PREDICTIVE MAINTENANCE STRATEGY BASED ON BIG DATA ANALYSIS AND MACHINE LEARNING APPROACH FOR ADVANCED BUILDING MANAGEMENT SYSTEM

M. Majidi Nezhad[1,*], S. Agostinelli[1], F. Cumo[2, 3], A. Heydari[3], F. Muzi[3]

1. Department of Astronautics, Electrical and Energy Engineering, Sapienza University of Rome, 00184 Rome, Italy; meysam.majidinezhad@uniroma1.it - sofia.agostinelli@uniroma1.it
2. Department of Planning, Design, and Technology of Architecture, Sapienza University of Rome, Italy. Email: fabrizio.cumo@uniroma1.it
3. CITERA Interdepartmental Centre, Sapienza University of Rome, 00196 Rome, Italy. azim.heydari@uniroma1.it- muzi.1716632@studenti.uniroma1.it

ABSTRACT

Predictive maintenance is a concept linked to Industry 4.0, the fourth industrial revolution that monitors equipment's performance and condition during regular operation to reduce failure rates. The present paper deals with a predictive maintenance strategy to reduce mechanical and electrical plants malfunctioning for residential technical plants systems. The developed strategy can guarantee a tailored maintenance service based on machine learning systems, drastically reducing breakdowns after a maximum period of three years. The developed strategy evaluates an acceptable components failure rate based on statistical data and combines the average labour costs with the duration of each maintenance operation. The predictive strategies are elaborated on the minimum cost increase necessary to achieve the abovementioned objectives. A case study based on a 3-year-period has been developed on a modern residential district in Rome composed of 16 buildings and 911 apartments. In particular, the analysis has been performed considering mechanical, electrical and lighting systems supplying the external and common areas, excluding the apartments, to avoid data perturbation due to differenced user's behaviours. The overall benefits of predictive maintenance management through Big Data analysis have proven to substantially improve the overall operation of different plants as mechanical and electrical plants of residential systems.

Keywords: Predictive Maintenance, Building Management, Residential Mistrict, Digital Modelling, Machine Learning.

1 INTRODUCTION

Due to the widespread use of industrial machinery, a huge amount of data can be collected every day, resulting in increased attention of production managers and data analysts to potential applications. Predictive maintenance (PdM) is a prominent approach in this regard, which intends to monitor and analyze a system in real-time to identify and prevent potential maintenance needs [1] promptly. Furthermore, predictive maintenance (PdM) intends to prevent incipient failures by paying attention to unusual behaviours providing a just-in-time maintenance intervention; such interventions are necessary to ensure both the quality and safety of devices and prevent unnecessary costs [2]. Building maintenance is a crucial section of facility management (FM), mainly because of maintenance-related expenditures for at least 65% of FM costs each year [3].

Several studies have investigated PdM models. For instance, Quatrini et al. (2020) performed an exhaustive literature review in this field. They mentioned four main areas, a) PdM fundamentals and implementation, b) PdM strategies, c) inspections and replacement plans, and d) prognosis [4]. Many studies focused on PdM plans reported Remaining Useful Life (RUL) as a condition index. In addition, Zhou et al. (2007) reported a reliability-oriented model based on a PdM continuous monitoring system, which is based on the hypothesis that such systems are prone to continuous degradation that can be monitored [5]. Such degradation processes can be modelled using the Markov decision process [6], proportional hazards model [7], a gamma process [8], Monte Carlo simulation [9][10]. Berka and Macek (2011) presented a model for fault identification to

