ADVANCING HVAC FAULT DETECTION USING INTEGRATED DYNAMIC SYSTEM MODELING, FAULT SIMULATION, AND DEEP LEARNING FRAMEWORK

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Wunna Tun, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Design, Architecture and Building at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Contents

Abstract

HVAC systems are essential to modern building infrastructure, but their performance can be compromised by faults, such as stuck valves, leaks, fouled coils, and malfunctioning sensors, leading to lower energy efficiency and poor indoor air quality. These operational challenges highlight the need for effective simulation methods that can replicate dynamic HVAC conditions and detect various faults. Simulation-based approaches offer a cost-efficient solution to the expensive and resource-intensive process of collecting real-world data, enabling the generation of reliable datasets that are important for testing and improving fault detection systems.

While earlier research has relied on controller-based methods using predefined rules and real-time sensor data, these approaches often prove insufficient in handling dynamic operational environments due to their limited adaptability and reduced reliability in the presence of sensor inaccuracies. Consequently, there is a growing need for more sophisticated tools and strategies incorporating robust system modeling, fault simulation, machine learning, and deep learning techniques that provide a comprehensive understanding of component interactions, thus improving fault diagnosis, optimizing energy consumption, and improving occupant comfort.

Various simulation tools, including TRNSYS, EnergyPlus, and HVACSIM+, have been utilized to analyze HVAC system performance. While TRNSYS is specialized in modeling thermal balance and airflow, and EnergyPlus offers precise physics-based models for energy prediction, both tools face limitations due to their complexity and restricted fault simulation capabilities, which can hinder real-time fault detection. In contrast, HVACSIM+ overcomes these limitations by offering dynamic system modeling, a user-friendly interface, and extensive fault simulation capabilities, including sensor and actuator faults, enabling the creation of cost-effective datasets, while avoiding the substantial financial, operational, and logistical demands associated with real-world data collection from physical HVAC systems.

Based on these simulations, a variety of fault detection techniques have been proposed, ranging from physical modeling to data-driven approaches. These methods include feedforward neural networks, adaptive fuzzy neural networks, and swarm-based artificial neural networks, which are further optimized using ensemble rapid centroid evaluation (ERCE) methods. Although these approaches have shown promising results under controlled conditions, they are often evaluated using only a single publicly available dataset, such as the ASHRAE benchmark. In practice, although the ASHRAE dataset is a widely recognized and respected benchmark in the field, reliance on a single data source may limit the ability to evaluate model robustness under varying conditions. To effectively assess generalization performance, broader validation across multiple datasets is essential.

To address these limitations, this study models a single-story, four-room building using HVACSIM+ to capture 194 sensor signals over a 24-hour period, which includes three days of normal operation and nine days of faulty operation. In this simulation, the occupancy effects were accounted by incorporating maximum room occupancy levels to represent upper-bound internal thermal loads, thereby enabling the evaluation of HVAC system performance under peak stress conditions. This approach enabled the analysis of indoor temperature and humidity responses under high-load operating conditions. Due to the unavailability of real-time occupancy data during the study period, the simulation did not incorporate dynamically varying occupancy profiles. Nevertheless, actual weather conditions were integrated into the simulation environment to capture realistic environmental dynamics and enhance the fidelity of system response modeling. While fixed occupancy values were used to approximate peak loading conditions, and this approach was considered valid and sufficient for the objectives of this simulation, the inclusion of real-time occupancy data is expected to further improve model precision and support the development of more responsive control strategies.

Given the simulation configuration, sensor data were recorded at one-minute intervals, yielding 1,440 samples per sensor per day. This high temporal resolution allowed for detailed monitoring of system behaviour under both normal and faulty operating conditions. The raw data were subsequently preprocessed to ensure consistency and suitability for analysis. Preprocessing involved noise filtering, normalization, and the handling of missing values, as well as timestamp alignment across sensor channels. Additionally, the data were segmented into labelled windows to facilitate model training and evaluation. These steps ensured that the final dataset was clean, temporally aligned, and representative of the full range of system behaviours. This preprocessing was critical to maintaining the quality and reliability of the input data used in the machine learning and deep learning models examined in this study.

Following preprocessing, the processed simulation datasets were systematically validated against the ASHRAE RP-1312 benchmark to ensure alignment with actual

HVAC operating conditions. The validation process, conducted across key performance indicators such as supply air temperature, airflow rate, fan speed, and power consumption, yielded low mean absolute errors and strong correlation coefficients. To ensure comparability, the datasets were preprocessed through sensor variable alignment, uniform temporal resolution, feature normalization, and consistent fault scenario mapping. Additionally, statistical analysis across nine representative fault types confirmed the robustness and applicability of the simulated data. These results establish a reliable foundation for developing and evaluating advanced fault detection and diagnosis models, while also addressing the practical constraints of collecting real-world operational fault data.

