Enhancing the Priority for the Maintenance Activities of the Hospitals' Mechanical Equipment Using the Fuzzy Expert System

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Abstract. Decision making has been highlighted important in asset management. Various generic decision making models were proposed and highlight the necessity for continuous autonomous suggestion of actions. On side of Maintenance activities priority for complex equipment, maintainers are manually deciding on crucial action to be performed prior to others. We claim that the integration of knowledge based expert system might support an effective predictive maintenance through accurate maintenance priorities. With purpose to enhance the decision making on maintenance priority, this work proposes the Fuzzy logic based expert system for small and medium sized hospitals. It considers the expertise of maintainers in faults detection and classification through the various monitoring of the physical condition parameters from equipment's components. Parameters' condition severity in respect of the total equipment downtime are considered to suggest maintenance activities priority. The proposed system is evaluated using random data in respect with the operating parameters' values range and the results show that the created Fuzzy expert system is capable to provide the maintenance activities priority by evaluating the inputted variables.

Keywords: Predictive maintenance · Real time · Fuzzy expert system · Condition parameters · Maintenance activities priority

1 Introduction

Within the scope of industry 4.0, the Internet of Things (IoT) based predictive maintenance techniques through continuous real time monitoring may lead to

Y. H. Sheikh et al. (Eds.): AFRICOMM 2021, LNICST 443, pp. 170–181, 2022.
https://doi.org/10.1007/978-3-031-06374-9_11

the failure prediction ahead of time. This shall increase the equipment availability, decrease the unnecessary preventive maintenance as well as allied cost, and improve the business reliability.

Till now, small and medium companies including hospitals conduct the regular preventive maintenance including costly periodical profession inspections to identify the exhausted components and servicing. This does not guarantee the full availability of the equipment and cannot avoid unplanned downtime of the equipment [1] as it may not be done in right time of an equipment deficit. However, as maintenance technologies are evolving, they need to adopt a systematic approach to proper predictive maintenance with capability of proactive activities prioritization [2].

Different research works [3] emphasized on predictions and related decision support using prognostic models to process, analyze data and then to provide recommendations. However, referring to the main parameters of decision making process [4], deciding on the urgency maintenance activity among others is still a challenging task. There is therefore an interest in real time activities prioritization methods.

Previous studies in this area summarized in Table 1, considered single critical component such as rotating elements as whole and simple equipment which is different for complex equipment.

Table 1. Some works in predictive maintenance decision making.

Study	Description
[5]	Adding to the literature that considered current signal to diagnostic signals for electrical machine failures,authors reviewed possible patterns of vibration signal of the motor parts as key fault for such machines
[6]	After reviewing the various failures and their root causes for electrical machine, they proposed an impedance based diagnostic model using voltages and currents signals of an induction machine
[7–11]	By monitoring vibration conditions of the rotating part of the machine and using a fuzzy system, authors presented the maintenance decision making tools for different type of machines

Contrary to single crucial component like in Table 1, for a complex equipment, different components may lead to an abrupt failure of the entire equipment.

Currently, especially in hospitals, the maintenance decisions and scheduling are made thanks to the knowledge of maintainers on the equipment operational manual together with various working condition parameters as well as impact severity of each component to the overall performance scenarios.

Hence, maintenance experts' knowledge could be converted into knowledge base system that may facilitate them to fully monitor their assets in real time and to prioritize the maintenance plan of activities depending on the health condition of different components and their impact to the total downtime of the equipment. The Fuzzy logic system [12] which is based on human experts' opinions shall be helpful. It is reasonably simple to build as it does not require a prevailing theoretical model to rely upon. It shall only require few sensors to get conditional parameters together with thin, affordable and energy efficient computer such as Raspberry Pi to host fuzzy inference.

This paper discusses a knowledge based expert system using a fuzzy logic approach to provide an enhanced means of maintenance activities priority for hospitals mechanical equipment. Powered by IoT based predictive maintenance capabilities, the real time data can be fed to the expert system and continuously provide insights to users. The presented expert system may also be adopted for all small and medium sized companies.