[*] Corresponding author

perform adequate maintenance interventions. Susto et al. (2015), reported a PdM system based on the availability of the current values of the physical factors acting on the production process and Support Vector Machines (SVMs) [11]. In order to detect faulty and non-faulty states of the machines, SVMs are applied, which can estimate the distance from failure as the equipment RUL. Yiwei et al. (2017), developed a prognostic model that can link the Extended Kalman Filter with a First-Order Perturbation technique. They developed a cost-based predictive maintenance (CDPM) framework and reported their model as a case study [12]. Wang et al. developed a cloud-based paradigm to predict maintenance using a mobile agent to allow in-time access to information and to apply them to enhance the accuracy and reliability of the fault identification process, estimating service life, and schedule maintenance procedures [13]. Nevertheless, their model does not contain a valid prediction algorithm for condition prediction. Ren and Zhao (2015) introduced a framework based on the Internet of Things (IoT) used to manufacturing, and Operation and Maintenance (O&M) data obtaining procedure for decision-making technique to predict the need for maintenance, including decision tree, k-Means, support vector machine (SVM), and neural network [14]. Nevertheless, their study does not explain how to apply this technique and the prediction procedure. Finally, Cheng et al. (2015) have performed a study to compare marker-based Augmented Reality (AR) and marker-less AR for indoor maintenance and decoration [15].

Nevertheless, this model is solely about maintenance and operational information and does not contain maintenance planning. Kang and Hong (2015) developed software intended to incorporate building information modelling effectively (BIM) with a GIS-based facilities management (FM) system [16]. In addition, they reported a BIM/GIS-based prototype intended to extract, transform, and load data from BIM and GIS to integrate FM data. Ayvaz and Alpay (2021), developed a maintenance system based on available data to predict production lines using machine learning techniques and IoT [17]. Vafaei et al. (2019), presented an alarm system based on fuzzy logic to predict early equipment degradation in a car manufacturing line, emphasising minimizing costs related to sudden failures [18]. Wei et al. [5] introduced a conditional maintenance framework intended to identify the optimal action to reduce the mean cost rate as much as possible [19]. Cheng et al. [8] introduced a data-based model to predict maintenance of mechanical, electrical, and plumbing components based on information modelling and IoT [20].

Based on what was mentioned before, the research gap contains (1) inadequate data integration for predictive maintenance, (2) absence of good predictive patterns, and (3) no description of predictive procedures. Therefore, this paper's main novelties and contributions provide an intelligent predictive maintenance strategy for mechanical, electrical, and plumbing sections of building facilities, like HVAC systems, electrical parts, and lighting, that have a crucial role in ensuring the functionality of buildings.

2 CASE STUDY

The Rione Rinascimento complex hosts 3000 tenants in 950 apartments divided into seven building complexes. Each complex consists of three eight-floor buildings. Therefore, it can be defined as an eco-neighbourhood. It is powered by 65% of renewable sources and 100% only regarding the thermal consumption for the production of hot water and air conditioning.

This result has been achieved thanks to the building envelope's high efficiency and installing the largest European geothermal power plant for residential use working through 190 geothermal probes of 150 meters depth, allowing favourable heat exchange with the ground in winter and summer conditions. In addition, a bio-mass cogeneration plant coupled with the geothermal plant allows reaching economic savings of 40% and a decrease in CO_2 emissions of 50%.

The case study is significant due to peculiar conditions related to energy and safety management and building maintenance strategies. In fact, from the energy management point of view, it is considered as self-sufficient; considering the safety management, it is characterized as a well-defined system, physically separated from the surrounding urban context; from the maintenance point of view, it allows to obtain numerous and structured data as it is based on a global services contract. This paper investigates the maintenance aspect with a view to the optimization of planned maintenance processes through predictive systems.

2.1 MAINTENANCE SYSTEM

The maintenance datasheets are the starting point of the entire process, as they provide the necessary information about the analysis of the considered elements divided into categories/disciplines. In the case study, customized datasheets have been created for the mechanical and electrical systems. However, both are only considered in the internal and external common areas, thus excluding spaces for private use.

