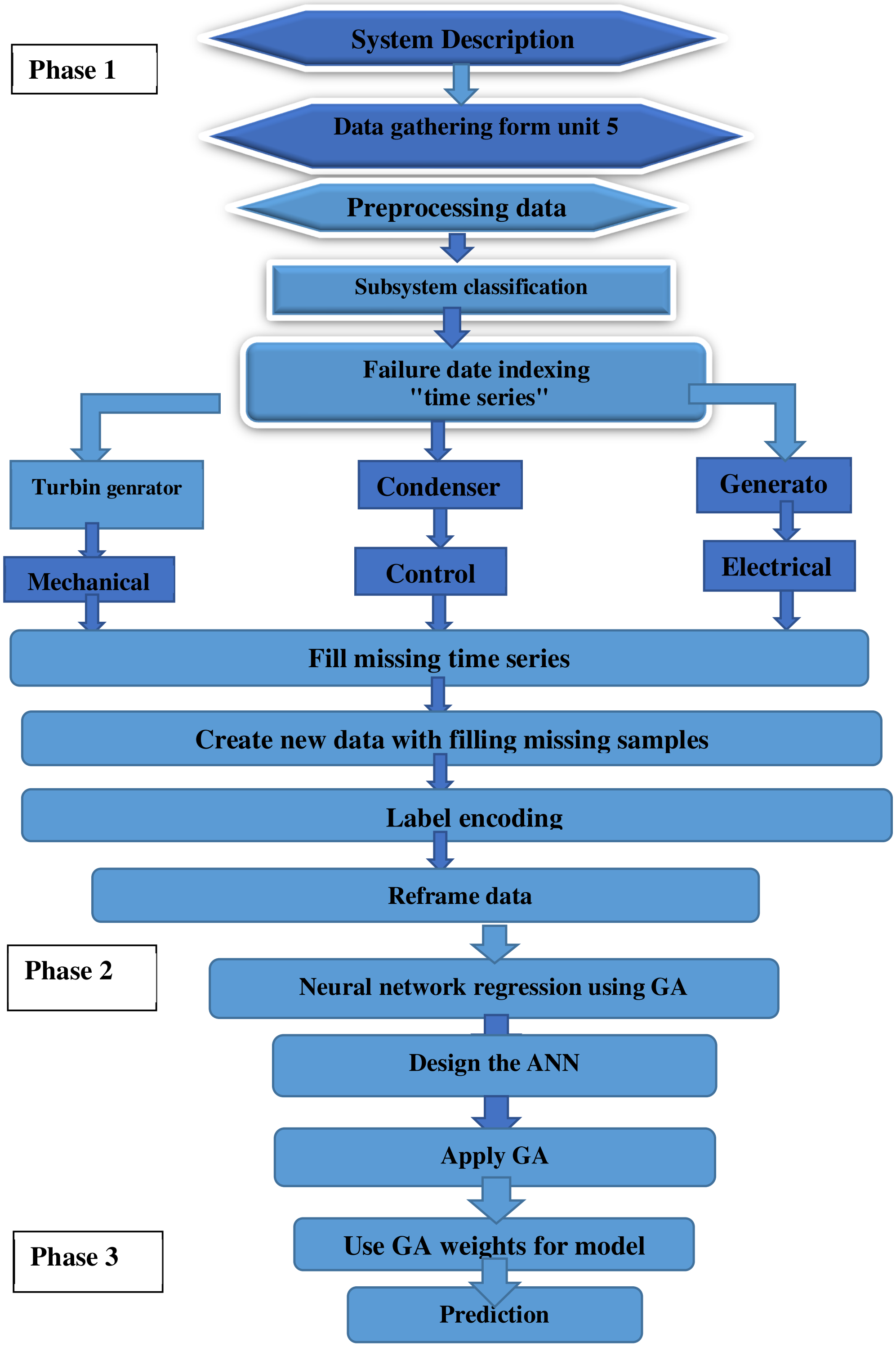

Fig. 1. Stages and steps proposed methodology.

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 are out of service because of the war conditions, and the branches 3,4,5, and 6 are currently working and generate electricity for the capital Baghdad with a production capacity estimated at (400 MW) per unit with 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 stopping of the parts (boiler, turbine, generator, and condenser). Unit 5 was chosen as a case study of race methodology; the data were collected over a span of four years (2015-2018).

