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Original Article

Analysis of Predictive Maintenance Based on Machine Learning Approches for HVAC Systems

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Abstract:

Residential and commercial buildings rely heavily on HVAC systems, which are notoriously power hogs, thus it's crucial that these systems be reliable and efficient. This paper explores the concept of implementing predictive maintenance and occupancy aware control in HVAC systems to improve the energy efficiency, operational stability, and occupant comfort. It discusses how maintenance practices have changed since the reactive and preventive methods to be data-driven, predictive maintenance facilitated by IoT technologies, automatic commissioning, and machine learning. Occupancy recognition methods and how these can be used to achieve intelligent HVAC control are also examined in the study with optimal start/stop timing, ramp down approaches and adaptive pressure control. More so, the supervised and unsupervised machine learning algorithms to fault detection and diagnosis are discussed, and their ability to manage complex and nonlinear HVAC behaviors. As the results have shown, the predictive maintenance should be coupled with the optimistic use of occupancy to lower the energy consumption, minimize downtime, and prolong the life of equipment, providing a complex of measures to control the HVAC system of a building as a set of sustainable and intelligent.

Keywords:

HVAC Systems, Predictive Maintenance, Machine Learning, Iot Technologies, Energy Efficiency.

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1. Introduction

A/C systems are required in many different kinds of buildings due to factors such as increasing populations, new technology, and people's way of life. The importance of HVAC systems in maintaining comfortable and safe indoor air quality (IAQ) is substantial. However, as stated by Rafique (2018), these systems account for around 40% to 60% of the overall energy used by buildings, which is equivalent to 15% of the total worldwide [1]. For these reasons, it is critical that scholars, businesses, and politicians all think about HVAC sustainability development. While decreasing energy consumption and costs, HVAC systems must incorporate sustainability considerations and technologies to create an exceptional, healthy, productive, and environmentally friendly built environment for occupants [2].

The acronym HVAC is used to refer to Heating, Ventilation, and Air conditioning. A number of components work together to control the flow of conditioned air: a supply air [3] fan to direct the flow of conditioned air, a heating and cooling coil to regulate the air temperature, an exhaust air damper to direct the outflow, a return air fan to direct the extraction of indoor air, and a return air damper to control the recirculation. The two main categories of controls are supervisory controls and local controls. When formulating an optimization or control issue of a local control kind, design factors such as valve position and damper position may be taken into account. Control variables at the supervisory level might include schedules and temperature setpoints.

Not only control optimization, but also the same principles of data-driven learning have been used in relation to maintenance strategies to transform the operation of the HVAC system to a proactive decision-making mode rather than a reactive operation. Predictive maintenance is the process of identifying when an appliance is likely to break down or develop a problem so that can take preventative measures to keep it running smoothly and reliably. An effective first step in investigating the problem is to create a model of the monitored appliance's operation utilizing its inputs, outputs, and any available sensor or telemetry data. Then, abnormal behaviors and the approaching danger of failure are identified using this model [4].

ML is a branch of AI that analyses data for correlations and patterns in order to train computers to learn and improve themselves. ML models adjust their behavior through experience, which allows predicting, classifying, and making decisions based on the data with the help of statistical techniques and optimization. Typically, ML approaches are categorized into supervised, unsupervised, and reinforcement learning according to the type of data provided and the learning goals. Because of its versatility and ability to handle massive amounts of data, machine learning has become an indispensable tool in a wide range of scientific and technical disciplines.

1.1. Structure of the Paper

The following structure is followed in this review: Section I gives an introduction of HVAC systems and maintenance issues, Section II is about foreseeable maintenance and commissioning measures, Section III is a discussion of occupancy-based HVAC control, Section IV examines the use of machine learning for preventative maintenance, In Section V, offer the literature evaluation, and in Section VI, draw conclusions and suggest avenues for further research.