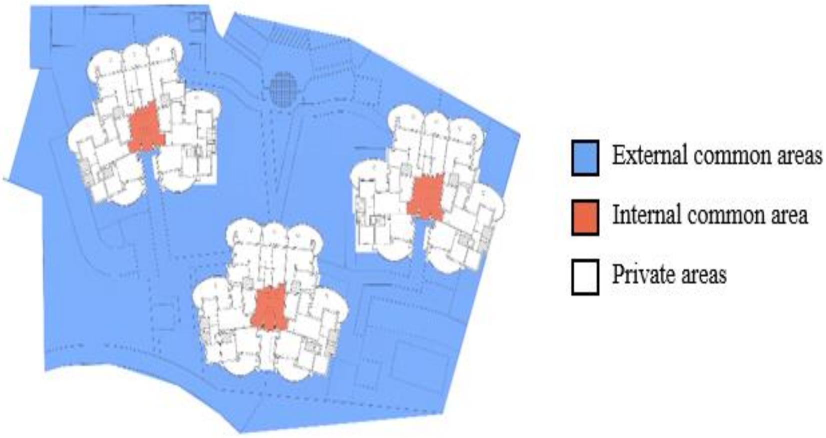


Figure 1. Building module in Rione Rinascimento complex.

The used maintenance datasheets only consider activities and elements that can cause faults and malfunctions involving replacing single components. These sheets are regularly compiled for each scheduled maintenance operation.

3 PROPOSED PREDICTIVE MAINTENANCE STRATEGY

The PdM contains three key stages [21], including data acquisition: obtaining data from different sources is equally essential for PdM. As it is structured, the data acquisition process is fully automated. The second one is unstructured, and the collection can be partially entrusted to the operator; Hence, accurate validation is required. Therefore, data processing should be performed because this process is crucial for dataset cleaning and to analyze data to assess its consistency with the physical phenomenon. The last process is the maintenance decision-making stage. It contains two main groups: a) fault identification and b) fault prediction. In this study, a maintenance strategy is presented for mechanical, electrical and lighting systems supplying the external and common areas excluding the apartments to avoid data perturbation due to differenced user's behaviours. The proposed strategy implementing are as follows:

A) Collecting data;
B) Determining the parameters affecting the system outputs;
C) Determine the optimal values of the obtained parameter;
D) Fault identification model;
E) Fault prediction intelligent strategy for electrical and mechanical systems;

In order to optimize the timing of the maintenance operations, the study started by considering the maximum initial values of the maintenance intervals taken from the Italian and European technical standards. A threshold value of tolerability of faults detected at the maintenance visit was chosen, estimating around 5% for all types of implemented components. This choice is related to factors such as avoiding excessively high malfunctioning values that would compromise the functionality of the systems or at least penalize the quality of service, preventing an excessive increase in costs associated with scheduled maintenance activities.
The proposed methodology is based on a statistical evaluation of the deviation between the failure rate of a single device and the set threshold value (as mentioned above, 5% was chosen for uniformity and simplicity in this case study). If this value is lower than the threshold, subsequent maintenance will be scheduled according to the time interval already provided by the standard; on the other hand, if the value of the failure rate is higher than the threshold limit, the scheduled time interval will be shortened, and subsequent maintenance will be anticipated. The shortened period will follow the percentage value exceeding the 5% threshold according to the formula (1):

$$Mp = Mppl - [Mppl * (fr-frth)] \qquad (1)$$

Where fr is the real failure rate; fourth is the threshold limit of the failure rate; Mppl is the planned maintenance period; Mp is the shortened maintenance period;
Whenever a scheduled maintenance cycle of components is completed, the failure rate statistics must be evaluated, and the timing for the following maintenance schedule is updated. When the failure rate curve falls below 5%, this means that the chosen interval is adequate and does not need to be shortened further. However, suppose robust requirements for continuity of service of the installations are needed, such as for some essential electrical power supply system components. In that case, it will be sufficient to lower the threshold limit to reach the desired reliability values, varying the time interval of the maintenance operations accordingly.