The rest of this paper presents the reviewed literature on decision making and Fuzzy logic utilization in predictive maintenance in Sect. 2. In the Sect. 3, a methodological review of Fuzzy expert system is described. Basing on the real time data analytics, maintainers expertise as well as impact of each parameter to the total downtime of the equipment, an expert and robust Fuzzy system to prioritize the predictive maintenance activities is proposed in Sect. 4. Section 5 discusses the results, whereas Sect. 6 concludes the work and suggests the future research works.

2 Review of Decision Making and Fuzzy Logic Application in Predictive Maintenance

Since the manufacturing and market requirements have been evolved from one level to another, maintenance techniques have also advanced from reactive approach to proactive maintenance. Similarly, Techniques may vary from one another depending on the technology in place, available infrastructures, monitoring techniques and capabilities.

Motivated by dynamic recommendations from literature on maintenance activities to be performed prior failure, authors identified gaps and put a call to the further researches including the dynamic decision making.

Authors [13,14] have reviewed the contributions of efficient maintenance toward a business sustainability and sustainable manufacturing. [15] highlighted limitations from the conducted researches under decision making in predictive maintenance, [16,17] reviewed maintenance decision and priority making techniques and models in last decade maintenance.

Researchers in [3,18,19] mostly considered historical data, administrative as well logistic processes and respectively have come up with a decision making framework.

Though, all works recommend further researches to mature the predictive maintenance especially by empowering the continuous monitoring, exploring real time data and maintainers knowledge.

Among developed decision making systems, fuzzy logic has been employed in predictive maintenance into different industries as knowledge based expert system that may combine available information to provide accurate predictions, suggestions and scheduling.

A fuzzy logic system that was introduced among others by Zadeh [12] was proven to be useful in monitoring of uncertain and vagueness systems. Fuzzy logic has been deployed in maintenance decision making process to select a favorable maintenance approach [20,21], activities planning [1,7,8,22] as well as risks level computation [23].

From literature, a single component was considered as only one crucial for an equipment failure. Yet for complex equipment: the working deficit from each among different components can lead to total downtime of the whole equipment. And the deficit from one component may affect the working status of another component. Thus, different parameters from each component can lead to make a priority on critical needed maintenance activities to be performed.

We noticed that real faults detection and linked decision on activities priority are at their infant stage. There is no universal or specific approach to adopt. Consequently, there is a gap especially when it comes to real time decision making intended from the asset real time data captured through sensors.

Furthermore, an autonomous decision making in maintenance mainly concentrated to the administrative and logistic process, but did not reflect on expertise of the maintainer to detect and resolve faults. To enhance the maintenance priority decision making based on an equipment health state, this research contributes by proposing a real time data based fuzzy expert system, whose inference designed referring to maintainers' expertise. This shall provide the real time commendations on the crucial activities to be prioritized while planning for maintenance execution.

3 Methodology for Maintenance Activities Priority Expert System

In a maintenance field, maintainers use their knowledge and tools to monitor the working status of their equipment and to fix them either when they are malfunctioning or they break. Even though different mechanical equipment present the common parameters [5,6] such as temperature, vibration, noise, oil level, power consumption, pressure, dust, etc.; their condition parameters for early faults detection may differ from one equipment to another due to its structure and assembled components.

The standards, maintenance historical data, literature and maintainers' expertise shall be used to assign a divergence severity of each parameter based on its associated failure and effect to the whole equipment. Table 2 summarizes the methodological steps followed to accomplish this work.

Table 2. Methodology used to create a Fuzzy Expert system.