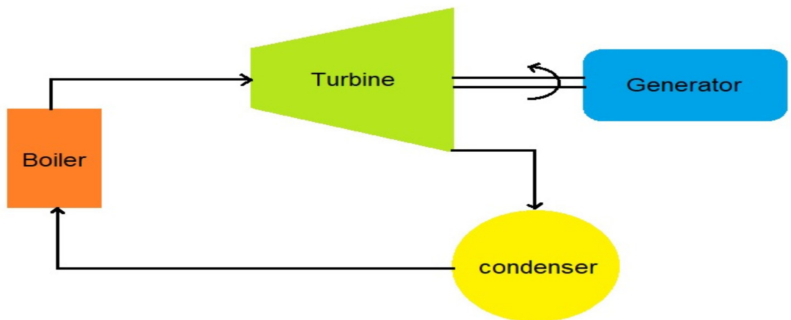

Fig. 2. Parts of Unit.

While filling the missing dataset, the dataset collected from previous studies suffers from random time jumps and missing values. There is also 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 data set. Then, the new dataset treats periodically within the standard period difference, coding failure, and reasons. Unit 5 has four parts (boiler, turbine, generator, and condenser), as shown in figure 2, this kind of failure is a system in one column labeled 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.

Table 1,
Coding failure and reason

Code value	BTGC	Failure type
0	Low vacuum	Mechanical
1	Check vibration	Mechanical
2	Electrical and 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 at the control valve	Mechanical
17	High vibration in all bearing	Mechanical

3.2 Second Stage

An artificial neural network (ANN) was utilized, the data that was enhanced is going to be an input of the ANN network, and then the output is the prediction of failure type and time delay. Most importantly, the model can predict until the year 2030. The design of a 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.

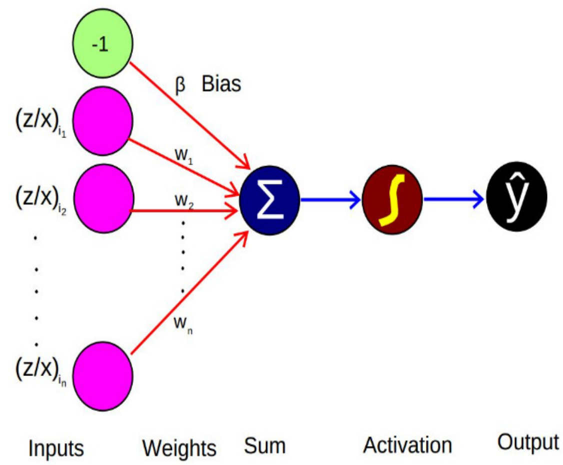

Fig. 3. ANN network Structural.

Training and testing are neural network processing phases. 80% of the data is used for training and 20% is used for testing. Training involves adjusting weights and biases to produce accurate results. Supervised training is most general type. Backpropagation trains and modifies the network to reduce output errors. Adjusting initial random weights and biases begins network training. Forward-propagation of intermediate results produces the output vector. The difference between the target and network outputs equals error. The backpropagating network error modifies the weights and biases to reduce cycle prediction error. During testing, the network's structure doesn't change. Using an ANN, the GA (genetic algorithms) 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 an ANN, weights in each layer contribute to the excellent accuracy that can be achieved. Because of this, a single solution in the GA will include all of the weights.

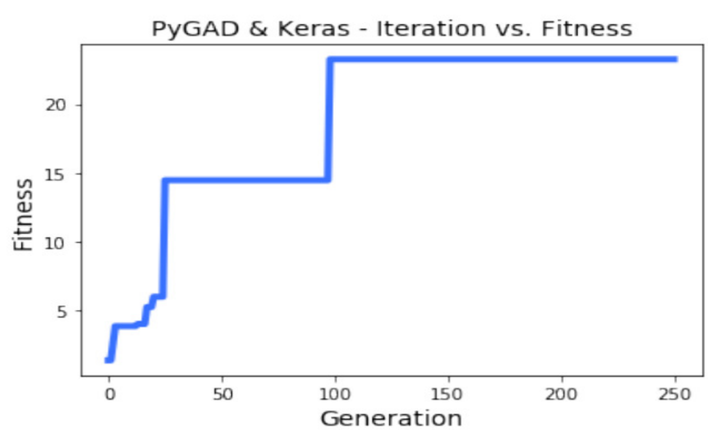

Fig. 4. Genetic algorithm to adjust the weight.