2. Predictive Maintenance in HVAC Systems

The idea of predictive maintenance in HVAC systems is a significant departure from the traditional reactive or time-based maintenance methods. Instead, it is a data-driven approach that aims to anticipate equipment problems in advance. Using real-time monitoring, sophisticated sensors and analysis algorithms, predictive maintenance continuously evaluates the status and performance of HVAC components so that facility managers can only intervene when required by the actual state of the equipment as opposed to arbitrary schedules. This method greatly decreases unforeseen downtimes, decreases the cost of maintenance, increases equipment life span and enhances energy savings and comfort to occupants. The use of IoT technologies, machine learning, and cloud-based [5][6] analytics has also improved predictive maintenance functionality to be able to diagnose and know more and more accurately about a fault. With this field still under development, two key developments have come out as the backbone to the promotion of predictive maintenance in the HVAC systems.

2.1. Evolution of Predictive Maintenance Strategies in HVAC Systems

The current state of maintenance practices in mechanical systems has been changing in the last several decades by shifting to more proactive and smart approaches rather than reactive ones. The early industrial operations were dominated by reactive maintenance, which is also referred to as the run-to-failure approach. The process used in this model was to solve equipment failures as they happened, and this tended to cause long downtimes, high cost of repairs and risks. Although it is applicable in the low-cost or non-critical equipment, this strategy failed to serve high-demand environments that require reliability. Preventive maintenance was created to overcome the shortcomings of reactive practices. Also, it could not be flexible to address the unforeseen operational changes and complicated wear patterns in current industrial systems. A paradigm shift in asset management has been the introduction of predictive [7] maintenance. Predictive strategies can then predict the equipment when they fail by using condition monitoring tools and data analytics. The construction of HVAC systems are often riddled with failure of devices, wrong control and poor maintenance that may lead to a lot of loss of energy. An intake fan and an exhaust fan comprise the equipment, which controls the air circulation in the HVAC system. The maintenance strategies are discussed below:

- Dampers: The airflow within the dampers is controlled by opening and closing the dampers, which in turn regulates the air velocity. Air filters and cooling coils are also part of the system, which may be used to change the air for cooling or clarification purposes.
- Coils: The system's coils either heat or cool the air as it passes through the channel in an effort to reach the desired temperature. A fan extracts air from each zone to facilitate air circulation, and reheating coils provide a respectable quantity of heat. Usually, most of the air that leaves the room is combined with air that comes in from outside, but the same amount of air that goes into the air channels is then expelled to the environment.

2.2. Predictive Maintenance Through Automatic Commissioning in HVAC Systems

Plan, design, build, install, use, and maintain all contribute to a building's overall energy consumption [8]. Building energy usage has been steadily rising in recent years due to factors such as the demands for healthier, more pleasant, and more productive interior environments and the impacts of climate change. The creation of eco-friendly and energy-efficient structures is a key concern for a sustainable society [9]. The following factors frequently contribute to HVAC system performance issues in real-world settings: insufficient documentation for verification purposes; insufficient information exchange among the many stakeholders (including architects, consultants, suppliers, contractors, and operators); incorrect equipment selection and installation; inadequate maintenance; delayed or non-existent feedback on operation performance; declining performance; and/or component failure. Figure 1 shows the general HVAC commissioning process with major phases of installation verification leading to operational monitoring and feedback all of them are aimed at ensuring that the performance of the systems is as intended by the design.

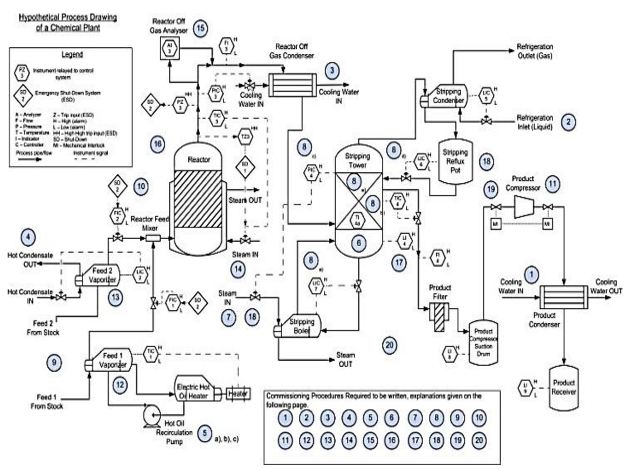

Figure 1. HVAC Commissioning Process Schematic

In order for commissioning to be done throughout the lifetime of a building, it is an important part of every step in the construction process. Differentiating between commissioning categories aids in defining commissioning activities, processes, and results. In general, four distinct kinds of commissioning are recognized [10] original, retro-, re-, and ongoing/continuous. Despite their malleability, the following four varieties are generally acknowledged as the most frequent.