Steps	Activities
Step 1: Define	i. Investigating the maintenance practices in place, assess the frequent failures and their root causes ii. Basing to assessed failure root causes, select an equipment as case study, identify crucial equipment physical performance condition parameters to be monitored iii. Classifying the value of physical condition parameters according to the working status of component
Step 2: Expert System components	i. Sorting the condition parameters severity according to the threat that may cause to the overall equipment performance ii. Elaborating possible scenarios of matching different condition parameters (facts) at their different levels to create rules iii Elaborating the maintenance priorities file
Step 3: Fuzzy expert system for case study	i. Create an expert system linguistic variables and database by considering the technical requirements, literature, as well as maintainers' expertise and judgments ii. Create rules based to deficit threshold limit and associated responses or actions
Step 4: Results	i. evaluate the created system and Discuss the results

4 Fuzzy Expert System for the Predictive Maintenance Activities Priority

4.1 Defining the Expert System Requirements

Following to the methodological steps in Table 2, with regards to maintainers' expertise and available historical data, considering that the equipment lifetime is extended depending on the applied maintenance strategies and inspectors' knowledge, also that the maintenance activities priority depends on the components' condition divergence severity impact to the overall performance of an equipment:

To understand the maintenance activities, procedures, applied techniques and to define the process for this work, four professionally trained and experienced maintainers from three hospitals in Kigali were repetitively visited to collect general information on their mechanical equipment, their healthy monitoring techniques, continuous monitoring tools, monitored conditional parameters, and maintenance practices in place.

Using the information and data from experts, we propose the maintainers' knowledge based expert system capable to diagnose faults and to reduce the ambiguity in the severity sorting by providing recommendation on proactive maintenance activities priority.

4.2 Fuzzy Expert System

The acquired knowledge from maintenance experts, literature and component marked industrial thresholds are arranged into knowledge base consisting of formed rules and facts to be generated by various variables mapping. The rules are created using IF-AND or OR-THEN syntax to associate more antecedents with fact. Facts might be generated in view of the threat to equipment that may be caused by the physical condition parameters' set.

The fuzzy inference engine shall be encrypted in appropriate setup to judge the inputs using rules and facts, then to generate desired conclusion. Using the data collector described in [24], real time data can be gathered from different components and being fed to the fuzzy expert system for judgment.

To reduce the additional cost that may be brought by the application of this fuzzy expert system, instead of using large computer, we recommend the hospitals to use of Raspberry Pi which is capable to perform things like other computer, yet is low cost, very small in size and lower power device [25,26].

Figure 1 illustrates the fuzzy expert system that can help maintainers to quickly decide on which part in critical condition than others depending on their working conditions, so that to prioritize critical maintenance activities among others.

The system working procedures are classified into three main activities:

1^{st}: The condition parameters to define the equipment working status shall be captured using sensors, fed to our system and being transformed in fuzzy input variables by fuzzifier.
2^{nd}: Fuzzified data are applied to the rules in knowledge base to be evaluated using fuzzy operators. The fuzzy inference engine also aggregates the rules outputs.
3^{rd}: Fuzzified output from inference engine are defuzzified and transformed into real world readable output.

To make the expert system more relevant, we considered common physical condition parameters to mechanical equipment that were underlined from literature [5,6] and by maintainers. The list of parameters and their severity grades may vary due to the nature of equipment and their frequency of occurrence but the most common parameters are Temperature, Pressure, Vibration, Lubricant, Power consumption, Noise and Dust.

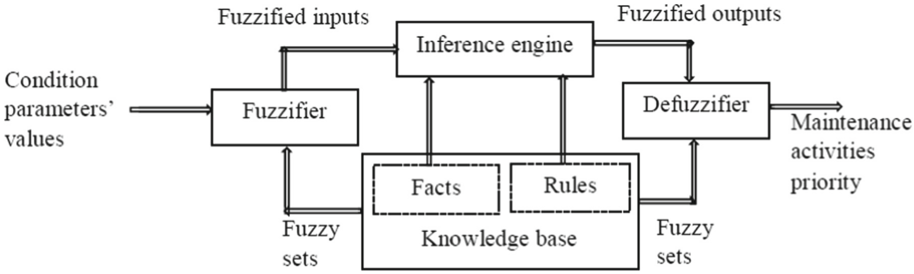

Fig. 1. Diagram for created Fuzzy expert system.