Therefore, the main objective of this research was to design and evaluate fault detection models based on simulation-generated data from HVACSIM+, with comparative analysis against benchmark data to assess model accuracy and reliability. This simulation-based approach enabled the generation of high-quality datasets that capture a diverse range of system behaviors and fault scenarios, while mitigating the financial, logistical, and temporal limitations associated with collecting real-world fault data. Furthermore, the study highlights the effectiveness of the simulated dataset in addressing these challenges, providing a viable alternative to direct real-world comparisons within the constraints of this research.

With these datasets, three novel hybrid fault detection approaches were developed, combining random forest (RF) with support vector machines (SVM), as well as convolutional neural networks (CNNs) applied to raw sensor data. Additionally, the Gramian Angular Field (GAF) method and two-dimensional CNNs (2D-CNNs) were used to convert time series sensor values into image representations, allowing the model to capture complex temporal and spatial relationships more effectively.

These techniques enhance the ability of the developed model to detect faults with high accuracy by leveraging both traditional machine learning algorithms and deep learning architectures. The generalization capability of these developed methods was further validated using a publicly available ASHRAE benchmark dataset. This cross-dataset evaluation demonstrates the robustness of the proposed models under different operational conditions and data sources.

Furthermore, to ensure a fair and meaningful comparison, the developed fault detection models were bench-marked against conventional baseline methods, specifically SVM and RF, using the same simulation dataset. This allowed for consistent evaluation under identical conditions. While the baseline models worked as reference points to establish initial performance bounds, they were not applied to the ASHRAE dataset due to their limited ability to capture complex temporal dynamics and generalize beyond the training distribution, as confirmed by their lower accuracy in the simulation-based experiments. This decision was made to maintain focus on the more advanced and scalable approaches developed in this study, which demonstrated superior performance and better potential for real-world deployment.

While the proposed framework demonstrates strong performance, achieving an accuracy of 97%, future research will aim to further enhance its effectiveness through techniques such as data augmentation, broader environmental scenario coverage, and the application of transfer learning to improve adaptability across varying system conditions. In summary, this study presents a significant advancement in HVAC fault detection by generating and validating simulation-based datasets and applying advanced machine learning and deep learning methods. The developed framework offers a practical, scalable, and cost-effective approach for improving HVAC system reliability. It not only contributes to the academic body of knowledge but also provides actionable insights for real-world implementation, supporting enhanced system performance, energy efficiency, and occupant comfort in modern building environments.

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Notation

$X = \{x_1, x_2, ..., x_n\}$	Dataset with input features.
$Y = \{y_1, y_2, ..., y_n\}$	Corresponding target labels.
y	Target label for classification.
$\tilde{x}_i$	Normalized data point.
$C_r(t)$	Feature map output for the r-th filter at step t.
$\omega_r(i, j)$	Weight of the r-th convolution filter at position i, j.
$b(r)$	Bias for the r-th convolution filter.
$P_r(t)$	Output of pooling operation for the r-th feature map at step t.
ϕ_i	Angle in polar coordinates corresponding to $\tilde{x}_i$.
r_i	Radius in polar coordinates.
t_i	Time index.
T_b	Individual tree in Random Forest.
B	Number of trees in Random Forest.
m	Number of features selected at each split.
$K(x_i, x)$	Kernel function in SVM.
C	Penalty factor in SVM.
α_i	Lagrange multiplier in SVM.
b	Offset parameter in SVM.
σ	Gaussian RBF kernel parameter.
η	Learning rate for gradient descent optimization.
I	Unit row vector.

Author's Publications

The contents of this thesis are based on the following papers that have been published, accepted, or submitted to peer-reviewed journals and conferences.

1. Wunna Tun, Johnny Kwok-Wai Wong, and Sai Ho Ling. Advancing Fault Detection in HVAC Systems: Unifying Gramian Angular Field and 2D Deep Convolutional Neural Networks for Enhanced Performance. *Sensors*, 2021, 23.

2. Wunna Tun, Johnny Kwok-Wai Wong, and Sai Ho Ling. An Experimental HVAC Faults Data Generation and Detection Using One-dimensional Convolutional Neural Networks. *19th International Conference on Automation Science and Engineering*, 2023, Auckland, New Zealand.

3. Wunna Tun, Johnny Kwok-Wai Wong, and Sai Ho Ling. Hybrid Random Forest and Support Vector Machine Modeling for HVAC Fault Detection and Diagnosis. *Sensors*, 2021, 21.