- Initial Commissioning: This method of commissioning is used when constructing a new building or installing new systems. The process is defined as a series of steps, beginning with the Program Step and ending with the Post-Acceptance Step.
- Retro-Commissioning: An existing building has never before had a recorded commissioning.
- Re-Commissioning: This type of commissioning is carried out by the owner after the first or retro-commissioning in order to confirm, enhance, and record the building systems' performance.
- On-going/ Continuous Commissioning: Commissioning of this kind is done periodically to make sure that systems in a building keep working well after the first commissioning or retro-commissioning.

3. Occupancy Recognition in HVAC Systems

These technologies present enormous opportunities to energy cost reduction and flexibility as emerging algorithms bring in occupancy count data as a part of a more advanced HVAC management. This research examines an EMIS for commercial buildings that uses AI to monitor and analyze HVAC systems depending on occupancy. The system incorporates several building data streams.

3.1. Occupancy-Based Automated Optimization

The occupancy data was combined with other data streams (weather, operational patterns, and proprietary ML algorithms) to estimate the start and stop times of the AHUs [11]. The adjustments to the static pressure setpoints could be enabled or disabled to reduce total energy consumption while still satisfying estimated human thermal comfort. Included in the offering are four energy conservation measures (ECMs).

3.1.1. Optimal start

Specialized ML algorithms gather information about previous occupancy, present temperature, temperature setpoints, and next day's weather prediction to aid in the startup of AHUs. recommend starting the AHUs at the most energy-efficient times so that the room is heated to the desired temperature before the leasing agreement period ends, while still minimizing energy consumption. Building thermal capacity, occupancy profiles, and temperature predictions for interior spaces made using ML techniques are utilized for day-ahead prediction.

3.1.2. Early Shutdown

An AHU's shutdown time is determined by the current occupancy level. A 15-minute delay is implemented before the air handling unit (AHU) is turned off for the day if a floor's occupancy count reaches zero after a pre-set period by the building operator. For the duration of the epidemic, this approach useful because very few tenants use the building during the week and even fewer of those who do usually leave before sunset.

3.1.3. Midday Ramp-Down/Up

Occupancy variations are used to implement tentatively lowering AHU static pressure setpoint in form of HVAC ramp-down sequences during the lunch periods. Decreases in the static pressure setpoint lead to lesser fan speeds. With the possibility of resetting the supply air temperature setpoint to lower values, the electricity consumption of the fans reduces while that of the chilled water systems climbs. For the purpose of determining when to enable and disable the midday ramp-down/up method, occupancy is calculated using past occupancy data in conjunction with a personalized ML algorithm. Enabling the technique and lowering the static pressure setpoint to a minimal pre-defined setpoint occurs when the occupancy level is dropped.

3.1.4. End-of-Day Static Pressure Setpoint Ramp-Down

This occupancy-based management system also gives the chance to ramp down at the end of the day when the occupancy level starts to drop.

3.2. Occupancy Model Generation and Discussion in HVAC Control

The possible energy savings and effects of occupancy-based HVAC control on models of residential buildings. In order to make this happen, needed to know how many people were actually living in the house. In order to develop non-probabilistic occupancy prediction models, actual occupancy data was gathered from a number of residences situated in Boulder, Colorado. The model's efficacy was assessed by contrasting the actual occupancy rate with the anticipated rate. The next sections elaborate on this procedure in detail.

3.2.1. Ground Truth Data Collection

During the course of four to nine weeks, six residences had their occupancy rates and eight distinct physical modalities (such as temperature and CO2) observed. An software called "geo-fencing" was downloaded into customers' mobile devices, and a paper sign-in form was left at the front door to track occupancy. The two collection methods were cross-referenced by the researchers to confirm correctness. The time of arrival and departure for every person living in the house for a specific period was recorded by using both of these methods. To find out the home's binary occupancy status, integrated data from each resident.