3.3 Third Stage

The predictions validation of the ANN algorithm was in 2018. The ANN algorithm was validated by comparing the predicted results of the failure type and its reasons of occurrence with the actual data (2018). Figure 5 shows a comparison of the actual data with the predicted data by using an ANN, which indicates the actual values of no failure are equal to 7605 hours and the predicted value was 7700 hours. The mechanical failure can also be seen to be equal to 1033 in reality and 1008 from the prediction, then the number of electrical failure hours in reality and prediction is 122 and 50, respectively.

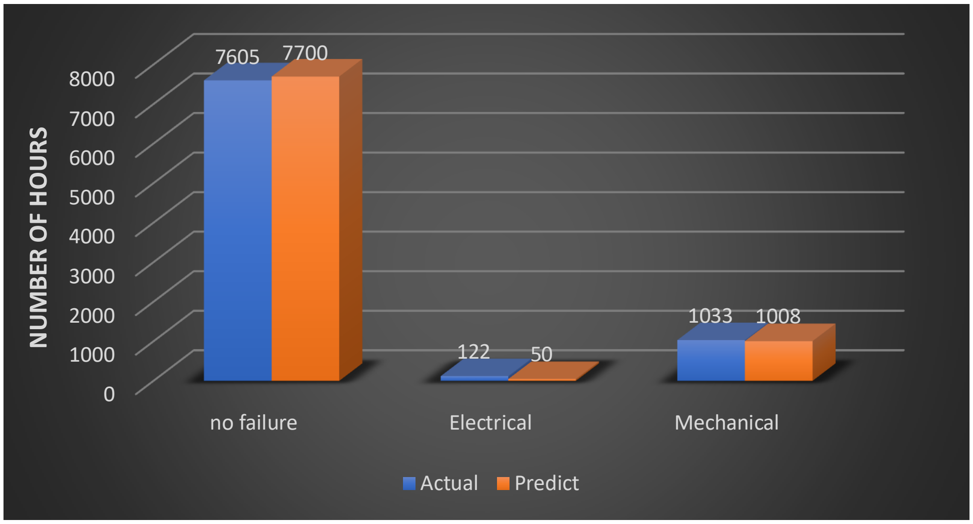

Fig. 5.comparing results using ANN based on failure type in 2018.

Validation of predictions using an ANN and GA in the year 2018 was achieved after optimizing the weights of the ANN by using the genetic algorithm. Figure 6 shows a comparison of the real data with the predicted data by using an ANN with a GA, which indicates the real values of no failure are equal to 7605 hours and the prediction's values were 7650 hours. The mechanical failure can also be seen to be equal to 1033 in reality and 1018 in the prediction, then the number of electrical failure hours in reality and in the prediction was 122 and 90, respectively.

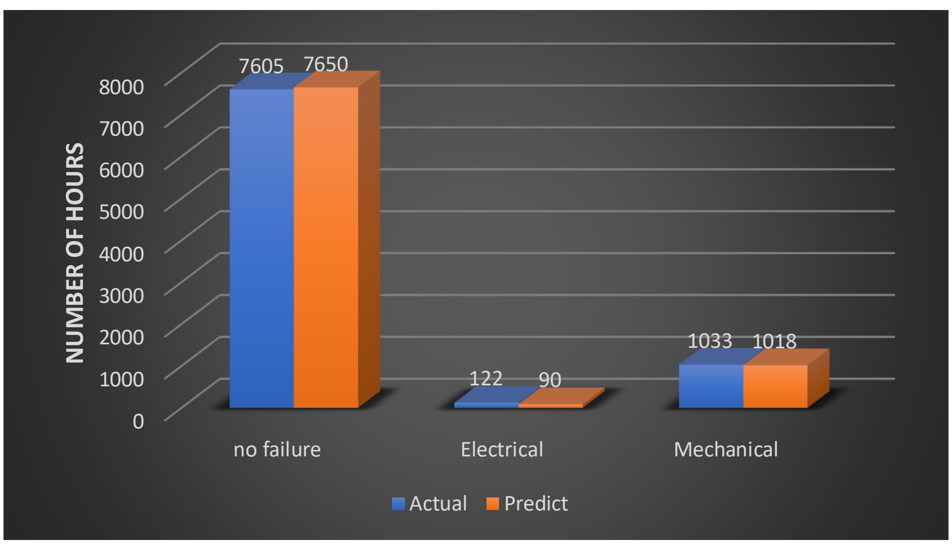

Fig. 6. Comparing results using ANN with GA based on failure type in 2018.