4. Wunna Tun, Johnny Kwok-Wai Wong, and Sai Ho Ling. Advancing HVAC Fault Detection with Integrated Dynamic Modeling, Fault Simulation, and Deep Learning Framework. *Building Engineering*, 2025, Submitted.

Chapter 1

Introduction

Heating, Ventilation, and Air Conditioning (HVAC) systems are critical for maintaining indoor air quality, thermal comfort, and energy efficiency in residential, commercial, and industrial buildings. With the increasing complexity of modern building environments and rising energy demands, ensuring the reliable operation of HVAC systems has become a significant research focus. However, due to their multi-component architecture, dynamic behaviour, and continuous operation under varying environmental and load conditions, HVAC systems frequently experience component-level faults. These faults can lead to substantial performance degradation, increased maintenance costs if not detected and addressed in a timely manner. In response to these challenges, this thesis presents a comprehensive fault detection and diagnosis (FDD) framework that integrates dynamic system simulation, fault scenario modelling, and data-driven diagnostic approaches to improve the operational reliability and energy efficiency of HVAC systems.

1.1 Introduction to the Research

Heating, ventilation, and air conditioning (HVAC) systems are essential for ensuring energy efficiency and comfort in building interiors. However, these systems frequently encounter operational challenges, particularly in buildings with complex energy systems. Over time, components within HVAC systems can deteriorate, leading to issues such as stuck valves, leaks, fouled coils, and sensor failures. When not properly managed or regulated, HVAC systems can account for a significant portion of energy consumption in commercial settings, typically between 15% and 30% [Basarkar et al., 2013]. The effect of HVAC operation on occupant comfort is noticeable with maintenance practices showing a direct correlation with occupant satisfaction [Karaguzel et al., 2014, Zhong et al., 2022]. Considering the impact of HVAC performance on energy consumption and occupant comfort, it is essential to understand HVAC operational faults by simulating and analyzing them through dynamic simulation tools.

In practice, obtaining reliable real-world HVAC operational data is challenging due to the high costs associated with extensive monitoring and data collection, as well as the difficulties in replicating the wide range of potential fault conditions. To manage HVAC systems effectively, developing advanced fault detection and maintenance strategies is essential to ensure reliable and efficient HVAC system performance. With the development of advanced fault detection systems based on simulated data, extensive testing and validation can be conducted under a wide range of fault conditions. This approach enhances the robustness and reliability of the systems without incurring the prohibitive costs and logistical challenges associated with real-world data collection.

Considerable research has focused on addressing HVAC operational faults through controller-based methods [Schibuola et al., 2018]. These techniques utilize complex strategies and control systems to enhance HVAC performance via real-time data for ongoing monitoring. In this approach, the feedback control mechanisms are implemented to dynamically adjust system operations, aiming to improve both efficiency and comfort. However, despite these technological improvements, challenges such as sensor inaccuracies, errors in control commands, damper failures, and blockages in coil valves continue, often exacerbated by environmental factors and unexpected interactions [Lymperopoulos et al., 2020, Moradi et al., 2016]. These issues can significantly decrease energy efficiency and result in substantial energy loss. In practical application, the reliability of these methods is often limited by data quality, environmental variables like dust, humidity, and temperature changes can compromise sensor precision, leading to the introduction of inaccurate data into the control system, thereby decreasing system performance and efficiency.

To address the complexities associated with multi-zone controller-based methods, dynamic modeling and fault simulation tools such as TRNSYS have been developed [Aibing et al., 2020, Laith and Miklos, 2021]. It employs state-space models that concentrate on thermal-mass balance and airflow dynamics, facilitating an in-depth analysis of transient behaviors for understanding system performance over extended periods. This functionality is important for precisely forecasting system responses to faults and environmental changes. Nevertheless, these models generally need careful calibration and validation to accurately show complex fault scenarios, which is both time-consuming and requires domain system expertise. Furthermore, the complexity of these models can pose challenges for their application in real-time fault detection, and the specialized knowledge needed for their operation may restrict their use in wider applications.

With its enhanced capabilities and adaptability, EnergyPlus has become a leading software for dynamic modeling and fault simulation in HVAC systems [Zhang and Hong, 2016, 2017]. This simulation tool models the thermal performance of buildings and HVAC systems through detailed physics-based models, enabling precise forecasts of energy usage and indoor environmental conditions. However, while capable of simulating a range of building and system scenarios, it may not specifically account for real-time operational faults in HVAC components. Consequently, issues such as sensor inaccuracies, control command errors, damper failures, and coil valve blockages might go undetected or unaddressed. Furthermore, it requires considerable learning time and extensive computational resources, which can make it less accessible.