3.2.2. Occupancy Model Generation

Using a non-probabilistic approach, the occupancy was estimated. Since non-probabilistic models depend on past data to produce an occupancy probability, optimizing them is as simple as choosing the right training data. In order to fine-tune the model, the collected occupancy data was split into two sets: training and testing. used the first set to train the models, and then compared their results to the second set to see how well they did. Not necessarily the case, with the exception of the moving training mode that used a receding horizon. Here, the cycle was constant: train the model, test it on hidden data, and then update it based on results compared to ground truth.

3.3. Classification of HVAC Control Methods:

There are various control methods of the HVAC. These methods are discussed below:

3.3.1. Classical or Traditional control:

- ON/Off: Only the highest value or zero may be used for the On/Off control mode. Only the thermostat, pressure switch, and humidistat may be activated or deactivated using this controller type. This approach is not precise enough since it is too easy to use.
- PID: PID controllers are a type of feedback controller that uses system errors—the gap between actual and target values—to adjust the system. The ratio pertains to the current offset, the integral to the accumulation of mistakes in the past, and the derivative, which takes the process's rate of change into account, to depict the offset in the future.

3.3.2. Hard control

- Optimal: The main goals of implementing optimum control in HVAC systems are to maximize thermal comfort while decreasing energy consumption and control effort.
- Robust: The robust control solution may be useful when dealing with nonlinearities in the system and uncertainty in the models. Set point tracking disturbances were effectively cancelled by utilizing the robust control, which has appealing properties with respect to uncertainty in model parameters, as well as measurable, unmeasured, or external disturbances [12].
- Adaptive: Nonlinear models, slow time-varying parameters, uncertainty, and complexity are some of the HVAC system's defining features; the adaptive control approach provides a variety of solutions to these problems.
- Nonlinear: Linear control techniques fail to deliver stable and performance-enhancing solutions for HVAC systems due to their significant time-varying and nonlinear behavior. This is especially true across a wide operating range and in situations where the nonlinearity of the system positively affects the system's behavior, like air conditioning.

4. Machine Learning Techniques for HVAC Systems Predictive Maintenance

ML is a subfield of CS that enables computers to acquire new knowledge automatically, without human intervention. It is possible to see the issue of defect identification and diagnosis in building energy systems as a problem of pure machine learning [13]. Fault identification, given enough training data, is telling whether monitoring data patterns resemble typical training data patterns [14]. For the sake of avoiding training for every possible acoustic component type, manufacturer, or operating condition, have opted for an unsupervised clustering-based machine learning strategy rather of a supervised algorithm. Take a look at some of the most well-known machine learning methods:

4.1. Supervised Learning Algorithms for HVAC Predictive Maintenance

Learning under supervision is a basic method in machine learning, in which an algorithm is trained using labeled, or annotated datasets, that is, by using data comprising of input features and the labels associated with their output, where the aim is to learn the function between the input and output to make precise forecasts on novel, unobserved data. In this procedure, the algorithm is given past data that contains input attributes and their appropriate output categories so that the model can acquire patterns and correlations in the data.

4.1.1. Support Vector Machine

The best categorization method is SVMs. Using a separating hyperplane, SVMs are able to discriminate between classes. Originally, the SVM model could only do binary classification, but later on, enhancements were made to allow it to tackle situations with more than one class. Some further class-separation constraints and parameters are added to them.

4.1.2. Decision Trees

A different kind of supervised learning technique that uses labels for every single data point is the decision tree method. By arranging the classes according to the values of the parameters, decision trees do categorization. The decision tree category includes algorithms such as ID3, C4.5, CHAID, and CART. The ability to deal with numerical and category characteristics is a big plus for this method. For small datasets, this approach works well, but when used to big datasets, it introduces latency [15]. Despite the fact that computing takes less time, developing the decision tree was a time-consuming process.

4.2. Unsupervised Learning Algorithms for HVAC Predictive Maintenance

Unsupervised learning is a kind of ML where the algorithms are trained on an unlabeled dataset, i.e., the desired values or labels are not known and are the aim to discover patterns or structures in the data without being instructed on what these values should be.

4.2.1. K-Means Clustering

Clustering is an unsupervised learning technique that does not rely on labels in the dataset being tested. Two kinds of clustering methods, agglomerative and divisive, form the basis of hierarchical clustering. In a bottom-up approach, Agglomerative Clustering pairs together to form large clusters. Divisive clustering works by breaking large clusters into smaller ones using a top-down approach. Divide and conquer Clustering is a method that uses cluster means to define each set of datasets once they have been divided into equal or unequal parts. Using the cluster mean as a metric, K-means clustering divides the dataset into K smaller groups.

