ISSN 2581 – 3781

AJCSE
ASIAN JOURNAL OF COMPUTER SCIENCE ENGINEERING

Available Online at www.ajcse.info
Asian Journal of Computer Science Engineering 2025;10(4):1-10

REVIEW ARTICLE

Review of Digital Twin Applications for Heating, Ventilation, and Air Conditioning Performance Monitoring and Fault Detection

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Received on: 12-11-2025; Revised on: 10-04-2026; Accepted on: 02-05-2026

ABSTRACT

One of the primary aspects of intelligent heating, ventilation, and air conditioning (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 artificial intelligence-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 is being considered alongside the potential research directions that would bring enabling scalability, automated, and highly adaptable DT solutions to the next generation of HVAC systems.

Key words: Digital twin, energy optimization, fault detection and diagnosis, heating, ventilation, and air conditioning system, predictive maintenance, real-time performance monitoring

INTRODUCTION

Digital twin (DT) technology is an innovative concept of the contemporary control system of the building, which provides a real-time virtual representation of the physical assets that represent their behavior, performance, and interactions.[1,2] The heating, ventilation, and air conditioning (HVAC) systems of DTs, specifically, are a combination of sensor data, simulation models, and machine learning algorithms that use 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 DT technology that allows highly advanced analytics and intelligent decision-making because buildings are increasingly becoming more connected and intelligent.

The primary role of HVAC systems is to ensure the comfort and safety of people in many different types of buildings.[5,6] Standard HVAC systems aim to do three things: regulate indoor temperatures (by means of cooling and heating), keep relative humidity levels constant, and with a DT, real-time population monitoring 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 very quickly when the system deviates from the optimal operation due to environmental changes, equipment wear, or wrong control settings.[8,9] DTs 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

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operational core *per se*, since it is the centerpiece of DT-based HVAC systems.

The predictive fault detection ability. With the help of advanced analytics and machine learning, the DT 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 tends 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 DT to display the present states of the system but also makes it possible to predict the future dangers. The predictive aspect of DTs considerably contributes to system safety and makes fewer maintenance expenses.

HVAC efficiency and optimization are a system management based on DT. The DT 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 (IEQ).[14,15] Furthermore, the DT's optimization suggestions can be utilized to manage tactics, resulting in an iterative process of improvement.[16] Therefore, a holistic strategy for achieving high-efficiency HVAC operation is to employ DT technology in conjunction with real-time monitoring and predictive mistake detection.

Structure of the Paper

The following is the outline of the paper: Section II HVAC system DT architecture, Section III DTs for fault detection and diagnosis (FDD), Section IV using a DT in HVAC systems, Section V review of the literature, and Section VI findings and future directions.

DT ARCHITECTURE FOR HVAC SYSTEMS

DT architecture is a complicated idea that combines different types of technology to make a DT system and keep it running smoothly. Common components of a DT include a physical system (PS), a virtual system (VS), service systems (SSs), and DT data (DTD). Everything down to the hardware, materials, and procedures is called the PS. By including models that stand in for the real system in a digital setting, the VS makes it easier to combine the real and virtual worlds, as illustrated in Figure 1. The transmission of information between physical and VSs is facilitated by communication architecture in SSs.[17] Finally, the datasets and information shared inside the DT framework are referred to as DTD.

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.

DT 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 DT development is the creation of a two-way data channel between the real object and the virtual analog of it. Internet of things (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 DT can always successfully emulate its physical equivalent. DTs architecture with simulation models, or data models, is used to make scientifically accurate copies of actual PSs of the real world. It demands the use of technologies including artificial intelligence (AI), machine learning, data mining, etc., to process these data. Finally, the user interacts with these data by means of visualization.

These methods have been theorized as a DT 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