4.3 Case Study: Customized Fuzzy Expert System

For our experiment, the steam sterilizer autoclave is selected as mechanical and critical equipment for all sized hospitals. It is used to sterilize surgical instruments, clothes and dressing materials. It is a must for infection control.

Thanks to King Faisal Hospital-Kigali and Teaching University Hospital of Kigali to allow the conduction of special discussions based to a well-structured questions with respective two and one expert maintainers on the steam sterilizer autoclave working principles. We highlight its main critical components and the available empirically-based thresholds of physical condition parameters. Only four metrics (Temperature (TE), Vibration (VI), Pump (PU) and Boiler (BO) power consumption) are then considered in building our fuzzy expert system to prioritize maintenance activities.

Table 3 and Table 4 respectively show the input variables and parameters healthy range, whereas Table 5 shows output variables and priority classification range.

Even though the data collector was developed in [24] and previously used to collect some real time data, the recent real data for all parameters in this work were not collected due to COVID-19 restrictions. Hence, the values range that reflect to the fault severity levels in Table 4 and maintenance priority indices in Table 5 are classified by considering previous available data recorded during regular inspections by maintainers on time basis, experiments, standards in literature, operating thresholds as well as experts judgments which are also referred to historical data and knowledge from professional training and long experience. We note that the power consumption thresholds are calculated by averaging the sterilization cycle to 50 min and considering the averaged time for power consumption of pumping as well as heating along the sterilization cycle.

The inputs and outputs linguistic variables are defined based on the grade of parameter indicators and the effect that could be caused by a certain indicated level. Our input Linguistic variables are notated as NO, SS and VS, whereas outputted maintenance priorities are notated as LO, MO, HI and VH.

Table 3. Input variables and nature of defect to be discovered.

Input variables	Notation	Nature of defect to be detected
Temperature	TE	Flow normality in pumping system and Working stress (gap, misalignment, or failure) of coupled motor
Vibration velocity	VI	Working stress (gap, misalignment, or failure) for integrated pumping system motor
Pump power consumption	PU	Normality of current flow
Boiler power consumption	BO	Healthy status of heaters

Table 4. Input variables healthy range.

Temperature (Celsius degree)	Vibration (mm/s)	Pump power consumption (KW)	Boiler power consumption (KW)	Membership functions	Notation
40 and Below	2.8 and below	0.25 to 0.44	9 to 13.5	Normal	NO
30 to 70	2.3 to 4.5	0.38 to 0.56	12.0 to 16.5	Slightly strange	SS
60 to 100	3.5 to 10	0.5 to 1	15.0 to 20	Very strange	VS

Table 5. Output variables range.

Maintenance priority variables	Notation	Range
Low	LO	0 to 30
Moderate	MO	20 to 60
High	HI	50 to 80
Very High	VH	70 to 100

Maintenance priorities are related to the urgency level to perform maintenance activity. Low (LO) indicates no action is required, Moderate (MO) requires close monitoring, High (H) recommends maintenance in the near future and Very high (VH) calls for immediate action.

The system is designed using Simpful library [27] in Python. Simpful was chosen because of its simplicity, richness and friendly usage while implementing any fuzzy membership function.

We realize membership functions using trapezoidal function. Figure 2 illustrates inputs and output variables membership depending on the range of values that classify the component health status.

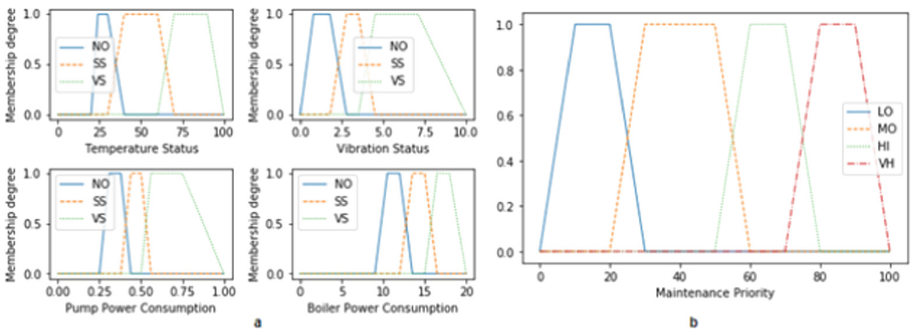

Fig. 2. Membership functions for (a): inputs and (b): output variables.