4.2.2. Principal Component Analysis (PCA)

PCA allows for the transformation of high-dimensional data into low-dimensional data, which is necessary for dimensionality reduction. Algorithms for learning with m inputs, m outputs, and n hidden layers are said to have m>n. Unfortunately, principal component analysis (PCA) can only handle linear transformations between two spaces, not beyond m and n.

5. Literature Review

In this section, the latest research sheds light on the growing use of machine learning in HVAC systems, whether it can be used to improve fault detection and equipment health predictions or to optimize energy and implement multi-zone control plans. Even with significant improvements, issues of irregular sensor outputs, the inability to use models across various buildings, and the necessity of dependable real-time performance are still the areas of research and development.

Qi et al. (2019) The utilization of CHP, a distributed generation system controlled by the community, is common in microgrid development. This study applies demand-side load management and regulates the ratio of electricity generation to heat output to lower the total operational cost of the microgrid. A smart building's energy cost is determined by a model that takes into account factors like real-time electricity pricing, the capacity and constraints within CHP operation, the operating condition of HVAC, and the indoor air temperature of the smart building. Efficient operation of HVAC load control and CHP systems is determined through optimization under DR. Using a case study, evaluate how well the proposed approach works. [16].

Cosman et al. (2019) This study delves into the construction of a real-time HVAC simulator for electric vehicles, utilizing a scaled converter and a scaled compressor motor (SR-Drive). If wants to know what the ideal motor size and converter specs are, this is a great tool to use. Test benches that replicate HVAC systems with various motors and converters utilizing the same components but with variable scaling gains may be performed more cheaply with this flexible scaling technique. Although other scaling methods exist, the Buckingham Pi approach is utilized in this work. Hysteresis control is used to regulate a switching reluctance motor (SRM), and the motor and converter models are generated in MATLAB / Simulink. Using the Dspace RTI unit, several simulation scenarios are implemented [17].

De Oliveira et al. (2019) This study explores the use of Demand Response (DR) to refrigeration systems in hotels, providing options that take thermal comfort into account and range from mild to aggressive. The simulations that are specific to Brazil are built on top of the DRQAT software. Findings from the study include a correlation between thermal comfort levels, the value of DR per application time, and an estimate of profits from DR based on a comparison with the short-term market power price. In this way, determine if the hotel sector is an appropriate match for DR [18].

Chiba et al. (2018) The focus of this research is on HVAC systems and how green buildings affect them. Specifically, the goal was to forecast the effectiveness of the air conditioning installation by using thermal balancing based on the Algerian standard. An in-depth description of the governing equations of thermal balance is provided to demonstrate the effects of environmentally friendly structures. Findings include contrasting the outcomes achieved with and without plant use in terms of thermal balance and thermal coefficient of construction [19].

Daher et al. (2018) This study addresses this gap and enhances HVAC's ability to participate. Consequently, the HVAC system is being redesigned to better represent the variance in chiller power. The temperature of the chilled water is connected to the temperature of the air being expelled by the new model. The simulation results demonstrate the method's improvement [20].

Rajith, Soki and Hiroshi (2018) This study introduces an easy-to-understand HVAC management system that automates HVAC operations in real-time using optimization and demand response. It achieves an excellent cost-comfort trade-off. The system's foundation is IoT technology, which calculates temperature parameters by real-time processing of user input and sensor data on their distributed cloud. The HVAC control issue is optimized using a MILP algorithm, and a predictive model based on time-series forecasting utilizing an ANN is introduced [21].

Gu et al., 2017, This article demonstrates the interconnected nature of production, quality, and maintenance. By identifying and preventing potential issues before they escalate, predictive maintenance helps production systems run more smoothly and reliably, which in turn improves product quality. Based on the "prediction and manufacturing" principle of intelligent manufacturing, this article suggests a different method of predictive maintenance that takes product quality control into account while making decisions [22].