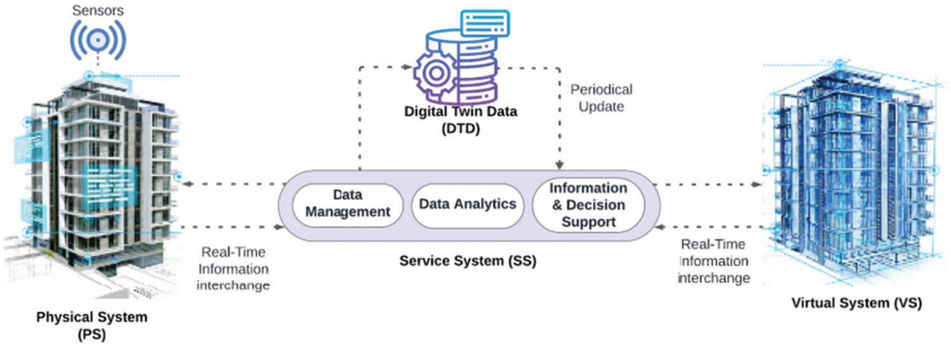

Figure 1: Architecture of digital twin

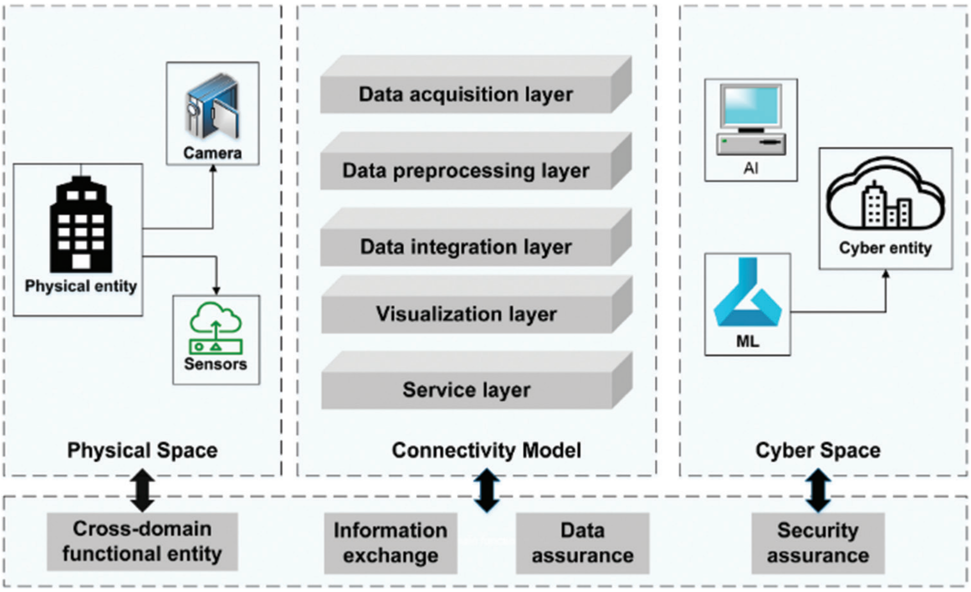

Figure 2: Layers of digital twin

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 AI, machine learning, and simulation engines.

Smart HVAC Control System

The combination of the Internet of Things (IoT), artificial intelligence (AI), and real-time data analytics has transformed the way HVAC systems are managed, making them more responsive, energy-efficient, and adaptable to dynamic operating conditions. Conventional HVAC systems were based on pre-programmed and set timetables, thus, tended to consume unnecessary energy and unreliable indoor comfort. Unlike traditional "blind" control approaches, IoT-based sensor networks monitor key environmental conditions in real time, including temperature, humidity, carbon dioxide (CO_2) levels, airflow, and occupancy, and can be seamlessly integrated into intelligent building management systems. A significant area of IoT use in HVAC is demand-controlled ventilation, 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), bidirectional long short-term memory model, and model predictive control can be used to forecast the change in temperature and reduce energy usage by up to 17% using intelligent preemptive adjustments. HVAC energy savings can be achieved using reinforcement learning–based control methods, such as Soft Actor–Critic (SAC) and Proximal Policy Optimization (PPO), which have been demonstrated to reduce energy expenditure by up to 18%. Furthermore, 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.

DT Technology in HVAC Systems

DTs are transforming HVAC management by establishing a direct, data-driven connection between physical systems (PSs) and intelligent control mechanisms. The DTs, 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 is energy-efficient and generates minimum wastage. In contrast to static BMS, DTs 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.

FDD IN DTS

FDD

Early fault diagnosis and fault detection are an urgent type of predictive maintenance which obtains more and more attention in the management of facilities. Data-driven fault detection and diagnosis (DFDD) is the process of identifying anomalies in 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 to identify errors and make decisions.

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 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 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 utilizing lumped parameter approaches and simplified assumptions to convert coupled space partial differential equations into ordinary differential equations.