The comparison between the percentages 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 GA is more up to date than the predictions using the ANN alone.

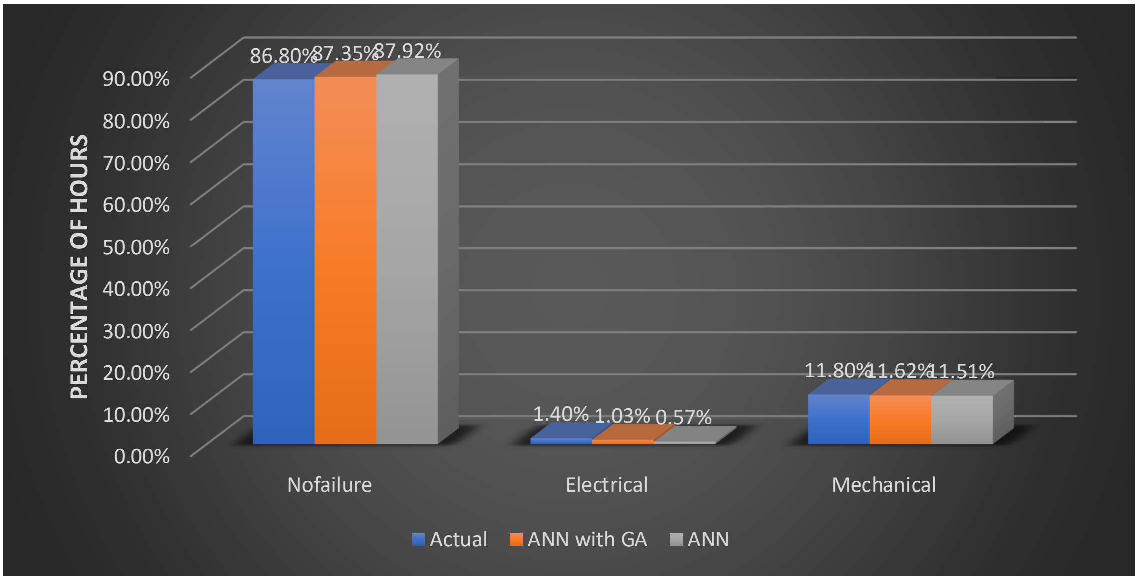

Fig. 7. comparing results between actual and after genetic and before genetic.

4. Results and Discussion

To show the results clearly, a comparison between the two proposed approaches was carried out in the predictive years 2019 and 2020. To verify and compare the two approaches, compare the prediction of failures for 2019 using ANN alone and an ANN with a GA, as shown in figure 8. It's clear from this figure that the predictions using an ANN with a GA are better than using an ANN alone. Note that the percentage of continuity of the system work using an ANN alone is 23%. In comparison, it increased to 28.6% using an ANN with a GA, while for mechanical failures; the percentage of predictions using ANN alone is 59.4%. It decreased when using ANN with GA to 56.4%. The rate of electrical failures in an ANN alone is 17.6%, while it decreased by using ANN with GA to 15%.

