HVAC Data-Driven Maintenance

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Buildings' heating, ventilation, and air-conditioning (HVAC) systems account for significant global energy use. Proper maintenance can minimize their environmental footprint and enhance the quality of the indoor environment. The adoption of Internet of Things (IoT) sensors integrated into HVAC systems has paved the way for data-driven predictive maintenance (PdM) grounded in real-time operational metrics.

health prognostics | heating ventilation and air-conditioning (HVAC) | predictive maintenance | data-driven maintenance | machine learning | artificial neural networks

1. Introduction

In 2021, approximately 135 Exajoules of energy was expended on the operations of residential and commercial buildings globally. These figures represent 30% of worldwide energy consumption and contribute to 27% of total greenhouse gas emissions [1]. Specifically, the energy consumption of heating, ventilation, and air-conditioning (HVAC) systems in buildings constitutes 38% of this expenditure [2]. Moreover, the upkeep of HVAC systems makes up over 65% of the annual costs associated with building facilities management [3]. Proper maintenance of HVAC systems can curtail these expenses, enhance HVAC system availability, and thereby elevate human comfort in enclosed spaces.

HVAC systems are pivotal in modulating indoor environmental quality (IEQ) by ensuring ventilation combined with filtration and upholding the comfort of inhabitants. A conventional HVAC setup is centralized, typically encompassing a central plant equipped with a hot water boiler and chiller, a pump mechanism facilitating the circulation of hot and chilled water via an interlinked pipe circuit, and an air-handling unit. Operational discrepancies in HVAC systems, whether due to equipment malfunctions, sensor issues, control system glitches, or design flaws, frequently remain undetected until they prompt equipment-level alarms. These undiagnosed issues can compromise occupants' thermal well-being and lead to increased energy use. Research indicates that HVAC systems are the primary energy consumers in buildings, with nearly 30% of energy in commercial structures being wasted due to unnoticed operational failures [4]. Early detection and diagnosis of such faults can substantially reduce electricity usage, underlining the importance of timely identification and rectification of HVAC system anomalies.

In facilities management, there are three main strategies toward maintenance management: corrective maintenance, preventive maintenance, and predictive maintenance [5][6]. Corrective maintenance is the simplest form of maintenance strategy, as it allows a piece of equipment to run to failure and only intervenes when the breakdown happens. While this can be effective for non-critical equipment, i.e., those that do not cause disruption to the normal operation of the buildings, corrective maintenance is not ideal for HVAC systems because an unplanned breakdown can have a large impact on the operation of a building. Preventive maintenance is a schedule-based maintenance strategy where equipment is inspected and maintained regularly following a schedule derived from its average-life statistics [5]. Traditionally, HVAC and many other systems in buildings are maintained following a preventive maintenance strategy because it minimizes the chance of breakdown. However, the downside to a preventive maintenance strategy is that equipment can still have a lot of remaining useful life at the time of scheduled maintenance, which can create unnecessary waste. Additionally, frequent maintenance drives up facilities management costs and, in turn, increases the total operational cost of the buildings.

Predictive maintenance endeavors to address the limitations of corrective and preventive maintenance by continuously monitoring and analyzing the operational status of equipment to inform maintenance decisions. In recent years, an increasing number of IoT devices have been placed in buildings and integrated into HVAC systems that seek to optimize the IEQ while reducing building energy consumption [7]. Integrated IoT sensors in HVAC systems also allow for operational data to be collected and analyzed with ease [8][9], hence fulfilling an essential prerequisite for modern data-driven predictive maintenance. IoT-enabled HVAC systems can greatly benefit from data-driven predictive maintenance. There are two prominent data-driven strategies for the predictive maintenance of HVAC systems: fault detection and diagnostics (FDD) and health prognostics (HP) [3].

Incorporating machine learning into FDD and HP methodologies has become prevalent. These approaches train machine learning models using historical HVAC operational data, subsequently leveraging these models to predict real-time system status. These technologies are crucial for fault detection in indoor thermal comfort areas [10]. IoT devices capture real-time data, while ML processes this information to aid engineers and technicians in effective decision making. Peng et al. [11] presented a strategy for managing indoor thermal comfort. Similarly, Yang et al. [12] developed a predictive method using IoT and ML to identify HVAC system failures impacting occupants' health, emphasizing early problem detection. Understanding outdoor environmental factors, as discussed by Rijal et al. [13], can influence indoor comfort, with Elnaklah et al. [14] highlighting the importance of these factors in assessing indoor conditions. Thus, utilizing IoT and ML enhances the precision of fault detection in indoor thermal comfort, providing valuable insights for specialists.