Knowledge-based method

Knowledge-based methods are often used when it is too expensive or hard to describe a system physically or mathematically or when there is not enough data to go around. In addition, they work well when modeling 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, structural graphs, and signed directed graphs 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

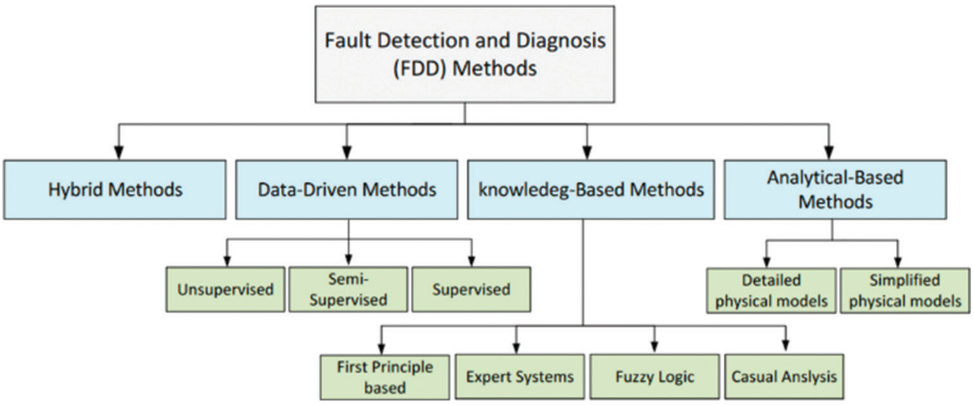

Figure 3: Classification of fault detection and diagnosis methods

unusual power usage by designing fan coil units. A clustering technique, error-free comparisons of neighborhood 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.

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 recognize 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 neural networks, K-nearest neighbors, DT, and support vector machine (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, generative adversarial networks, principal component analysis, and association rule mining.

Hybrid method

Hybrid approaches within the FDD are 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 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.

FDD Workflow of DT Framework

FDD process flow comprises gathering relevant data from target building systems, analyzing 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.

A major roadblock to automating FDD is the data comprehension, preparation, and analysis that frequently necessitate human involvement. To automate FDD and reduce human intervention, it is necessary to ensure that computational systems can interpret *ad hoc* knowledge learned from real-time data using statistical and symbolic artificial intelligence (AI) techniques, in addition to 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 target particular faults ready to be used by the FDD by annotating it with brick model fault tags.

APPLICATION OF DTS IN HVAC PERFORMANCE MONITORING

DT technology is a leading-edge tool that is used to improve the performance of HVAC systems. A DT 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.

Real Time Performance Monitoring

DTs 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 such as 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.

Energy Consumption Analysis and Optimization

DTs 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 such as wrong setpoints, excessive cycling, or poor heat transfer performance.[24] With DTs, operators have the freedom to experiment with and fine-tune various control strategies such as temperature setpoint adjustment, ventilation rate modification, or operation schedule changing in a virtual environment before the real system implementation.

Predictive Maintenance and Degradation Tracking

DTs 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 identification of the first signs of wear and tear. The DT, by analyzing vibration, temperature, pressure, and airflow patterns sensor data, can

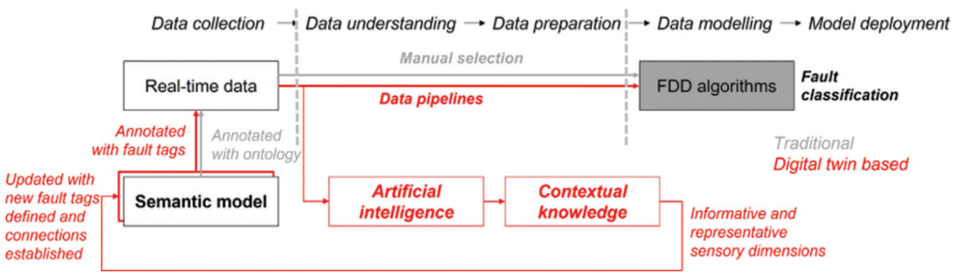

Figure 4: Fault detection and diagnosis workflow based on the digital twin analytical framework

isolate a number of different abnormalities such as coil fouling, filter clogging, refrigerant leaks, or declining equipment efficiency.

- Condition-based monitoring using DTs
  Continuous monitoring of equipment is critical for assessing its operational condition, particularly by tracking parameters such as vibration, pressure, temperature, and airflow, which enables early detection of abnormal behavior and performance degradation.
- Remaining useful life prediction and maintenance scheduling
  DTs employ both data-driven and physics-based models to locate the time till which the HVAC parts are usable, thus giving maintenance staff the time for action to be most efficient in both cost and effectiveness.

IEQ Assessment

HVAC systems are major factors that determine indoor comfort, productivity, and the general health of the occupants. DTs 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, Volatile organic compounds (VOCs), particulate matter), and ventilation effectiveness in different zones of a building.

a. DTs 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. DT 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.

FDD Support

DTs improve the effectiveness of 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.

