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REVIEW ARTICLE

Review of Digital Twin Applications for HVAC Performance Monitoring and Fault Detection

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Abstract--One of the primary aspects of intelligent HVAC management that is changing at a rapid rate is Digital Twin (DT) technology. It achieves this by creating virtual replicas of the physical systems which combine real-time sensor data, physics-based models and AI-based analytics. The current paper includes an overview of the novel application of DT in the HVAC performance monitoring, energy optimization, and fault detection and diagnosis (FDD). The system visibility is significantly increased, the predictive maintenance is facilitated, and the operational reliability is enhanced with the assistance of the DT-enabled real-time monitoring. Different approaches of FDD are discussed, including analytical models, knowledge-based methods, and the use of the data-driven approach to machine learning methods the application of DTs in degradation monitoring, indoor environmental quality monitoring, and even in the prediction of the remaining useful life can be considered an indicator of the ability of DTs to reduce energy consumption, detect anomalies in the system at an early stage, and improve the quality of decisions made. One of the issues that are being considered alongside the potential research directions that would bring enabling scalability, automated, and highly adaptable digital twin solutions to the next generation of HVAC systems.

Keywords— Digital Twin, HVAC system, Fault Detection and diagnosis (FDD), predictive maintenance, Real time performance monitoring, Energy optimization.

I. INTRODUCTION

Digital Twin Technology is an innovative concept of the contemporary control system of the building, which provide a real-time virtual representation of the physical assets that represent their behavior, performance, and interactions [1][2]. The HVAC systems of digital twins, specifically, are a combination of sensor data, simulation models, and machine learning algorithms that uses the data to create an ever-changing portrait of how the system functions. Through this, it is possible to have engineers and facility managers view the state of the system, perform scenario testing and make predictions of the outcomes of the system operation with a certain degree of accuracy [3][4]. Basic layer is the introduction of digital twin technology that allows highly advanced analytics and intelligent decision-making because buildings are increasingly becoming more connected and intelligent.

The primary role of heating, ventilation, and air conditioning (HVAC) systems is to ensure the comfort and safety of people in many different types of buildings [5][6]. Standard heating, ventilation, and air conditioning (HVAC) systems aim to do three things: regulate indoor temperatures (by means of cooling and heating), keep relative humidity levels constant, and With a digital twin, RTPM becomes much more effective. By the minute data transfer from HVAC components to the digital model, real-time monitoring gives almost immediate insight into the system's behavior and the performance trends[7]. Consequently, it is possible to find out very quickly when the system deviates from the optimal operation due to environmental changes, equipment wear, or wrong control settings[8][9]. Digital twins and real-time monitoring experience enhance the visibility of the system, so, a self-perpetuating loop can be created that enables the implementation of corrective measures in a fast fashion. Thus, real-time performance monitoring is made the operational core per se, since it is the centerpiece of a digital twin-based HVAC systems.

the predictive fault detection ability. With the help of advanced analytics and machine learning, the digital twin can identify an abnormal behavior, identify a sign of faults, and anticipate, even, it appears, the most implausible failure, well before the system performance is impacted [10][11]. Predictive fault detection transforms the lifecycles of the conventional HVAC maintenance that tend to be reactive or scheduled into condition-based strategies [12][13]. It is a type of real-time based telecommunication between the predictive analytics and real-time monitoring that enables not only the digital twin to display the present states of the system, but also makes it possible to predict the future dangers. the predictive aspect of digital twins considerably contributes to system safety and makes fewer maintenance expenses.

HVAC Efficiency & Optimization a system management based on digital twin. The digital twin in essence is an energy conservation and performance enhancement tool, as it achieves this by pointing out inefficiencies, predicting faults, and suggesting the best operating conditions. Reduced faults lead to better energy use, longer equipment life, and improved indoor environmental quality[14][15]. Furthermore, the digital twin's optimisation suggestions can be utilised to manage tactics, resulting in an iterative process of improvement [16]. Therefore, a holistic strategy for achieving high-efficiency HVAC operation is to employ digital twin technology in conjunction with real-time monitoring and predictive mistake detection.