4 RESULTS AND DISCUSSIONS

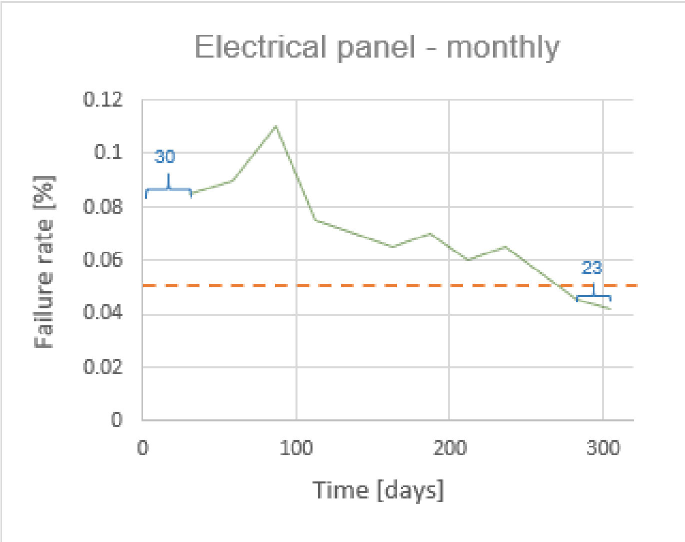
Therefore, for the application of the previously illustrated methodology, the following components with their base maintenance intervals obtained from the related regulations were taken into account in the period 2018-2020:

Table 1. Base maintenance frequency plan.

HVAC	Frequency
Boiler	annual
Piping insulation	annual
Cooling system	annual
AHU belt and motion parts	monthly
AHU flat filters	quarterly
Valves	monthly

ELECTRICAL	Frequency
Electrical panel	monthly
Lightning systems lamps	quarterly
Lightning system equipment	monthly

By graphically describing the 3-year data obtained following the maintenance datasheets as described in paragraph 2, it is possible to evaluate the trends in the failure rate (shown on the y-axis) as a function of the shortening of the maintenance intervals carried out according to the formula described above.



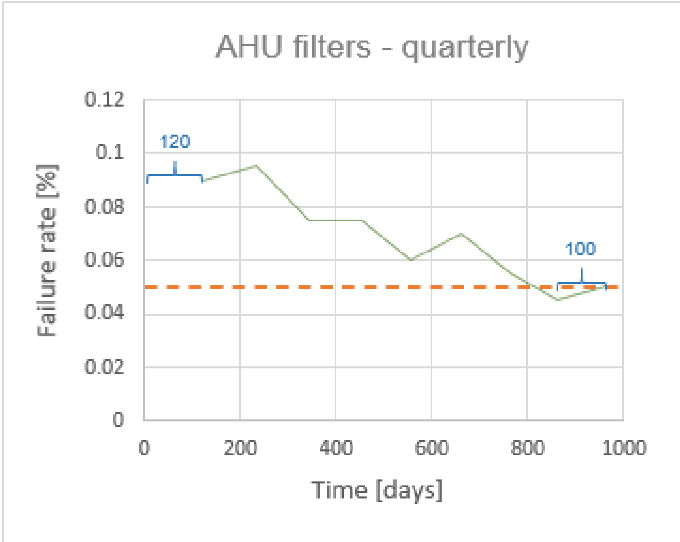


Figure 2. Electrical panel and Hair Handling Unit monthly and quarterly failure rate reduction.

Figure 2 shows how the failure rate tends to fall below 5% after a period varying according to the performed maintenance cycles. The threshold is reached after less than a year for monthly maintenance activities while quarterly maintenance activities take about two and a half years; however, if the number of maintenance

cycles is assessed (12 for the electrical panel and 9 for Air Handling Unit - AHU filters, respectively), it can be observed that the trend is similar. Furthermore, the percentages of shortening maintenance intervals are also similar and range from 24% for the electrical panel and 17% for AHU.
Therefore, it is always possible to reach the desired failure rate level with a proportional increase in expense as maintenance intervals are shortened. Therefore, to optimize the operational cost-benefit, it is crucial to precisely identify the value of the most suitable threshold limit for the specific conditions.