LITERATURE OF REVIEW

The research works have been done to implement DT technology in the HVAC sector and other intelligent systems. Table 1 provides an organized comparison of the works usage of DTs for fault detection, predictive maintenance, energy optimization, and system-level monitoring challenges and limitation.

In Rastogi *et al*., 2025, DT technology, a virtual representation of an electric vehicle (EV), 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 DT of an EV 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, a deep learning model that integrates CNN. Critical issues such as overheating, sensor malfunctions, battery wear, and motor failures were identified by the model efficiently.[25]

In Nagy *et al*., 2025, real-time DT technology, the simulation reproduces subsystem behavior with high fidelity, offering valuable insights into system-level power dynamics and energy usage. The results demonstrate that DT-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.[26]

Ababsa *et al*., 2024 investigated the application of Digital Twin (DT) technology for enhanced fault diagnosis in smart buildings, with the objective of optimizing energy performance. Indeed, the emergence of DTs represents a significant advance in this field, as they enable the monitoring and

Table 1: Comparative analysis of literature review of DT in hvac monitoring and fault detection

Author (s), year	Study on	Key findings	Application	Limitations	Future work
Rastogi *et al.*, 2025	DT of EV and battery management system using Simulink	DT integrates real-world data with virtual simulations. 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 DT 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 DTs to more complex multi-system architectures.
Ababsa *et al.*, 2024	An HVAC DT for Problem Finding in Intelligent Buildings	The HVAC system may be optimised and monitored in real-time with the use of DTs. Highly efficient at predicting and detecting faults	Smart building management; HVAC FDD; 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	DT–based fault detection using OCSVM optimized by CSA	Missing data filled using cubic spline interpolation. CSA optimizes OCSVM hyperparameters improving detection. DT 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	DT of a MIMO non-linear HVAC system using HIL + SIL and DRL	Developed DT combining HIL and SIL for HVAC control 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 *et al.*, 2023	BIM + MR + DT for HVAC Maintenance	BIM + MR improves remote visualization and troubleshooting DT 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.

EV: Electric vehicle, HTSAN: Hybrid temporal spatial attention network, CNN: Convolutional neural networks, FDD: Fault detection and diagnosis, OCSVM: One-class support vector machine, CSA: Clonal selection algorithm, MIMO: Multi-input multi-output, HIL: Hardware-in-loop, SIL: Software-in-loop, HVAC: Heating, ventilation, and air conditioning, NIB: Nonlinear Integral backstepping, BIM: Building information modeling, MR: Mixed reality, AI: Artificial intelligence, DRL: Deep reinforcement learning, DT: Digital twin

regulation of 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 DT. This study considers the fault detection and diagnosis (FDD) process for building HVAC systems as a representative use case.[27]

In Tian *et al.*, 2024, fault detection method based on DT and one-class SVM (OCSVM) optimized by clonal selection is proposed. First, the cubic spline interpolation method is used to fill in missing data. To tackle the issue of data imbalance, a one-class support vector machine (OCSVM) is employed. In addition, the clonal selection algorithm is used to optimize the OCSVM hyperparameters, thereby improving fault detection accuracy. Finally, to address visualization issues, DT 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.[28]

In Abrazeh *et al.*, 2023, a DT for an HVAC system, which stands for multi-input multi-output nonlinear, is created and studied. Integrating hardware-in-loop (HIL) and software-in-loop (SIL) helps to create the concept of DT 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 are used to update the virtual controller's NIB controller coefficients using deep reinforcement learning (DRL). Using a multi-objective method, the DRL algorithm designs the NIB controllers in the HIL and SIL for the HVAC system's temperature and humidity.[29]

In Haigang *et al.*, 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 DT technology to augment the interaction capabilities of 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 DT technology-based HVAC system equipment maintenance process by facilitating remote visualization engagement in an immersive environment.[30]

CONCLUSION AND FUTURE WORK

FDDs 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 DT-based HVAC systems is significantly better compared to the traditional monitoring and maintenance models, thus making the DTs a groundbreaking technology of an intelligent and highly responsive system to manage the building. Future work will DT frameworks, enhancing integration of multi-source data and application of advanced machine learning techniques for automated fault diagnosis and prognostics. Besides, the use of MR, edge computing, and adaptive control strategies is also likely to be beneficial in real-time responsiveness and user interaction.Future research should focus on expanding DT applications to multi-building ecosystems, renewable energy–integrated HVAC systems, and autonomous smart-building platforms. Resolving these issues will speed up the implementation of highly sophisticated and smart DT solutions for HVAC operations.

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