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A. *Structure of the paper*

The following is the outline of the paper: Section II HVAC system digital twin architecture. Section III Digital Twins for Fault Detection and Diagnosis Section IV Using a digital twin in HVAC systems Section V Review of the Literature, Section VI Findings and future directions.

II. Digital Twin Architecture for HVAC Systems

Digital twin architecture is a complicated idea that combines different types of technology to make a digital twin system and keep it running smoothly. Common components of a Digital Twin (DT) include a Physical System (PS), a Virtual System (VS), Service Systems (SS), and DT Data (DTD). Everything down to the hardware, materials, and procedures is called the Physical System. By including models that stand in for the real system in a digital setting, the Virtual System makes it easier to combine the real and virtual worlds. As seen in figure 1. The transmission of information between physical and virtual systems is facilitated by communication architecture in service systems [17]. Lastly, the datasets and information shared inside the DT framework are referred to as DT Data.

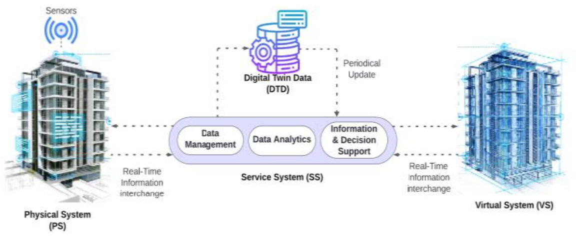

Figure 1: Architecture of Digital twin

The capability improves decision-making among three primary approaches; diagnosis, the evaluation of past decisions; monitoring, which is the oversight and control of current processes; and prognosis, which is the forecasting of future behaviors and outcomes.

A. *Digital Twin layer*

this architecture is composed of three fundamental components: the physical space, the virtual space and the connectivity model (as indicated in Figure 2). The main secret of digital twin development is the creation of the two-way data channel between real object and the virtual analog of it. IoT sensors are used to gather real-time data of physical building projects [18]. Not only are these data used to generate correct numerical models but they are also manipulated to model how physical objects behave in specific circumstances. The continuous process of gathering and analyzing the information contributes to the development of these models so that the digital twin can always successfully emulate its physical equivalent. Digital twins architecture with simulation models, or data models, are used to make scientifically accurate copies of actual physical systems of the real world. It demand the use of technologies including AI, ML, DM, etc., to process these data. Finally, the user interacts with these data by means of visualization.

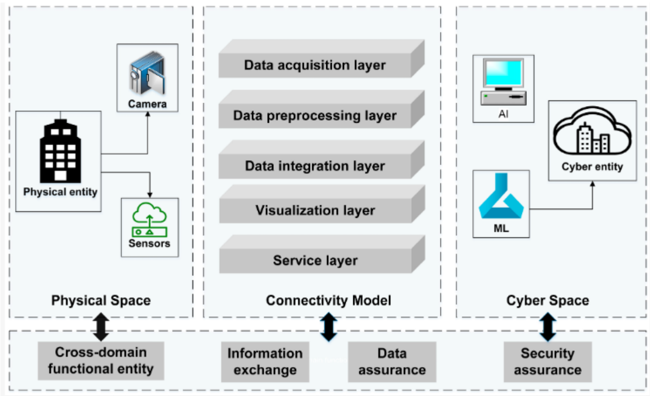

Figure 2: layers of digital twin

These methods have been theorized as a digital twin system architecture having five development layers, including data collection layer, data transfer layer, data integration layer, data visualization layer and services. The data collection techniques and existing datasets are considered in the data collection layer. Instead, network technologies, communication protocols, and data transfer mechanisms are covered by the transmission layer. The digital modeling layer is concerned with the techniques of quantifying the properties of physical entities, and techniques of building virtual models. The data integration layer combines a diverse range of technologies that facilitate data storage, data and model integration, processing and analysis, visualization and use of artificial intelligence, machine learning and simulation engines.