In response to the challenge of replicating real-world HVAC fault conditions, HVACSIM+ was adopted in this study due to its proven effectiveness in modeling the dynamic behaviour of HVAC systems, including the interactions among components such as fans, pumps, valves, and control systems [Bushby et al., 2001, Galler, 2020]. Unlike many other simulation tools, HVACSIM+ enables the emulation of various fault scenarios—including sensor inaccuracies, actuator malfunctions, and control logic failures within a controlled environment. While it does not explicitly model fault probabilities or stochastic occurrence rates, the simulated faults are based on well-documented operational issues and are aligned with ASHRAE-guided severity levels, thereby approximating real-world behaviour. This approach supports the generation of labelled datasets under known fault conditions, which is critical for developing and validating fault detection models. Given the unpredictable and often latent nature of faults in actual HVAC systems, HVACSIM+ offers a practical and cost-effective solution for conducting robust and repeatable performance evaluations of diagnostic algorithms [Norford and Wright, 2002].

To address this need, an HVAC fault simulation and detection system was investigated [Davood, 2013]. In this system, a real-time fault detection using an online SVM was developed, enabling real-time training and incorporating a method to detect and update the classifier with unknown faults. However, it focuses only on three faults which limits comprehensive fault detection. Additionally, using Matlab Simulink for dynamic simulation is costly and may lack specialized HVAC functionalities, affecting practical reliability and accuracy. This highlights the need for more advanced fault detection framework that consider all aspects of dynamic modeling, fault simulation, industry benchmark data validation, and faults detection. Addressing these areas comprehensively will enhance the effectiveness of HVAC fault detection systems.

Given the limitations of previous studies that focused on only a few fault types, this study expands the scope to consider a wider range of fault scenarios, including sensor faults, actuator failures, and damper and valve malfunctions. This broader fault coverage ensures that anomalies are represented, enhancing the fidelity and applicability of the simulated data. Although there is no fixed standard for the ideal number of fault types, the selection in this study reflects a deliberate balance between achieving comprehensive coverage and maintaining manageable data size, model complexity, and training demands. This strategy facilitates the development of more resilient and generalizable fault detection models capable of operating effectively under a variety of real-world HVAC conditions.

In this chapter, the key components of the study are introduced and structured across four main sections. Section 1.1 provides a detailed review of existing literature and research relevant to HVAC systems, highlighting the challenges of fault detection and the role of simulation tools in addressing limitations in real-world data. Section 1.2 discusses the motivations for this research, identifying current gaps in fault detection methods and the need for more accurate, scalable, and reliable solutions. Section 1.3 presents the research objectives and describes the proposed integrated fault detection framework, which includes system modeling, fault simulation using HVACSIM+, validation against benchmark datasets, and the use of advanced detection techniques. Finally, Section 1.4 describes the structure of the thesis, summarising the methodologies used for modeling, simulation, and the development of cost-effective and accurate fault detection systems aimed at improving HVAC system performance in practical applications.

1.2 Motivation of Thesis

Heating, Ventilation, and Air Conditioning (HVAC) systems are critical for maintaining thermal comfort, indoor air quality, and energy efficiency in residential, commercial, and industrial buildings. These systems account for a substantial portion of global building energy consumption, and their reliable operation is vital for sustainable and cost-effective facility management [Beghi et al., 2015]. However, HVAC systems are prone to various operational faults, including sensor drift, actuator malfunctions, control command errors, and component degradation. Such faults, often occurring unexpectedly, can lead to decreased system efficiency, increased energy usage, higher maintenance costs, and occupant discomfort [Lee et al., 2004, Xiao et al., 2014]. As a result, there is a strong need for early and accurate fault detection to maintain optimal performance, extend equipment lifespan, and support the broader goals of energy sustainability and intelligent building operation.

Motivated by this need, extensive research has explored both model-based and data-driven fault detection and diagnosis (FDD) methods. Statistical techniques, such as Principal Component Analysis (PCA), have been used for chiller system monitoring [Beghi et al., 2015], while probabilistic graphical models like Diagnostic Bayesian Networks (DBNs) have been applied to variable air volume (VAV) terminals [Xiao et al., 2014]. Although these methods provide valuable insights, they often struggle with scalability, computational cost, and their reliance on rule-based decision logic and expert knowledge, limiting their adaptability in complex or unforeseen conditions.