4.1 Digital Twin for Building Management Systems

The proposed Building Management system can achieve much more considerable efficiency by configuring the Digital Twin of the building through the integration of the BIM (Building Information Modelling) model aimed at AIM (Asset Information Model) [22] with information systems, BMS, IoT, Machine Learning, Mixed Reality for the optimization and automation of maintenance activities;
In addition, working on the BIM model as the core of the management system architecture, it is possible to improve the potential related to physical/spatial information for space management, optimizing maintenance activities, integrating machine learning systems and rule-based methods such as association rule mining [23]. Therefore, it is helpful to create a hierarchy in the classification of spaces, using machine learning techniques defined as "clustering", automatically identifying groups/classes of similar spaces for their digital representation.
The proposed system, therefore, involves the integration of three components: i) data related to BIM Model objects (Autodesk Revit); ii) data flow programmed through visual programming systems (Autodesk Dynamo) relating the AI systems with the BIM model bidirectionally; iii) Artificial Intelligence (AI) algorithm through Python language improving efficiency and compatibility with flows programmed through Dynamo [24]. Furthermore, the AI system can use mixed techniques of regression and hybrid reasoning.

5 CONCLUSIONS

Big Data is becoming a preponderant issue in many technological fields; predictive maintenance should develop innovative methodologies to increase technical plant’s reliability levels towards a near-zero-failure rate. In the present paper, the applied methodologies show the importance of implementing Big Data unsupervised machine learning systems to highlight connections between different maintenance conditions and strategies to obtain the most suitable threshold failure rate values for each kind of equipment. Such an approach is confirmed by the failure of traditional supervised analyses, depending on great difficulties in relating involved variables to their actual impact on the maintenance strategies. The collection of a significant amount of maintenance data from different building systems, coupled with a data acquisition tool able to filter inadequate information, will improve the predictive maintenance strategy in public and private organizations.

REFERENCES

[1] S. Selcuk, “Predictive maintenance, its implementation and latest trends,” Proc. Inst. Mech. Eng. Part B J. Eng. Manuf., vol. 231, no. 9, pp. 1670–1679, 2017.
[2] L. Krishnamurthy et al., “esign and Deployment of Industrial Sensor Networks: Experiences from a Semiconductor Plant and the North Sea,” in In Proceedings of the 3rd international conference on Embedded networked sensor systems, 2005, pp. 64–75.
[3] C. Eastman, P. Teicholz, R. Sacks, and K. Liston, BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors. John Wiley & Sons, 2011.
[4] E. Quatrini, F. Costantino, G. Di Gravio, and R. Patriarca, “Condition-Based Maintenance — An Extensive Literature Review,” Machines, vol. 8, no. 2, p. 31, 2020.
[5] X. Zhou, L. Xi, and J. Lee, “Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation,” Reliab. Eng. Syst. Saf., vol. 92, pp. 530–534, 2007, doi: 10.1016/j.ress.2006.01.006.
[6] S. Sheu, C. Chang, Y. Chen, and Z. George, “Optimal preventive maintenance and repair policies for multi-state systems,” Reliab. Eng. Syst. Saf., vol. 140, pp. 78–87, 2015, doi: 10.1016/j.ress.2015.03.029.