B. *Smart HVAC control system*

The combination of the IoT, AI, and real-time data analytics has changed the way HVAC is managed, making the system more responsive, efficient, and adaptable. Conventional HVAC systems were based on pre-programmed and set timetables, thus, tended to consume unnecessary energy and unreliable indoor comfort. Blinking in the dark Where IoT-based sensor networks monitor major environmental conditions in real-time including temperature, humidity, CO2 levels, airflow and occupancy, and can be seamlessly integrated into intelligent building systems. A significant area of IoT use in HVAC is demand-controlled ventilation (DCV), which constitutes a dynamically changing airflow measurement in real-time occupancy and air quality to reduce the number of unnecessary energy consumed by the equipment. AI goes a step further and allows predictive analytics and machine learning models to predict any changes in the indoor climate and adjust settings. Convolutional neural networks (CNNs), Bi-LSTM model and Model Predictive Control (MPC) can be used to forecast the change in temperature, and reduce energy usage by up to 17 percent using intelligent preemptive adjustments. HVAC energy saving by reinforcement learning methods (Soft Actor-Critic (SAC), Proximal Policy Optimization (PPO) are also demonstrated to reduce up to 18% of energy expenditure. Also, predictive maintenance which is an AI-based implementation has been a game-changer, where past and real-time diagnostic is used to identify potential malfunctions in the system even before they take place and therefore, minimizing downtime and repair expenses.

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C. Digital Twin Technology in HVAC Systems

Digital twins are changing the way HVAC is managed through the development of a direct connection between the physical systems and the control that is well-informed and data-driven. The digital twins, unlike the traditional Building Management System (BMS), offer a dynamic and real-time virtual representation of an HVAC system based on their reliance on a manual monitoring system and set rules [19]. These models constantly combine real-time data about temperature, humidity, flow of air, and occupancy, and predictive maintenance, optimization of performance, and testing of scenarios are possible, but the real world is not disrupted. Using the methods of the latest modeling technologies, one can be able to test various strategies using Building Information Modeling (BIM) and AI-driven models and implement them with certainty that the facility energy-efficient and generate minimum wastage. In contrast to static BMS, digital twins change dynamically, responding to variations in the weather, occupancy levels, and energy prices to achieve optimal system operation. To maintain a correct real-time synchronization of the physical HVAC systems and the virtual one, it is necessary to have good sensor networks, powerful computing power, and precise model calibration.

III. FAULT DETECTION AND DIAGNOSIS IN DIGITAL TWINS

A. Fault detection and diagnosis

Early fault diagnosis and fault detection (EFDD) is an urgent type of predictive maintenance which obtains more and more attention in management of facilities. DFDD is the process of identifying anomalies to the behavior of building systems and components using the data analysis tools and algorithms, before they lead to major failures [20]. Through the detection of errors at the initial stage, facility managers are able to deal with them before it escalates into expensive repair or replacement as indicated in figure 3. The analytical-based techniques are based on mathematical models and physical laws that make use of faults and abnormalities in building systems. Knowledge-based approaches on the other hand apply expert knowledge and rules in order to identify errors and make decisions.

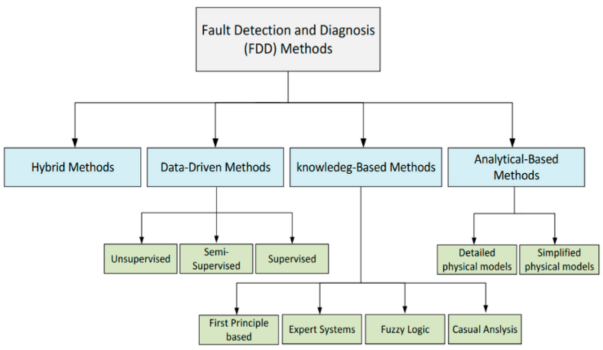

Figure 3: Classification of FDD methods

1) Analytical-Based methods

Analytical approaches to FDD begin with fundamental concepts and a physical knowledge of the system; this knowledge is then used to construct a mathematical model that compares measured data with residuals in order to identify errors. These techniques, which can be classified into simplified and complex physical models, are helpful for reducing errors in smart building routine operations and maintenance.

- Detailed Physical Models: Detailed physical models, including feedforward and autoregressive exogenous (ARX) models, can mimic both healthy and broken states of the system; they just necessitate an exhaustive knowledge of the physical interactions among all constituent parts.
- Simplified Physical Models: Physical models that are simplified A variety of HVAC systems can be enhanced in terms of system reliability, energy consumption, and maintenance costs by utilising lumped parameter approaches and simplified assumptions to convert coupled space partial differential equations into ordinary differential equations.