Machine learning approaches, including artificial neural networks (ANNs), general regression neural networks (GRNNs) [Lee et al., 2004], and wavelet-based neural networks [Fan and Guo, 2010], have further demonstrated the potential to automate fault classification. However, these methods commonly depend on extensive feature engineering and data preprocessing, which can affect their generalizability across different HVAC configurations. Unsupervised methods such as Ensemble Rapid Centroid Estimation (ERCE) [Yuwono et al., 2015], and hybrid techniques integrating Support Vector Machines (SVMs) with residual analysis [Liang and Du, 2007], as well as tree-based classifiers like Random Forest and XGBoost [Chakraborty and Elzarka, 2019, Zhang et al., 2018], have also been proposed. While each contributes to improving FDD, challenges persist related to computational complexity, interpretability, and limited fault coverage.

In recent years, deep learning methods have gained traction for their ability to automatically extract features from time-series sensor data. One-dimensional convolutional neural networks (1D-CNNs), in particular, have shown promising results for fault detection tasks in HVAC systems due to their classification accuracy and computational efficiency [Li et al., 2021, Liao et al., 2021]. However, their effectiveness is often constrained by a reliance on single-source simulation data and a limited ability to capture spatial dependencies across sensor inputs. To address this, more advanced approaches such as Gramian Angular Fields (GAF) combined with two-dimensional CNNs (GAF-2DCNNs) have been explored to transform time-series signals into spatial representations for improved detection performance [Gao et al., 2023, Pham et al., 2020]. These methods show potential in increasing the accuracy through techniques like pruning and layer-wise relevance propagation.

Despite these advances, there remains a lack of holistic frameworks that integrate simulation-driven fault generation, standardized validation, and scalable model development. Existing approaches often emphasize building energy modeling over realistic fault simulation and may not leverage benchmark datasets such as those provided by ASHRAE for validation. Furthermore, conventional rule-based and shallow learning models are often limited in their ability to capture dynamic interactions and complex patterns in HVAC data, particularly under varying operational conditions.

This thesis is motivated by the need to improve the accuracy and reliability of fault detection in HVAC systems, with the broader goal of supporting more efficient and robust system operation. The work explores the integration of simulation-based fault generation using HVACSIM+ and the use of standardized ASHRAE datasets to evaluate detection performance under realistic conditions. It investigates a hybrid deep learning approach combining GAF-2DCNNs, 1D-CNNs, and RF-SVM classifiers to address limitations in existing methods, particularly in handling time-series data and fault variability. By building on recent advances and aligning with practical considerations, this research aims to contribute toward the development of more reliable data-driven solutions for HVAC fault detection and diagnosis.

1.3 Objectives and Methodological Framework

The objective of this thesis is to develop a comprehensive and reliable framework for dynamic system modeling, fault simulation, validation, and fault detection in HVAC systems. This is accomplished by simulating HVAC system dynamic behavior through the structured definition of building geometry, specification of key HVAC components, configuration of design parameters, and validation of outcomes against established industry benchmarks. The study focuses on generating operationally realistic and cost-effective simulation datasets using HVACSIM+, where cost-effectiveness refers to the ability to produce diverse and representative fault scenarios without incurring the financial, operational, or safety risks typically associated with real-world data collection.

To ensure the simulated data accurately reflects real-world HVAC system behaviour, the HVACSIM+ model was validated using the ASHRAE RP-1312 benchmark dataset under normal operating conditions. This benchmark worked as an established industry reference for assessing the accuracy and consistency of simulation outputs. The validation process focused on key performance variables, including supply air temperature, airflow rate, fan speed, and power consumption. The strong correlation results indicated the alignment between simulated and benchmark data, demonstrating the ability of model to replicate actual system dynamics. To support this validation, a series of preprocessing steps were implemented, including the alignment of sensor variables, standardisation of temporal resolution to one-minute intervals, feature normalisation, and systematic mapping of operational states. These measures ensured comparability between the simulation results and real-world measurements. Nevertheless, the benchmark does not fully capture the range and complexity of fault conditions typically encountered in real-world operational settings

To address this limitation, the validated model was further extended to simulate nine major HVAC fault conditions, which were not represented in the ASHRAE RP-1312 dataset. These fault scenarios were selected to represent a broad range of realistic system failures, encompassing control, airflow, temperature, and component-level anomalies. A comprehensive statistical evaluation comparing fault conditions to normal operation confirmed the robustness and diagnostic relevance of the extended dataset. This approach not only enhances the accuracy of the simulated data but also provides a scalable and cost-effective framework for developing and evaluating advanced fault detection and diagnosis methodologies, addressing key limitations in the availability and scope of existing public HVAC datasets.