2. Data-Driven Predictive Maintenance

Nowadays, along with the popularization of IoT devices, data-driven predictive maintenance studies have been conducted by researchers in many fields of the industry, including on wind turbines [15], photovoltaic cells [16], and electrical motors [17][18]. HVAC systems are also among the fields of interest for predictive maintenance. As discussed in the last section, the data-driven predictive maintenance of HVAC systems is categorized into two approaches, which are fault detection and diagnostics (FDD) and health prognostics (HP). The FDD approach aims to detect and classify incipient mechanical faults in HVAC systems. Satta et al. [19] used mutual dissimilarities of multiple HVAC systems within a cohort to detect individual HVAC faults. Bouabdallaoui et al. [20] compared the root mean square error (RMSE) reconstruction error produced by an LSTM autoencoder with a threshold to detect HVAC faults. Taheri et al. [21] investigated different configurations of LSTM networks for HVAC fault detection. Tasfi et al. [22] combines a convolutional autoencoder with a binary classifier to first learn an embedding of the data and then detect faults using an electrical signal. The above studies show that fault detection and diagnostics are promising approaches to data-driven predictive maintenance for HVAC systems. However, FDD approaches do not provide a macroscopic view of the degradation, which is crucial to understanding the degradation dynamics for HVAC systems.

- Neural networks for health prognostics:

In recent years, artificial neural networks (NN) have emerged as a pivotal tool for health prognostics across various applications. In the domain of facility maintenance management, a study presented by Cheng et al. [23] demonstrates the potential of integrating building information modeling with IoT devices to elevate the efficiency of facility maintenance strategies. This integration, using NNs and support vector machine (SVM), has shown promise in predicting the future conditions of mechanical, electrical, and plumbing components. The authors presented an effective framework for forecasting effective maintenance planning based on real-time data assimilation from multiple sources. On another front, Riley and Johnson [24] used model-based prognostics and health management systems to monitor the health of photovoltaic systems. Unique to this approach was the use of an NN that was trained to predict system outputs based on variables like irradiance, wind, and temperature. Lastly, in the challenge of engineering prognostics under fluctuating operational and environmental conditions, NNs have been used for data baselining. Specifically, a self-organizing map was implemented by Baptista et al. [25] to discern different operating regimes, followed by the application of an NN to normalize sensor data within each detected regime. Such a technique showcases the potential to be integrated into a comprehensive deep learning system, streamlining the prognostics process.

- Support vector machine and machine learning for health prognostics:

In the domain of health prognostics for HVAC systems, the use of the SVM as a diagnostic tool has been increasingly recognized. Liang and Du [26] developed an approach for preventive maintenance in modern HVAC systems, particularly showing the importance of cost-effective FDD methods. Their approach uniquely integrated a model-based FDD with an SVM, demonstrating that by scrutinizing certain system states indicative of faults, they could develop an efficient multi-layer SVM classifier to maintain HVAC health while reducing both energy consumption and maintenance expenses. Building on this paradigm, Yan et al. [27] highlighted a prevalent challenge in data-driven FDD techniques for air-handling units. They innovated a semi-supervised learning FDD framework that leveraged SVM. By iteratively incorporating confidently labeled testing samples into the training pool, this model emulated early fault detection scenarios, offering a diagnostic performance on par with traditional supervised FDD approaches despite the limited availability of faulty training samples. Further expanding on this SVM-based analytical approach, Li et al. [28] proposed an FDD solution rooted in statistical machine learning. Their methodology capitalized on SVM to discern the nature of various HVAC faults, utilizing statistical correlations across measurements to pinpoint fault types in subsystems. The integration of principle component analysis further streamlined the learning process, allowing for timely and accurate fault identification in commercial HVAC setups. Yang et al. [12] utilized machine learning methodologies to estimate the remaining useful life of HVAC systems, harnessing data from sensors and actuators leading up to the occurrences of HVAC failures. Such endeavors underscore the potential efficacy of the HP approach in HVAC predictive maintenance. Notably, the aforementioned studies predominantly frame HVAC health prognostics as regression challenges.

References

1. IEA. Buildings; Technical Report; IEA: Paris, France, 2022.
2. González-Torres, M.; Pérez-Lombard, L.; Coronel, J.F.; Maestre, I.R.; Yan, D. A review on buildings energy information: Trends, end-uses, fuels and drivers. Energy Rep. 2022, 8, 626–637.
3. Es-sakali, N.; Cherkaoui, M.; Mghazli, M.O.; Naimi, Z. Review of predictive maintenance algorithms applied to HVAC systems. Energy Rep. 2022, 8, 1003–1012.
4. International Energy Agency. Transition to Sustainable Buildings: Strategies and Opportunities to 2050; Organization for Economic Co-Operation & Development: Paris, France, 2013.
5. Mobley, R.K. An Introduction to Predictive Maintenance; Elsevier: Amsterdam, The Netherlands, 2002.
6. Susto, G.A.; Schirru, A.; Pampuri, S.; McLoone, S.; Beghi, A. Machine learning for predictive maintenance: A multiple classifier approach. IEEE Trans. Ind. Inform. 2015, 11, 812–820.
7. Broday, E.E.; Gameiro da Silva, M.C. The role of internet of things (IoT) in the assessment and communication of indoor environmental quality (IEQ) in buildings: A review. Smart Sustain. Built Environ. 2023, 12, 584–606.
8. Dalzochio, J.; Kunst, R.; Pignaton, E.; Binotto, A.; Sanyal, S.; Favilla, J.; Barbosa, J. Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges. Comput. Ind. 2020, 123, 103298.
9. Zonta, T.; da Costa, C.A.; da Rosa Righi, R.; de Lima, M.J.; da Trindade, E.S.; Li, G.P. Predictive maintenance in the Industry 4.0: A systematic literature review. Comput. Ind. Eng. 2020, 150, 106889.
10. Merenda, M.; Porcaro, C.; Iero, D. Edge machine learning for ai-enabled iot devices: A review. Sensors 2020, 20, 2533.
11. Peng, Y.; Rysanek, A.; Nagy, Z.; Schlüter, A. Using machine learning techniques for occupancy-prediction-based cooling control in office buildings. Appl. Energy 2018, 211, 1343–1358.
12. Yang, C.; Gunay, B.; Shi, Z.; Shen, W. Machine Learning-Based Prognostics for Central Heating and Cooling Plant Equipment Health Monitoring. IEEE Trans. Autom. Sci. Eng. 2021, 18, 346–