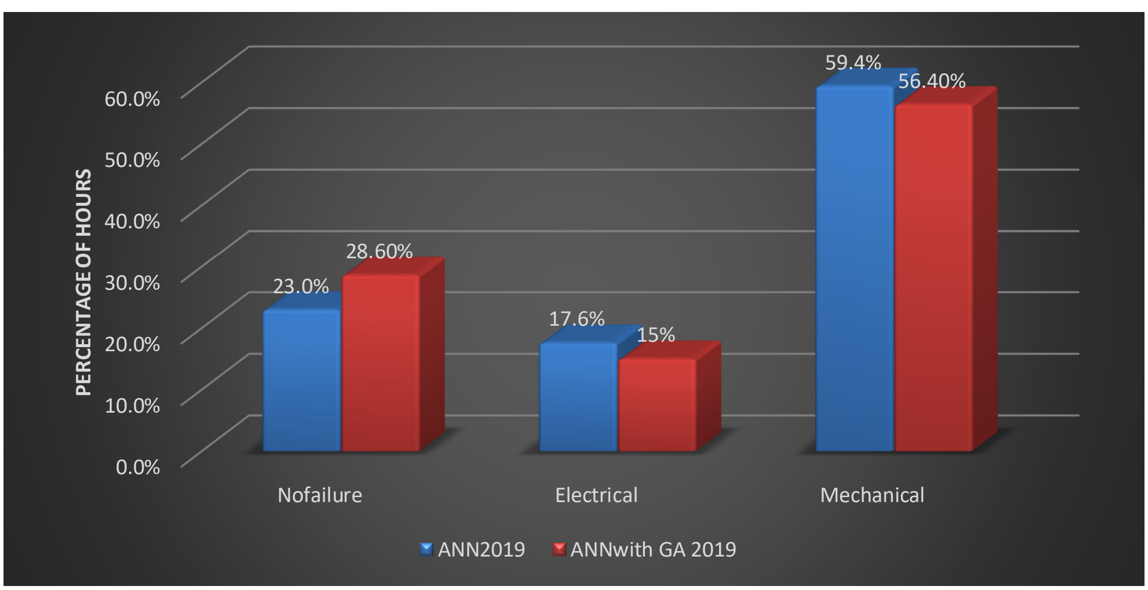

Fig. 8. The general percentage of failure types using ANN and ANN with GA in 2019.

To verify and compare the two approaches, compare the predictive failures for 2020 using ANN alone and an ANN with a GA, as shown in figure 9. It's clear from this figure that the predictions using an ANN with a GA are better than using ANN alone, Note that the percentage of continuity of the system work using an ANN with a GA is 30%, while it decreased to 27% when using an ANN alone. For mechanical failure, the percentage of predictions when using an ANN with a GA is 41%, while it increased when using an ANN alone to 43%. The rate of electrical failure in an ANN with a GA is 27.5%, while it increased when using ANN alone to30%. It was concluded by comparing the predictions for 2020 that the use of an ANN with a GA is the best option for improving the accuracy of predictions, as well as for the years 2018 and 2019, which indicates that the use of an ANN with a GA represents the best model for obtaining more accurate predictions.