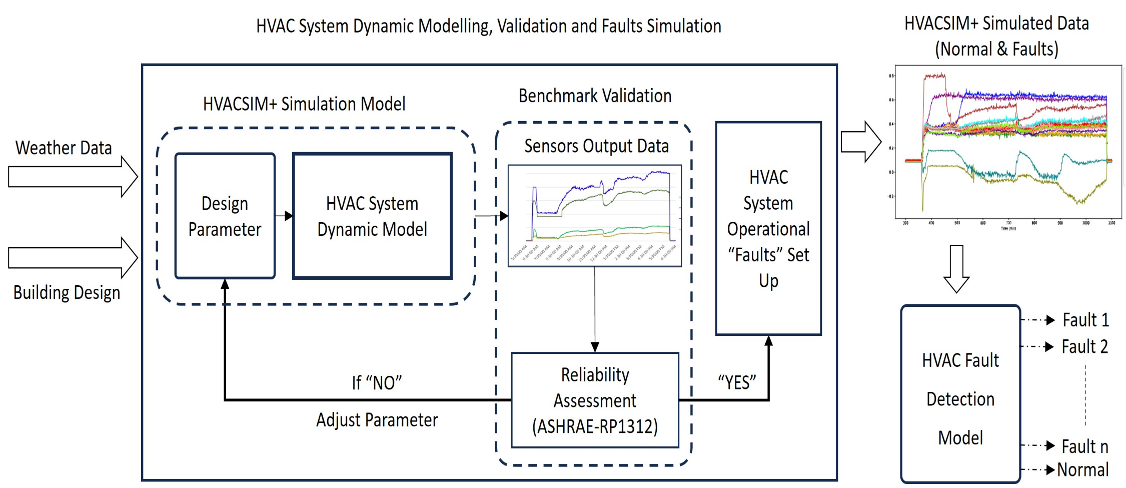


Figure 1.1: Proposed Approach: HVAC Systems Dynamic Modeling, Fault Simulation, Validation, and Detection.

For improving fault detection, three advanced systems such as Gramian angular field (GAF) and two-dimensional convolutional neural networks (GAF-2DCNNs), one-dimensional convolutional neural networks (1DCNNs), and a hybrid approach integrating random forest (RF) and support vector machine (SVM) classifiers are proposed. Through this innovative integrated approach, the study aims to optimize fault detection accuracy and efficiency using various state-of-the-art deep learning techniques, thereby contributing to the enhanced performance and reliability of HVAC systems in real-world settings.

The use of simulation-generated datasets addresses the limitations of real-world data collection and enables the development of more generalizable and reliable fault detection models, which outperform baseline methods, namely SVM and RF in accuracy and robustness. The comparison studies showed that the baseline methods achieved relatively lower accuracy, which can be attributed to their limited ability to capture the complex temporal dependencies and nonlinear dynamics characteristic of HVAC system behaviour. As these models had sufficiently worked their purpose in building a performance benchmark, they were not subjected to further evaluation on the external benchmark dataset. Instead, the validation efforts focused on examining the robustness and generalization capabilities of the proposed deep learning-based and hybrid approaches using a publicly available benchmark dataset.

The proposed integrated system is illustrated in Figure 1.1 and formalized in Pseudocode 1.2. It operates through a step-by-step process that integrates data generation, preprocessing, feature transformation, model training, and evaluation. This comprehensive framework is designed to enhance the performance and reliability of HVAC fault detection systems and to contribute toward more intelligent and efficient building management practices.

Algorithm 1 HVACSIM+ Modeling Process

```
building_geometry: Building, Room, Window Dimensions, Insulation Levels
HVAC_equipment: Specifications for each component
function DefineBuildingGeometry
    DEFINE building geometry
end function
function SpecifyHVACSystemComponents
    DEFINE HVAC components
    INCLUDE heating coil, cooling coil, valves
    INCLUDE dampers, ducts, supply air fan, return air fan, VAV
end function
function SetDesignParameters
    SET building_parameters
    SET HVAC equipment specifications
end function
function InitializeSimulationEnvironment
    INITIALIZE T_indoor, T_outdoor, Q_solar, humidity
end function
function RunBaselineSimulation
    Calculate Q_wall, Q_window, Q_internal, Q_total, T_indoor
    Update Temperature, T_indoor, T_initial, Q_total
end function
function ReliabilityAssessment
    Validate Simulation against ASHRAE-RP1312
    if (results aligned) then
        Proceed next step
    else
        Adjust parameters and rerun simulation
    end if
end function
function IntroduceFaultConditions
    Apply fault condition and run simulation
    Generate normal and faulty operational data
    Evaluate normal Vs. faults distribution
    Dataset ready for FDD systems
end function
```

Figure 1.2: Pseudocode for the proposed HVAC modeling and fault detection approach.