2) Knowledge-Based Method

Knowledge-based methods are often used when it's too expensive or hard to describe a system physically or mathematically, or when there isn't enough data to go around. Additionally, they work well when modelling requires specific knowledge or when the system has few inputs, outputs, and states. There are various types of knowledge-based approaches. Some of these include expert systems, causal analysis, fuzzy logic, and first-principle method.

- Causal Analysis: Fault tree diagrams (FTDs), structural graphs, and signed directed graphs (SDGs) are some of the tools used for causal analysis in FDD.
- Fuzzy Logic: Fuzzy logic, a kind of Boolean logic, can be used to identify instances of unusual power usage by designing fan coil units. A clustering technique, error-free comparisons of neighbourhood and average values, and statistical analysis of defect identification are all part of the suggested approach.
- First-Principle-Based Method: Rule-based approaches based on first-principle knowledge of physical processes in systems, such mass and energy, are known as first-principle models. Mathematical models of the HVAC system's physical parts and their interactions with one another are created using these techniques. These parts include heat exchangers, fans, and pumps.

3) Data-Driven Methods

Data-driven methods are those that rely on data rather than explicit mathematical or physical models of the system to construct models or generate predictions [21]. On the contrary, these approaches rely on statistical or machine learning methods to discover data patterns and linkages, which then inform predictions. Three distinct types of data-driven approaches exist: supervised, semi-supervised, and unsupervised learning.

- Supervised Methods: The goal of supervised machine learning is to train a model to recognise patterns in data by adjusting weights in training datasets that have labelled inputs and outputs. Both classification and regression fall under the umbrella of supervised learning. A few examples of classification algorithms are supervised NNs, KNN, DT, and SVM. Polynomial, logistical, and linear regression are all types of regression methods.

- Semi-Supervised Methods: Semi-supervised procedures find application when training set is scarce and erroneous training data are not abundant to FDD in HVAC buildings. These approaches include learning a model to identify and diagnose faults with a limited quantity of labelled data, consisting of both normal and faulty system behavior and a significant quantity of unlabeled data. The common methods of exploiting labeled and unlabeled data in an effective way include the clustering technique, active learning, and the generative models.
- Unsupervised Methods: Unsupervised machine learning is a kind of machine learning which is able to analyze and categorize unlabeled datasets [22]. This comes in handy especially in real world complex systems like HVAC systems where there may be a difficulty or cost in getting correctly labeled data to train on. Typical non-supervised algorithms are clustering, autoencoders, GANs, principal component analysis (PCA) and association rule mining (ARM).

4) Hybrid method

Hybrid approaches within the FDD is the combination of analytical, knowledge-based, and data-driven approaches to provide more accurate and reliable FDD outcomes. The hybrid approaches have the ability to capitalize and give support to the strengths of each technique to overcome the weaknesses and achieve a better performance of FDD. a problem-solving method that uses open-loop rules for lambda tuning to automate control hunting. A commercial FDD program made use of the algorithm. Suboptimal performance and premature HVAC equipment failure can be caused by control hunting, a prevalent issue in commercial buildings.

B. FDD workflow of digital twin framework

FDD process flow, which comprises gathering relevant data from target building systems, analysing that data, creating models, and finally, deploying those models. Figure 4 shows that the majority of FDD studies have been on data modelling and how to use it for fault classification with supervised or unsupervised FDD methods.

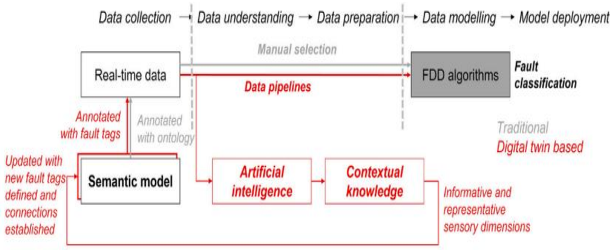

Figure 4: FDD workflow based on the digital twin analytical framework

A major roadblock to automating FDD is the data comprehension, preparation, and analysis that frequently necessitate human involvement. If wants to automate FDD and cut down on human interaction, and need to make sure that computers can understand ad hoc knowledge that has been learnt from real-time data using statistical and symbolic AI techniques, on top of the existing ontological knowledge [23]. The FDD process makes use of contextual and temporal knowledge in relation to the sensor dimensions that are devoted to the identification of individual defects. This research adds fault tags to the Brick ontology, which help identify the chosen sensors with machine-readable fault tags, so keep the new information for future reference. The data pipelines get the real-time data that targets particular faults ready to be used by the FDD by annotating it with Brick model fault tags.