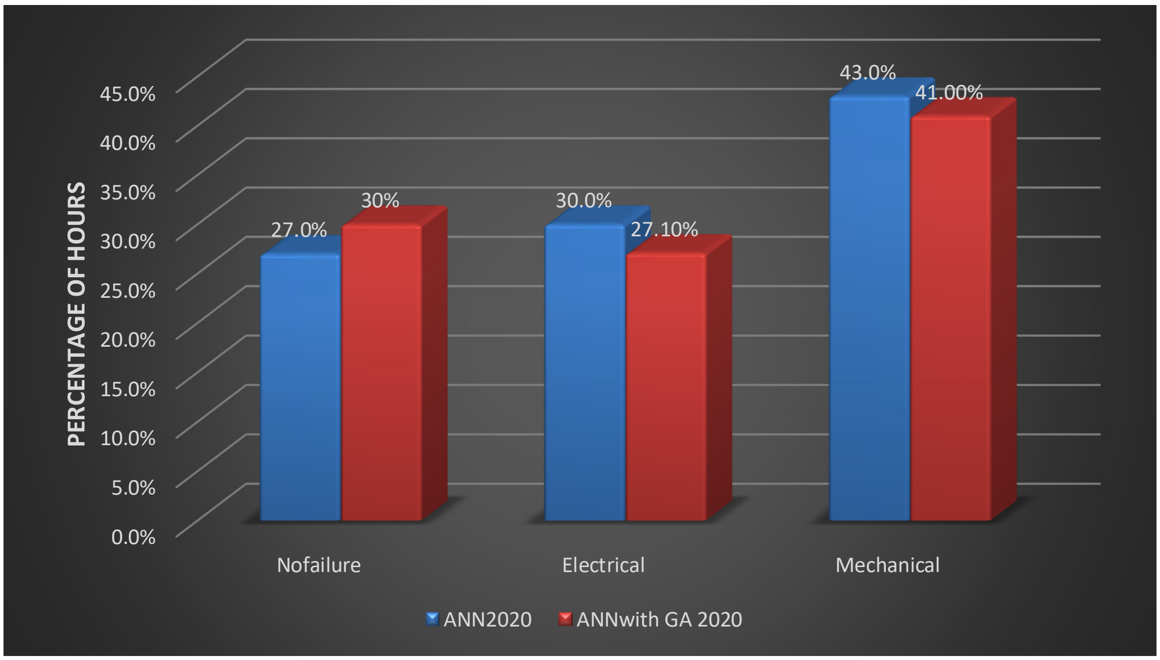

Fig. 9. Percentage of failure type in general by using ANN and ANN with GA in 2020.

A failure prediction program that can predict from 2018 until 2030 was designed; the user can enter the application system after completing the registration and enter the data including year, month, day, and hours to predict the failure time and type. Solutions for long-range time prediction can estimate the failure time and type util 2030 as explained in Figure 10.

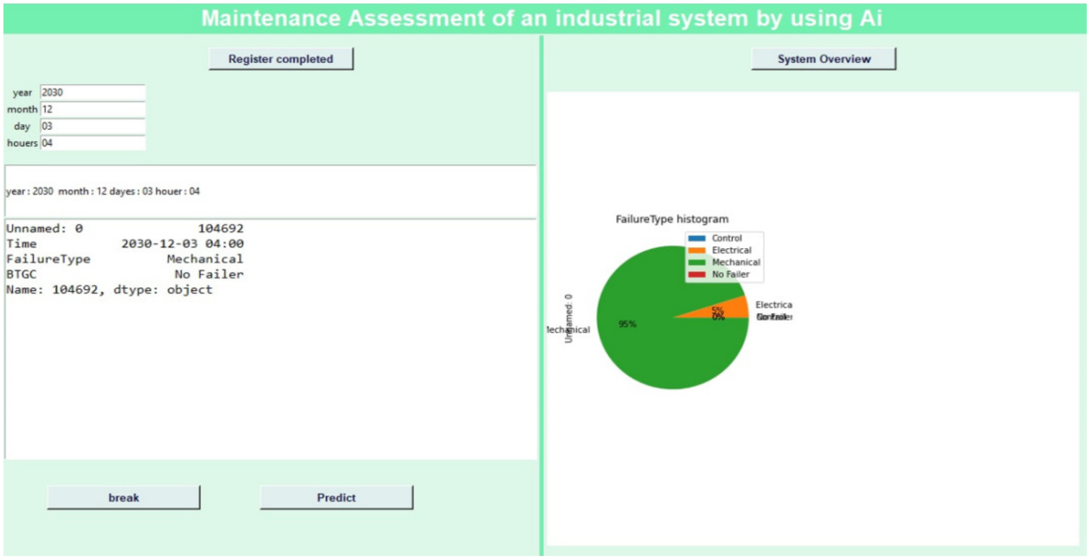

Fig. 10. predicate of 2030.

5. Conclusions

ANNs can be used extensively in prediction and modeling, especially in solving problems with a non-linear pattern that change with time, which causes difficulty in modeling the relationship between input and output. A GA 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 help 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 depends 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 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. 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, 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.

6. References

[1] N. M. Durakbasa, G. Bas, L. Kräuter, and G. Poszvek, “The Assessment of Industrial Manufacturing Systems Towards Advanced Operations by Means of the Integrated Modeling Approach,” Vis. 2020 Innov. Dev. Sustain. Econ. Growth - Proc. 21st Int. Bus. Inf. Manag. Assoc. Conf. IBIMA 2013, vol. 2, no. January, pp. 1418–1426, 2013.

[2] J. Rosén, “Development of Industrial Information Systems based on Standards,” 2010.

[3] H. Pacaiova and J. Glatz, “Maintenance Management System,” MM Sci. J., vol. 2015, no. OCTOBER, pp. 665–669, 2015, doi: 10.17973/MMSJ.2015_10_201532.