Firstly it defines the building geometry including parameters such as building dimensions, room layouts, window dimensions, and insulation levels. It ensures that the simulation accurately represents the physical characteristics of the building being modeled. Secondly, the HVAC system components are specified, encompassing heating coils, cooling coils, valves, dampers, ducts, supply, and return air fans, and variable air volume (VAV) systems. This step ensures that all relevant components of the HVAC system are included, allowing for a comprehensive analysis of system performance. Following the specification of HVAC components, design parameters are set to configure building parameters and equipment specifications, thereby establishing the simulation environment. This includes defining the dimensions and insulation levels for the building, rooms, and windows, and specifying HVAC components such as heating/cooling coils, valves, dampers, ducts, supply/return air fans, and VAV units.

Upon initialization, the simulation environment includes indoor and outdoor temperatures, humidity levels, and solar gain data. A baseline simulation calculates heat gains and losses, updating indoor temperatures based on these factors. Figure 1.1 outlines the overall workflow considering weather data and building design inputs. It is acknowledged that real-time occupancy dynamics also play a significant role in influencing indoor thermal conditions and system performance. In this study, occupancy was incorporated through the specification of maximum room occupancy levels as part of internal heat gain parameters during the simulation setup as given in Chapter 3. This approach allowed for a realistic representation of internal loads under typical design conditions.

However, due to the simulation-based nature of this study and the absence of access to real-world occupancy datasets, especially time-varying occupancy profiles were not modelled. Instead, the framework focused on evaluating fault detection under controlled, repeatable conditions, using benchmarked simulation data validated against

ASHRAE RP-1312 standards. While incorporating dynamic occupancy data could further improve the accuracy, this aspect was not addressed in the current work and may be considered as part of future studies.

1.4 Structure of Thesis

The thesis is organized into eight chapters. Chapter 1 starts with an exploration of the background studies, research objectives, motivation, and the proposed integrated framework. The subsequent chapters collectively contribute to a thorough understanding of HVAC system dynamics, the simulation of operational faults, and their validation and detection, as presented in Figure 1.3.

Chapter 2 provides with a literature review of HVAC systems, highlighting the importance of Air Handling Units (AHUs) and the role sensors and controllers in optimizing system performance. It further examines the application of dynamic simulation tools to model HVAC system dynamics and simulate operational faults. In addition, the research also reviews existing HVAC fault detection systems, exploring various methods including AHU controller strategies, statistical methodologies, and artificial intelligence-based techniques. Ultimately, it proposes an integrated fault detection framework that seamlessly considers system dynamics, fault simulation, validation, and detection, aiming to improve system reliability and performance while addressing current limitations in the field.

Chapter 3 outlines the proposed integrated frameworks for simulating and evaluating HVAC system performance. It details steps such as defining building geometry, specifying HVAC components, configuring design parameters, initializing the simulation environment, and validating results against industry standards.