5 Results Discussion

Basing on the data and information from expertise maintainers, for four selected inputs with three variables each, 81 rules are possible using 'AND' operator. In our case, rules have been created by using both 'OR' and 'AND' operators, whereby only 17 seizures all possibilities. The Fig. 3 that shows created rules is taken from our created expert system.

Bearing in mind that real time data may change over time due to the working environment of the component, the possible operating universe of discourse for real values from each parameter and their significance to the health status of the component are defined in Table 4. Our expert system is therefore evaluated using random values in the various defined range for each variable.

Rules and their evaluation were presented to expert maintainers for their assessment and approval. Table 6 shows some variables' values and the obtained outputs. As the real time data have to be collected with an equal time interval between two readings, and that the used data were not recorded with respect to that time interval, timestamps is not shown.

We conclude that the created Fuzzy expert system is capable of evaluating the inputted variables to produce the maintenance activities priority (M_P) for mechanical equipment, thus to enhance the existing prioritization method.

R1 = "IF (TE IS VS) OR (VI IS VS) OR (PU IS VS) OR (BO IS VS) THEN (MP IS VH)"
R2 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS SS) AND (BO IS NO) THEN (MP IS HI)"
R3 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS NO) AND (BO IS SS) THEN (MP IS HI)"
R4 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS SS) AND (BO IS SS) THEN (MP IS HI)"
R5 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS SS) AND (BO IS SS) THEN (MP IS HI)"
R6 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS SS) AND (BO IS SS) THEN (MP IS HI)"
R7 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS NO) AND (BO IS NO) THEN (MP IS LO)"
R8 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS NO) AND (BO IS NO) THEN (MP IS MO)"
R9 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS SS) AND (BO IS NO) THEN (MP IS MO)"
R10 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS NO) AND (BO IS SS) THEN (MP IS MO)"
R11 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS NO) AND (BO IS NO) THEN (MP IS MO)"
R12 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS SS) AND (BO IS SS) THEN (MP IS MO)"
R13 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS NO) AND (BO IS SS) THEN (MP IS MO)"
R14 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS NO) AND (BO IS SS) THEN (MP IS MO)"
R15 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS SS) AND (BO IS NO) THEN (MP IS MO)"
R16 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS SS) AND (BO IS NO) THEN (MP IS MO)"
R17 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS NO) AND (BO IS NO) THEN (MP IS MO)"

Fig. 3. Created rules.

Table 6. Evaluation using random data.

TE	VI	PU	BI	M_P	Priority level
37	4.00	0.57	13.64	0.85	Very High
59	2.00	0.29	9.09	0.40	Moderate
29	1.33	0.29	12.73	0.29	Low
98	1.33	0.71	8.18	0.50	Moderate
27	6.00	0.14	16.36	0.50	Moderate
61	1.33	0.43	14.55	0.61	High
85	6.00	0.57	10.00	0.85	Very High
39	4.00	0.43	14.55	0.70	High

6 Conclusion and Future Work

The mechanical equipment is generally a complex system made up by different components and each component may present various physical condition parameters. The information from single component does not summarize the health status of the whole complex equipment. As a result, the full monitoring and control of an equipment overall performance is influenced by many features depending on its components' condition parameter levels and level of hazards that may cause. To save time used by maintainers to diagnose fault and to avoid unplanned prompt downtime, also benefiting from the simplicity of fuzzy logic, an expert system was developed to enhance the maintenance activities prioritization in relation with the working status of equipment's components.