Elnour and Meskin (2017) The article delves into the topic of designing a two-zone HVAC management system with feedback linearization, taking into account the interaction between the zones. Using the rules of physics and thermodynamics, the interaction between the zones is modelled. The simulation results are used to examine the influence of the interaction on tracking error and control effort [23].

Table I provides a synthesized summary of recent literature on the topic of CHP systems, HVAC optimization, demand response, and smart-building energy management and describes the methodology of each work, its key findings, the challenges outlined, and the future research directions.

Table 1. Summary of Recent Studies on Hvac, Demand Response, Chp, and Energy Optimization

Reference	Study On	Approach	Key Findings	Challenges / Limitations	Future Directions
Qi et al. (2019)	CHP-based smart buildings, microgrids	Optimization of CHP–HVAC operation using demand response, real-time pricing, HVAC thermal constraints	Coordinated CHP–HVAC control reduces microgrid operational cost	Real-time pricing volatility; CHP operational constraints	Advanced DR integration; improved CHP ratio optimization; coupling with renewable energy
Cosman et al. (2019)	EV HVAC system simulation	Real-time HVAC simulator using scaled motors and SR-Drive converter based on Buckingham Pi scaling	Scaled HVAC testbench supports optimal motor–converter sizing	Complexity in selecting scaling gains; hardware limits	Advanced real-time HVAC simulation tools; adaptive scaling methods
de Oliveira et al. (2019)	Hotel refrigeration under DR	DRQAT-based simulation adapted to Brazilian energy scenario	DR strategies provide cost savings while maintaining thermal comfort	Comfort–cost conflict in aggressive DR levels	Better comfort-aware DR methods; improved forecasting for hotel sector
Chiba et al. (2018)	Green buildings and HVAC performance	Thermal balance modeling using Algerian norms	Green building materials reduce cooling load and improve HVAC efficiency	Lack of comprehensive thermal datasets	Plant-based cooling integration; stronger building energy standards
Daher et al. (2018)	HVAC chiller modeling	New model linking chilled water temperature to leaving-air temperature	More accurate chiller power estimation improves HVAC	Sensitivity under highly dynamic loads	Adaptive chiller modeling; DR integration for large buildings

			control		
Rajith, Soki & Hiroshi (2018)	IoT-based HVAC optimization	IoT thermal sensor data + ANN/MLP forecasting + MILP optimization	Real-time automated HVAC optimizes energy cost and comfort	Sensor noise; data latency; MILP computational load	Stronger IoT integration; hybrid deep learning forecasting models
Gu et al. (2017)	HVAC-related predictive maintenance in manufacturing	Predictive maintenance model integrating product quality with failure prediction	Boosts reliability and product quality consistency	Requires high-quality operational data	Scalable predictive-maintenance frameworks using Industry 4.0
Elnour & Meskin (2017)	Multi-zone HVAC control	Two-zone feedback linearization model accounting for zone interaction	Improves temperature tracking accuracy by capturing zone coupling	High computational complexity; dependence on accurate models	Advanced multi-zone control; hybrid nonlinear control strategies

6. Conclusion and Future Work

HVAC systems have their roots in the comfort and health of long-gone cultures. Central heating systems were common in Roman residences, while public baths and wind towers provided cooling. This paper highlights the relevance of predictive maintenance and occupancy-aware control in enhancing the efficiency, reliability, as well as sustainability of HVAC systems. The transition to data-driven predictive approaches instead of reactive and preventive prevents fault detection in time, decrease downtime, increase equipment lifespan, and decrease maintenance and energy expenses. These benefits are automated and continuous commissioning to keep the systems in operation during the entire building life even when the operational conditions change. The occupancy recognition and occupancy-based HVAC control can also save a lot of energy and keep people comfortable by using strategies like optimal start-stop schedule, ramp-down operations, and adaptive static pressure control. The use of machine learning algorithms, both supervised and unsupervised, enhances fault detection, diagnosis and optimization of a system under complex and nonlinear HVAC conditions.

The next generation of work can be aimed at combining the sophisticated methods of deep learning and reinforcement learning with real-time IoT data to enhance the precision of the fault prediction and the adaptive control of HVAC even more. Further expansions of the occupancy modeling capabilities with multimodal sensing and privacy-conscious approaches and large-scale testing on real buildings might increase the scalability, resilience, and feasibility in a wide range of building models.

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