[7] Z. Tian and H. Liao, “Condition based maintenance optimization for multi-component systems using proportional hazards model,” Reliab. Eng. Syst. Saf., vol. 96, no. 5, pp. 581–589, 2011, doi: 10.1016/j.ress.2010.12.023.
[8] H. Liao, E. A. Elsayed, and L. Chan, “Maintenance of continuously monitored degrading systems,” Eur. J. Oper. Res., vol. 175, pp. 821–835, 2006, doi: 10.1016/j.ejor.2005.05.017.
[9] M. Marseguerra, E. Zio, and L. Podofillini, “Condition-based maintenance optimization by means of genetic algorithms and Monte Carlo simulation,” Reliab. Eng. Syst. Saf., vol. 77, pp. 151–165, 2002.
[10] J. Barata, C. G. Soares, M. Marseguerra, and E. Zio, “Simulation modelling of repairable multi-component deteriorating systems for ‘on condition’ maintenance optimisation,” Reliab. Eng. Syst. Saf., vol. 76, pp. 255–264, 2002.
[11] G. A. Susto, A. Schirru, S. Pampuri, S. Mcloone, S. Member, and A. Beghi, “Machine Learning for Predictive Maintenance: A Multiple Classifier Approach,” IEEE Trans. Ind. INFORMATICS, vol. 11, no. 3, pp. 812–820, 2015.
[12] Y. Wang, C. Gogu, N. Binaud, C. Bes, R. T. Haftka, and N. H. Kim, “A cost driven predictive maintenance policy for structural airframe maintenance,” Chinese J. Aeronaut., vol. 30, no. 3, pp. 1242–1257, 2017, doi: 10.1016/j.cja.2017.02.005.
[13] J. Wang, L. Zhang, L. Duan, and R. X. Gao, “A new paradigm of cloud-based predictive maintenance for intelligent manufacturing,” J. Intell. Manuf., vol. 28, no. 5, pp. 1125–1137, 2017.
[14] S. Ren and X. Zhao, “A predictive maintenance method for products based on big data analysis,” in In Proc. Int. Conf. Mater. Eng. Inf. Technol. Appl.(MEITA), 2015, pp. 385–390.
[15] “Comparison of marker-based AR and marker-less AR: a case study on indoor decoration system,” in In Lean and Computing in Construction Congress (LC3): Proceedings of the Joint Conference on Computing in Construction (JC3), 2017, pp. 483–490.
[16] T. W. Kang and C. H. Hong, “Automation in Construction A study on software architecture for effective BIM / GIS-based facility management data integration,” Autom. Constr., vol. 54, pp. 25–38, 2015, doi: 10.1016/j.autcon.2015.03.019.
[17] S. Ayvaz and K. Alpay, “Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time,” Expert Syst. Appl., vol. 173, no. September 2020, p. 114598, 2021, doi: 10.1016/j.eswa.2021.114598.
[18] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-matos, “Fuzzy early warning systems for condition based maintenance,” Comput. Ind. Eng., vol. 128, no. December 2018, pp. 736–746, 2019, doi: 10.1016/j.cie.2018.12.056.
[19] G. Wei, X. Zhao, S. He, and Z. He, “Reliability modeling with condition-based maintenance for binary-state deteriorating systems considering zoned shock effects,” Comput. Ind. Eng., vol. 130, no. July 2018, pp. 282–297, 2019, doi: 10.1016/j.cie.2019.02.034.
[20] J. C. P. Cheng, W. Chen, K. Chen, and Q. Wang, “Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms,” Autom. Constr., vol. 112, p. 103087, 2020, doi: 10.1016/j.autcon.2020.103087.
[21] A. K. S. Jardine, D. Lin, and D. Banjevic, “A review on machinery diagnostics and prognostics implementing condition-based maintenance,” A Rev. Mach. diagnostics Progn. Implement. Cond. Maint., vol. 20, pp. 1483–1510, 2006, doi: 10.1016/j.ymssp.2005.09.012.
[22] UNI EN ISO 19650 Standard Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) — Information management using building information modelling — Part 3: Operational phase of the assets
[23] A. Telikani, A. H. Gandomi, A. Shahbahrami, A survey of evolutionary computation for association rule mining, Information Sciences, Volume 524, 2020, pp 318-352, ISSN 0020-0255, https://doi.org/10.1016/j.ins.2020.02.073.
[24] M. Salamak, M. Jasiński, T. Płaszczyk, M. Żarski Analytical Modelling in Dynamo, Transactions of Vsb, Technical University of Ostrava, Civil Engineering Series - 2018, Volume 18, Issue 2, Pages 36-43 doi: 10.31490/tces-2018-0014.