IV. APPLICATION OF DIGITAL TWINS IN HVAC PERFORMANCE MONITORING

DT technology is a leading-edge tool that is used to improve the performance of HVAC systems. A Digital Twin basically models HVAC parts, the system, or even the whole building atmosphere in a computer, thus it becomes possible to have uninterrupted checking, review, and tuning performance assessment but also predictive analytics.

A. Real time performance monitoring

Digital Twins allow for performance monitoring in real-time as they keep updating the data from the physical HVAC systems to the virtual ones. Various sensors and IoT devices installed in the system gather essential operational parameters like temperature, humidity, airflow rates, pressure differentials, equipment status, and energy consumption and then send them to the DT platform. The digital replica takes in this information and also has a look at the best operating conditions or the results of the predictive models.

B. Energy consumption analysis and optimization

Digital Twins are essential in the assessment and subsequent enhancement of the energy consumption of HVAC systems. Through nonstop data collection of equipment power use, cooling/heating loads, occupancy, and environmental conditions, the DT is capable of pinpointing the areas where energy inefficiencies are emerging, it could be situations like wrong setpoints, excessive cycling, or poor heat transfer performance[24]. With Digital Twins, operators have the freedom to experiment with and fine-tune various control strategies such as temperature setpoints adjustment, ventilation rates modification, or operation schedules changing in a virtual environment prior to the real system implementation.

C. Predictive maintenance and degradation Tracking

Digital Twins make it possible for the HVAC system to stay in shape with predictive maintenance through the ongoing visual check of the system parts and the identifying of the first signs of wear and tear. The DT, by analyzing vibration, temperature, pressure, and airflow patterns sensor data, can isolate a number of different abnormalities like coil fouling, filter clogging, refrigerant leaks, or declining equipment efficiency.

a) Condition-Based Monitoring Using Digital Twins

Continuous monitoring of the equipment is very crucial to the condition of the equipment are the mentioned aspects of the vibrations, pressure, temperature, and airflow, whereafter it becomes possible to firsthand detect abnormal behavior and performance degradation.

b) Remaining Useful Life (RUL) Prediction and Maintenance Scheduling
Digital Twins employ both data-driven and physics-based models to locate the time till which the HVAC parts usable, thus giving maintenance staff the time for action to be most efficient in both cost and effectiveness.

D. Indoor Environmental Quality (IEQ) Assessment

HVAC systems are major factors that determine indoor comfort, productivity, and the general health of the occupants. Digital Twins enable a thorough measurement of IEQ through the simulation and evaluation of various parameters that include temperature distribution, humidity levels, air quality indices (e.g., CO_2, VOCs, particulate matter), and ventilation effectiveness in different zones of a building

a. Digital Twins are always matching real-time IEQ measurements with well-established standards, thus they are very helpful in maintaining the best possible thermal comfort and indoor air quality for the users of the building.
b. By means of airflow simulations and virtual testing, DTs locate the places where the ventilation is insufficient, the air is stagnant, or the distribution is not even, thus they make it possible to be very precise in the targeted improvements.
c. Digital twin may find temperature imbalances, hot/cold spots, or humidity deviations, which is enabling the facility managers to make adjustments to the system for a better level of occupant comfort.

E. **Fault Detection and Diagnosis support**

Digital Twins improve the effectiveness of fault detection and diagnosis (FDD) in HVAC systems by constantly checking performance data for the real system against the expected behavior of the model departure from the norm is detected an unusual temperature, a reduced airflow, a pressure imbalance, or even an irregular energy use the DT not only locates the fault but also identifies its cause. By integrating physics-based models with data-driven algorithms, the DT is able such as a fault in the sensor, the leakage of the refrigerant, coil fouling, or a malfunction of the equipment.