The priority is classified as Normal whereby there is no need of maintenance, Moderate, High and Very High that appeals respectively for close monitoring, to perform the maintenance within few days and for immediate or closer maintenance intervention. We expect that this system will provide support to the maintainers in continuous monitoring of their equipment, early fault detection as well as in enhancing the priority making of critical maintenance activities among others.

For future work, the real time data from operating equipment till failure will be collected and being used to determine the useful remaining time (URT) from one status to another and to provide proactive suggestions to each component of the equipment.

References

1. Andrew, A., Kumanan, S.: Development of an intelligent decision making tool for maintenance planning using fuzzy logic and dynamic scheduling. Int. J. Inf. Technol. **12**(1), 27–36 (2020). https://doi.org/10.1007/s41870-019-00384-w
2. Gopalakrishnan, M., Bokrantz, J., Ylipää, T., Skoogh, A.: Planning of maintenance activities - a current state mapping in industry. Procedia CIRP **30**, 480–485 (2015). https://doi.org/10.1016/j.procir.2015.02.093
3. Bousdekis, A., Magoutas, B., Apostolou, D., Mentzas, G.: A proactive decision making framework for condition-based maintenance. Ind. Manag. Data Syst. **115**(7), 1225–1250 (2015). https://doi.org/10.1108/IMDS-03-2015-0071
4. de Almeida, A.T., Bohoris, G.A.: Decision theory in maintenance decision making. J. Qual. Maint. Eng. **20**(4), 39–45 (1995). https://doi.org/10.1108/13552519510083138
5. Nandi, S., Toliyat, H.A., Li, X.: Condition monitoring and fault diagnosis of electrical motors - a review. IEEE Trans. Energy Convers. **20**(4), 719–729 (2005). https://doi.org/10.1109/TEC.2005.847955
6. Basak, D., Tiwari, A., Das, S.P.: Fault diagnosis and condition monitoring of electrical machines - a review. In: Proceedings of the IEEE International Conference on Industrial Technology, pp. 3061–3066 (2006). https://doi.org/10.1109/ICIT.2006.372719
7. Baban, M., Baban, C.F., Moisi, B.: A fuzzy logic-based approach for predictive maintenance of grinding wheels of automated grinding lines. In: 2018 23rd International Conference on Methods and Models in Automation and Robotics, MMAR 2018, pp. 483–486 (2018). https://doi.org/10.1109/MMAR.2018.8486144
8. Baban, M., Baban, C.F., Suteu, M.D.: Maintenance decision-making support for textile machines: a knowledge-based approach using fuzzy logic and vibration monitoring. IEEE Access **7**, 83504–83514 (2019). https://doi.org/10.1109/ACCESS.2019.2923791
9. Susin, A.A., et al.: Predictive maintenance in rotating machines with vibration analysis and fuzzy logic. In: 11 IMEKO TC-4 Symposium, Lisbon, Portugal, vol. 1, pp. 258–261 (2001)
10. Janier, J.B., Fazrin Zaim Zaharia, M.: Condition monitoring system for induction motor using fuzzy logic tool. In: Proceedings of the 1st International Conference on Informatics and Computational Intelligence, ICI 2011, pp. 3–7 (2011). https://doi.org/10.1109/ICI.2011.11
11. Pereira, R.R., Diniz Da Silva, V.A., Brito, J.N., Daniel Nolasco, J.: On-line monitoring induction motors by fuzzy logic: a study for predictive maintenance operators. In: 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery, ICNC-FSKD 2016, pp. 1341–1346 (2016). https://doi.org/10.1109/FSKD.2016.7603373