355.

13. Rijal, H.B.; Yoshida, K.; Humphreys, M.A.; Nicol, J.F. Development of an adaptive thermal comfort model for energy-saving building design in Japan. Archit. Sci. Rev. 2021, 64, 109–122.
14. Elnaklah, R.; Walker, I.; Natarajan, S. Moving to a green building: Indoor environment quality, thermal comfort and health. Build. Environ. 2021, 191, 107592.
15. Vallim Filho, A.R.d.A.; Farina Moraes, D.; Bhering de Aguiar Vallim, M.V.; Santos da Silva, L.; da Silva, L.A. A machine learning modeling framework for predictive maintenance based on equipment load cycle: An application in a real world case. Energies 2022, 15, 3724.
16. Klinsuwan, T.; Ratiphaphongthon, W.; Wangkeeree, R.; Wangkeeree, R.; Sirisamphanwong, C. Evaluation of Machine Learning Algorithms for Supervised Anomaly Detection and Comparison between Static and Dynamic Thresholds in Photovoltaic Systems. Energies 2023, 16, 1947.
17. Cazacu, E.; Petrescu, L.G.; Ioniță, V. Smart Predictive Maintenance Device for Critical In-Service Motors. Energies 2022, 15, 4283.
18. Martins, A.; Mateus, B.; Fonseca, I.; Farinha, J.T.; Rodrigues, J.; Mendes, M.; Cardoso, A.M. Predicting the Health Status of a Pulp Press Based on Deep Neural Networks and Hidden Markov Models. Energies 2023, 16, 2651.
19. Satta, R.; Cavallari, S.; Pomponi, E.; Grasselli, D.; Picheo, D.; Annis, C. A dissimilarity-based approach to predictive maintenance with application to HVAC systems. arXiv 2017, arXiv:1701.03633.
20. Bouabdallaoui, Y.; Lafhaj, Z.; Yim, P.; Ducoulombier, L.; Bennadji, B. Predictive Maintenance in Building Facilities: A Machine Learning-Based Approach. Sensors 2021, 21, 1044.
21. Taheri, S.; Ahmadi, A.; Mohammadi-Ivatloo, B.; Asadi, S. Fault detection diagnostic for HVAC systems via deep learning algorithms. Energy Build. 2021, 250, 111275.
22. Tasfi, N.L.; Higashino, W.A.; Grolinger, K.; Capretz, M.A. Deep neural networks with confidence sampling for electrical anomaly detection. In Proceedings of the 2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), Exeter, UK, 21–23 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1038–1045.
23. Cheng, J.C.; Chen, W.; Chen, K.; Wang, Q. Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms. Autom. Constr. 2020, 112, 103087.
24. Riley, D.; Johnson, J. Photovoltaic prognostics and heath management using learning algorithms. In Proceedings of the 2012 38th IEEE Photovoltaic Specialists Conference, Austin, TX, USA, 3–8 June 2012; pp. 1535–1539.

25. Baptista, M.L.; Henriques, E.M.P.; Goebel, K. A self-organizing map and a normalizing multi-layer perceptron approach to baselining in prognostics under dynamic regimes. Neurocomputing 2021, 456, 268–287.
26. Liang, J.; Du, R. Model-based Fault Detection and Diagnosis of HVAC systems using Support Vector Machine method. Int. J. Refrig. 2007, 30, 1104–1114.
27. Yan, K.; Zhong, C.; Ji, Z.; Huang, J. Semi-supervised learning for early detection and diagnosis of various air handling unit faults. Energy Build. 2018, 181, 75–83.
28. Li, J.; Guo, Y.; Wall, J.; West, S. Support vector machine based fault detection and diagnosis for HVAC systems. Int. J. Intell. Syst. Technol. Appl. 2019, 18, 204–222.