V. LITERATURE OF REVIEW

The research works that have been done to implement digital twin technology in the HVAC sector and the other intelligent system. Table I provides an organized comparison of the works usage of digital twins for fault detection, predictive maintenance, energy optimization, and system-level monitoring challenges and limitation.

Rastogi, Agrawal and Singh, 2025, Digital Twin technology, a virtual representation of an EV that integrates real-world data with simulations, allowing for continuous analysis, proactive maintenance, and better decision-making which has emerged as a game changer in automotive industry. In this research, the authors have created a Digital Twin of an electric vehicle and its Battery Management System using Simulink, incorporating real-world fluctuations, potential errors, and system faults development of the proposed Hybrid Temporal-Spatial Attention Network (HTSAN), a deep learning model that integrates CNN. Critical issues like overheating, sensor malfunctions, battery wear, and motor failures were identified by the model efficiently[25].

Nagy *et al.*, 2025, real-time digital twin technology, the simulation reproduces subsystem behavior with high fidelity, offering valuable insights into system-level power dynamics and energy usage. The results demonstrate that digital twin-based modeling is highly effective for evaluating and forecasting electric power consumption, and it holds significant potential for predictive diagnostics. In particular, the ability to replicate electrical subsystems in real time enables proactive monitoring and failure prediction for safety-critical components–areas where traditional diagnostic tools may fall short due to increasing system complexity[27].

Ababsa *et al.*, 2024, digital twin technology for enhanced fault diagnosis in smart buildings, aiming to optimize energy performance. Indeed, the emergence of digital twins represents a significant advance in this field, as they enable the monitoring and regulation of the various systems as HVAC. They can also analyze the data generated by such systems to detect possible faults, and even make predictions to anticipate potential problems. Nevertheless, managing the interoperability of heterogeneous data remains a challenge to achieve an operational and efficient digital twin. Taking the FDD process for building HVAC systems[28].

Tian *et al.*, 2024, fault detection method based on digital twin and OCSVM optimized by clonal selection is proposed. First, the cubic spline interpolation method is used to fill in missing data. tackle the issue of data imbalance, the One-Class Support Vector Machine (OCSVM). Meanwhile, leveraging the Clonal Selection Algorithm(CSA)'s ability to search for the optimal OCSVM hyperparameters, improving detection accuracy. Finally, to address visualization issues, digital twin technology is used to visualize the dust removal system, offering higher monitoring accuracy compared to traditional methods and allowing users to intuitively understand the environmental conditions, facilitating time[30].

Abrazeh *et al.*, 2023, A digital twin for an HVAC system, which stands for multi-input multi-output (MIMO) nonlinear, is created and studied. Integrating hardware-in-loop (HIL) and software-in-loop (SIL) helps to create the concept of digital twin control in a clear manner. Integrating the HIL and SIL controllers with a nonlinear integral backstepping (NIB) model-free control technique allows for HVAC system control without dynamic feature identification. The measured data is used to update the virtual controller's NIB controller coefficients using DRL. Using a multi-objective method (MO), the DRL algorithm designs the NIB controllers in the HIL and SIL for the HVAC system's temperature and humidity [26].

Haigang, Rui and Linfeng, 2023, The building's air conditioning system fault diagnosis process is frequently hindered by on-site work collaboration factors, leading to low fault repair efficiency, and the operation and maintenance of HVAC system equipment is often complicated because some of the equipment installation locations are hidden within the building. In response to the aforementioned issues, it is recommended to leverage digital twin technology to augment the interaction capabilities of Building Information Models (BIM) with Mixed Reality (MR) during the maintenance of HVAC system equipment. The goal of developing the BIM+MR fault diagnosis system was to enhance the digital twin technology-based HVAC system equipment maintenance process by facilitating remote visualisation engagement in an immersive environment [29].