[4] F. Trojan and R. F. M. Marçal, “Proposal of Maintenance-types Classification to Clarify Maintenance Concepts in Production and Operations Management,” J. Bus. Econ., vol. 8, no. 7, pp. 560–572, 2017, doi: 10.15341/jbe(2155-7950)/07.08.2017/005.

[5] K. B. Misra, “Handbook of Performability Engineering,” Handb. Performability Eng.,

no. August 2008, 2008, doi: 10.1007/978-1-84800-131-2.
[6] B. Dergisi, "Atatürk Üniversitesi İ ktisadi ve İ dari Bilimler Dergisi, Cilt: 23, Say ı : 4, 2009 125," pp. 125–134, 2009.
[7] M. Naser, Determine the Optimum time for Preventive Maintenance Time in Al-Hilal Industrial Company LTd September 2010 . Journal of Economics and Administrative science 16(59):210 DOI:10.33095/jeas.v16i59.1512
[8] K. S. Moghaddam, "Preventive Maintenance and Replacement Scheduling : Models and Algorithms," Comput. Ind. Eng., no. November, pp. 1–85, 2008.
[9] H. Ab-Samat, E. I. Basri, N. A. Harun, S. C. Wee, and S. Kamaruddin, "Preventive Maintenance Checklist Towards Effective Maintenance System: A Case Study in Semiconductor Industry," Adv. Mater. Res., vol. 748, no. August, pp. 1208–1211, 2013, doi: 10.4028/www.scientific.net/AMR.748.1208.
[10] I. Badi and A.Shetwan, Measuring Performance Indicator for Maintenance Work:A Case Study in the longitudinal Rolling Mill at the Libyan Steel Company ,,pp.147-165,2016.The Scientific Court Journal,the tenth year,Issue 16 September 2016
[11] A. B. Adulghafour, "Developing of Reliability-Centered Maintenance Methodology in Second Power Plant of South Baghdad," Eng. Technol. J., vol. 36, no. 8A, 2018, doi: 10.30684/etj.36.8a.3.
[12] L. M. Dawood, "Study of Using Weighting Property Index for Selecting the Best Maintenance Management System (M.M.S.) at Power Plants," Djes, vol. 11, no. 4, pp. 20–27, 2018, doi: 10.24237/djes.2018.11404.
[13] Y. Ran, X. Zhou, P. Lin, Y. Wen, and R. Deng, "A Survey of Predictive Maintenance: Systems, Purposes and Approaches," vol. XX, no. Xx, pp. 1–36, 2019, [Online]. Available: http://arxiv.org/abs/1912.07383.
[14] A. Mohammed, A. Ghaithan, M. Al-Saleh, and K. Al-Ofi, "Reliability-based Preventive Maintenance Strategy of Truck Unloading systems," Appl. Sci., vol. 10, no. 19, pp. 1–17, 2020, doi: 10.3390/app10196957.
[15] A. Mansour and N. Makhoul, Restore Service in Electrical Power Distribution Systems to Increase their Reliability Using Genetic Algorithm, Damascus University Journal of Engineering Sciences., Vol. 28,no.2, December, pp.19,93-111, 2012.
[16] R. H. Fouad and M. Samhouri, "A fuzzy logic Approach for Scheduling Preventive Maintenance in ERP System," Int. Conf. Manag. Serv. Sci. MASS 2011, no. December, 2011, doi: 10.1109/ICMSS.2011.5999330.
[17] D. Król, L. Madeyski, and N. T. Nguyen, "Preface," Stud. Comput. Intell., vol. 642, no. February, pp. v–vii, 2016, doi: 10.1007/978-3-319-31277-4.
[18] H. Javanmard and A. al W. Koraeizadeh, "Optimizing the Preventive Maintenance Scheduling by Genetic Algorithm Based on Cost and Rreliability in National Iranian Drilling Company," J. Ind. Eng. Int., vol. 12, no. 4, pp. 509–516, 2016, doi: 10.1007/s40092-016-0155-9.
[19] M. Gregor, M. Haluška, M. Fusko, and P. Grznár, "Model of Intelligent Maintenance Systems," Ann. DAAAM Proc. Int. DAAAM Symp., vol. 2015-Janua, no. January, pp. 1097–1101, 2015, doi: 10.2507/26th.daaam.proceedings.154.
[20] K. Alhamad, M. Alardhi, and A. Almazrouee, "Preventive MaintenanceSscheduling for Multicogeneration Plants with Production constraints Using Genetic Algorithms," Adv. Oper. Res., vol. 2015, 2015, doi: 10.1155/2015/282178.
[21] A. Holman Montiel, S. Fernando Martínez, and F. H. Martínez S, "Genetic Algorithm Used for Improving the Preventive Maintenance Processes for Electricity Distribution Companies," Int. J. Appl. Eng. Res., vol. 12, no. 19, pp. 8120–8124, 2017.
[22] M. Vannucci, V. Colla, S. Dettori, and V. Iannino, "Fuzzy Adaptive Genetic Algorithm for Improving the Solution of Industrial Optimization Problems," J. Intell. Syst., vol. 29, no. 1, pp. 409–422, 2020, doi: 10.1515/jisys-2016-0343.
[23] X. Bampoula, G. Siaterlis, N. Nikolakis, and K. Alexopoulos, "A Deep learning Model for Predictive Maintenance in Cyber-Physical Production Systems Using LSTM Autoencoders," Sensors (Switzerland), vol. 21, no. 3, pp. 1–14, 2021, doi: 10.3390/s21030972.
[24] T. Miller, "Explanation in Artificial Intelligence: Insights from the Social Sciences," Artif. Intell., vol. 267, pp. 1–38, 2019, doi: 10.1016/j.artint.2018.07.007.