12. Zadeh, L.A.: Fuzzy sets. Inf. Control (1965). https://doi.org/10.1016/S0019-9958(65)90241-X
13. Franciosi, C., Iung, B., Miranda, S., Riemma, S.: Maintenance for sustainability in the industry 4.0 context: a scoping literature review. IFAC-PapersOnLine **51**(11), 903–908 (2018). https://doi.org/10.1016/j.ifacol.2018.08.459
14. Jasiulewicz-Kaczmarek, M., Gola, A.: Maintenance 4.0 technologies for sustainable manufacturing - an overview. IFAC-PapersOnLine **52**(10), 91–96 (2019). https://doi.org/10.1016/j.ifacol.2019.10.005
15. Bousdekis, A., Lepenioti, K., Apostolou, D., Mentzas, G.: Decision making in predictive maintenance: literature review and research agenda for industry 4.0. IFAC-PapersOnLine **52**(13), 607–612 (2019). https://doi.org/10.1016/j.ifacol.2019.11.226
16. Ruschel, E., Santos, E.A.P., de Freitas Rocha Loures, E.: Industrial maintenance decision-making: a systematic literature review. J. Manuf. Syst. **45**, 607–612 (2019). https://doi.org/10.1016/j.jmsy.2017.09.003
17. Wing, A.C.K., Mohammed, A.H., Abdullah, M.N.: A review of maintenance priority setting methods. Int. J. Real Estate Stud. **10**(1), 1–9 (2016)
18. Martorell, S., Villamizar, M., Carlos, S., Sánchez, A.: Maintenance modeling and optimization integrating human and material resources. Reliab. Eng. Syst. Saf. **95**(12), 1293–1299 (2010). https://doi.org/10.1016/j.ress.2010.06.006
19. Medina-Oliva, G., Weber, P., Iung, B.: Industrial system knowledge formalization to aid decision making in maintenance strategies assessment. Eng. Appl. Artif. Intell. **95**, 343–360 (2015). https://doi.org/10.1016/j.engappai.2014.09.006
20. Kumar, E.V., Chaturvedi, S.K.: Prioritization of maintenance tasks on industrial equipment for reliability: a fuzzy approach. Int. J. Qual. Reliab. Manag. **28**(1), 109–126 (2011). https://doi.org/10.1108/02656711111097571
21. Borjalilu, N., Ghambari, M.: Optimal maintenance strategy selection based on a fuzzy analytical network process: a case study on a 5-MW powerhouse. Int. J. Eng. Bus. Manag. **10**, 1–10 (2018). https://doi.org/10.1177/1847979018776172
22. Baban, C.F., Baban, M., Suteu, M.D.: Using a fuzzy logic approach for the predictive maintenance of textile machines. J. Intell. Fuzzy Syst. **30**(2), 999–1006 (2016). https://doi.org/10.3233/IFS-151822
23. Gallab, M., Bouloiz, H., Alaoui, Y.L., Tkiouat, M.: Risk assessment of maintenance activities using fuzzy logic. Procedia Comput. Sci. **148**, 226–235 (2019). https://doi.org/10.1016/j.procs.2019.01.065
24. Niyonambaza, I., Zennaro, M., Uwitonze, A.: Predictive maintenance (PDM) structure using internet of things (IoT) for mechanical equipment used into hospitals in Rwanda. Future Internet **12**(12), 1–23 (2020). https://doi.org/10.3390/fi12120224
25. Bekaroo, G., Santokhee, A.: Power consumption of the Raspberry Pi: a comparative analysis. In: 2016 IEEE International Conference on Emerging Technologies and Innovative Business Practices for the Transformation of Societies, EmergiTech 2016, pp. 361–366 (2016). https://doi.org/10.1109/EmergiTech.2016.7737367
26. Anwaar, W., Shah, M.A.: Energy efficient computing: a comparison of Raspberry PI with modern devices. Int. J. Comput. Inf. Technol. **4**(2), 410–413 (2015)
27. Spolaor, S., Fuchs, C., Cazzaniga, P., Kaymak, U., Besozzi, D., Nobile, M.S.: Simpful: a user-friendly python library for fuzzy logic. Int. J. Comput. Intell. Syst. **13**(1), 1687–1698 (2020). https://doi.org/10.2991/ijcis.d.201012.002