TABLE I. COMPARATIVE ANALYSIS OF LITERATURE REVIEW OF DIGITAL TWIN IN HVAC MONITORING AND FAULT DETECTION

Author(s), Year	Study On	Key Findings	Application	Limitations	Future Work
Rastogi, Agrawal & Singh, 2025	Digital Twin of Electric Vehicle (EV) and Battery Management System using Simulink	Digital twin integrates realworld data with virtual simulations. Hybrid Temporal Spatial Attention Network (HTSAN) using CNN detects faults like overheating, sensor errors, battery wear, motor failures.	Automotive industry; EV battery management; fault detection; predictive maintenance.	Real-world data variability and system complexity may affect model robustness; computational load of HTSAN.	Enhance generalization across different EV models; improve real-time fault detection accuracy integrate more diverse sensor data.
Nagy et al., 2025	Real-time digital twin modeling of electrical subsystems	High-fidelity simulation replicates subsystem behavior Strong potential for predictive diagnostics in safety-critical systems.	Electric power systems; subsystem monitoring; energy forecasting; predictive diagnostics.	High computation required for real-time high-fidelity simulations; integration challenges with legacy systems.	Improve scalability integrate AI-based prediction; apply digital twins to more complex multi-system architectures.
Ababsa et al., 2024	An HVAC Digital Twin for Problem Finding in Intelligent Buildings	The HVAC system may be optimised and monitored in real-time with the use of digital twins. Highly efficient at predicting and detecting faults	Smart building management; HVAC FDD (Fault Detection & Diagnosis); energy optimization.	Data interoperability issues; dependency on high-quality sensor networks.	Develop standardized data frameworks improve cross-platform compatibility for smart building systems.
Tian et al., 2024	Digital twin–based fault detection using OCSVM optimized by Clonal Selection Algorithm (CSA)	Missing data filled using cubic spline interpolation. CSA optimizes OCSVM hyperparameters improving detection. Digital twin enables intuitive visualization of dust removal system	Industrial dust removal systems; predictive fault detection; real-time visualization.	Sensitive to data quality and imbalance; high computational cost of CSA optimization.	Extend method to other industrial systems integrate deep learning for improved anomaly detection.
Abrazeh et al., 2023	Digital Twin of a MIMO nonlinear HVAC system using HIL + SIL and Deep Reinforcement Learning	Developed digital twin combining HIL & SIL for HVAC control Nonlinear Integral Backstepping (NIB) model-free control.	Advanced HVAC control; robotics-inspired model-free controllers; DRL-based adaptive HVAC optimization.	DRL training requires significant time and data; model complexity; potential instability in early learning stages.	Apply to larger building systems integrate renewable energy-based HVAC; enhance controller robustness.
Haigang, Rui & Linfeng, 2023	BIM + Mixed Reality (MR) + Digital Twin for HVAC Maintenance	BIM + MR improves remote visualization and troubleshooting Digital twin enhances fault diagnosis and maintenance efficiency.	HVAC maintenance; MR-based training; immersive repair guidance; remote collaboration.	MR hardware cost; alignment and tracking accuracy; adoption difficulty for technicians.	Improve MR accuracy integrate AI for automated diagnostics; expand system to multi-building facilities.

VI. Conclusion And Future Work

Fault detection and diagnosis are critical to the construction of facilities because they are complex and require a smooth and effective monitoring of maintenance HVAC performance and fault detection. DTs improve the visibility of systems and enable the ongoing system performance assessment and the early identification of system malfunctions by establishing the real-time relationship between the real and virtual HVAC systems. The high diagnostic accuracy and the reduced amount of manual intervention were brought about by the use of analytical, knowledge-based, and data-driven FDD techniques incorporated in DT frameworks. Furthermore, real-time monitoring provided by DT enhances the understanding of the system behavior in various environmental and operating conditions, and predictive maintenance capabilities help minimize the downtime and increase the equipment lifespan provided by the digital twin-based HVAC systems is significantly better compared to the traditional monitoring and maintenance models, thus making the digital twins a groundbreaking technology of an intelligent and highly responsive system to manage the building. Future work will digital twin frameworks, enhancing integration of multi-source data and application of advanced machine learning techniques for automated fault diagnosis and prognostics. Besides, the use of Mixed Reality (MR), edge computing, and adaptive control strategies is also likely to be beneficial in real-time responsiveness and user interaction. The expansion of DT applications to multi-building ecosystems, renewable-integrated HVAC systems, and autonomous smart-building platform. Resolving these issues will speed up the implementation of highly sophisticated and smart DT solutions for HVAC operations.

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