منهجية لتقييم وجدولة الصيانة الوقائية لوحدة حرارية كهربائية باستخدام الذكاء الاصطناعي

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الخلاصة

قد لا يتم إجراء جدولة الصيانة لأنظمة التدفق والإنتاج التي يتم توصيل قطعها على التوالي لأن المشاكل تحدث في أوقات مختلفة (محطات الكهرباء، مصانع الأسمنت، محطات تحلية المياه). لتحقيق أهداف البحث من خلال تطوير برنامج الصيانة التنبؤية والبرمجيات المعاصرة والذكاء الاصطناعي وتم العمل ع بيانات الوحدة الخامسة لمحطة الدورة الحرارية، أجريت ثلاث مراحل في البحث. أولاً، تمت معالجة البيانات المفقودة التي كانت بدون تسلسل زمني. تم ملء البيانات باستخدام السلاسل الزمنية ساعة بعد ساعة وأوقات الملء كساعات عمل النظام، مما يجعل حجم البيانات مرتفعًا نسبيًا للفترة ٢٠١٥-٢٠١٦-٢٠١٧، وتم استخدام ٢٠١٨ كسنة اختبار لتقييم عمل النمذجة والتحقق من صحة النتائج التجريبية. في الخطوة الثانية، استخدم نهج الشبكات العصبية الاصطناعية برنامج بيثون كذكاء اصطناعي، ونسبة التقارب إلى البيانات الحقيقية باستخدام قياس الأداء (متوسط الخطأ المطلق) .(0.005) MAE ولتحسين وتقليل نسبة الخطأ المطلق، تم استخدام الخوارزمية التطورية لتحسين أوزان الشبكة العصبية، وأصبحت نسبة التقارب .(0.001) MAE يستدل من ذلك كفاءة الخوارزمية في تحسين النتائج وبذلك تقدم الخوارزميات الجينية نتائج أفضل مع أخطاء أقل من الشبكات العصبية وحدها. يخلص هذا إلى أن الشبكة المبنية تتمتع بأداء متفوق عن الآخرين وإمكانيتها ع التنبؤ طويل الأمد لسنة ٢٠٣٠، وأن استخدام السلاسل الزمنية ساعد في اكتشاف الحالات المستقبلية من خلال قراءة بيانات النظام واستنتاجها. وسيؤدي وضع خطط عمل مناسبة إلى خفض النفقات الداخلية والخارجية للأنظمة والمساعدة في تكامل القدرات الأخرى من خلال إعطاء البيانات الصحيحة كمصادر للمواد الخام والتكاليف وغيرها. ولتسهيل التنبؤ للعاملين ع الصيانة تم انشاء واجهات تسهل ع المستخدمين تطبيقها باستخدام برنامج بايثون ممثلة بإدخال الازمان ساعة-يوم –شهر – سنة للتنبؤ بنوع ومكان الفشل.