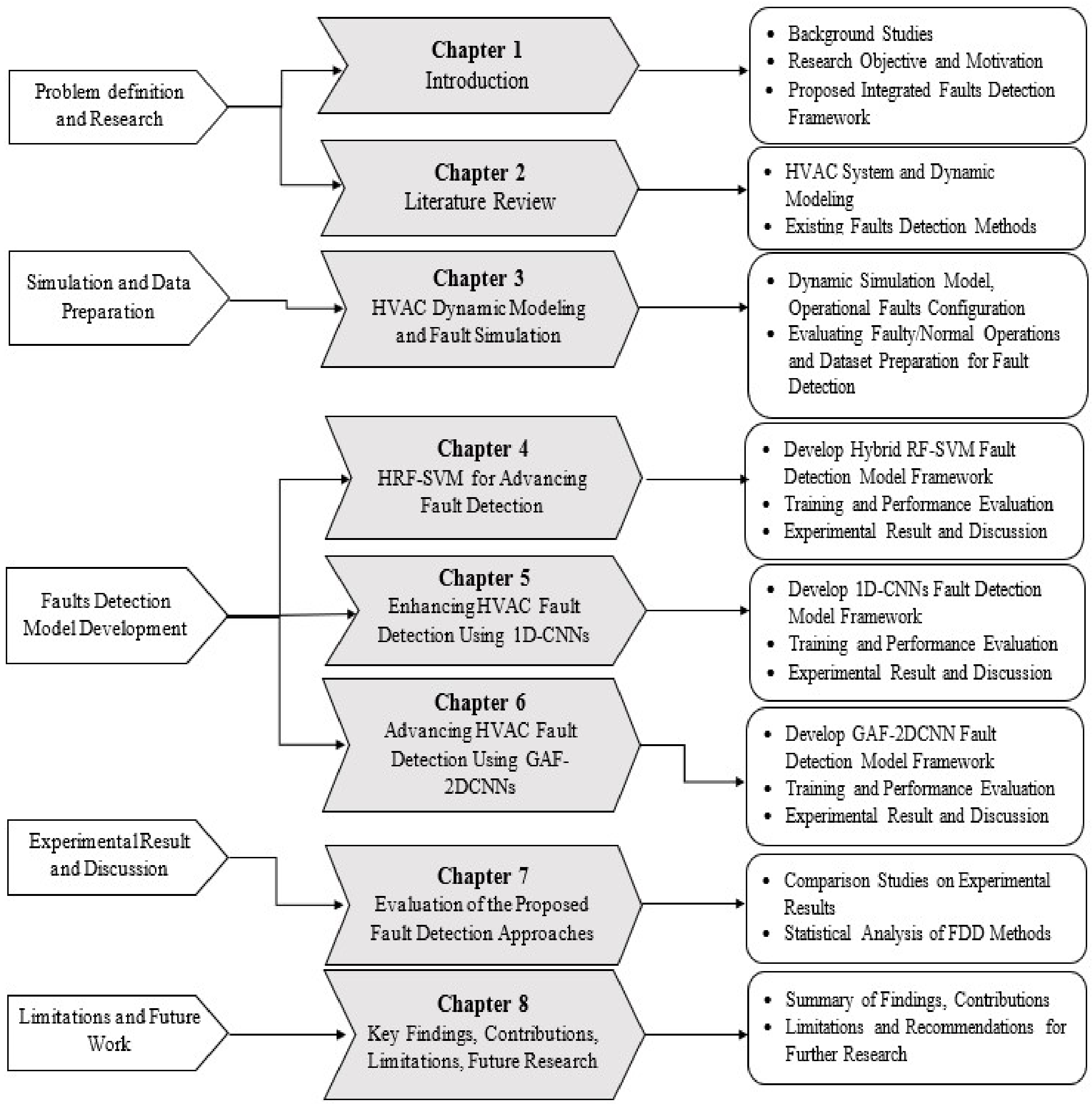


Figure 1.3: Structure of Thesis

The chapter also provides insights into dynamic system modeling using the HVAC-SIM+ simulation tool, illustrates the HVAC control algorithm through pseudocode, and considers mathematical models for individual components and critical design parameters. Additionally, it discusses the validation of HVACSIM+ simulation data for summer conditions to ensure that the simulated data closely aligns with real-world conditions, enhancing reliability. The implementation and evaluation of nine major HVAC faults are highlighted, emphasizing the need for reliable datasets for advanced fault detection and diagnosis. Finally, conclusions drawn from the study and future research directions are proposed.

Chapter 4 provides a comprehensive overview of the hybrid Random Forest and Support Vector Machine (RF-SVM) fault detection and diagnosis system for HVAC applications. It begins with an exploration of the theoretical background of Random Forest and Support Vector Machine, outlining their fundamental principles. The chapter then introduces the proposed hybrid fault detection system, detailing its innovative procedures and unique features. It also covers the training of the hybrid RF-SVM FDD system, including dataset preparation, design parameters, feature selection, and performance metrics. The experimental results and discussions, including comparison studies, are presented next. Finally, the chapter concludes with a summary of key findings and future research directions.

Chapter 5 presents a robust method for diagnosing HVAC system faults through the application of deep convolutional neural networks (CNN). Specifically, this Chapter details the theoretical foundations of CNNs, providing a thorough understanding of their underlying principles. It outlines the process of preparing the training dataset using simulations generated by HVACSIM+ from Chapters (3) and 4, ensuring the data accurately represents both “Normal” conditions and various HVAC faults. The discussion then moves to present the parameter configurations fine-tuned during training and evaluates the effectiveness of the proposed CNNs-based fault detection and diagnosis system, highlighting its strengths and areas for improvement. Finally, it addresses the limitations of the current approach, draws conclusions from the findings, and suggests avenues for future research to enhance the 1D-CNNs detection system further.

Chapter 6 presents an advanced fault detection solution utilizing a unified framework (GAF-2DCNNs) that combines Gramian Angular Fields (GAF) and 2D Convolutional Neural Networks (2D-CNNs). This section explains the theoretical foundation of transforming time series data into images using GAF, which enables the use of 2D-CNNs for fault detection by capturing temporal dependencies in a spatial format. It details the proposed unified framework, including the training process, dataset used, and optimized design parameters. The chapter also provides an evaluation and discussion of the GAF-2DCNNs fault detection system, along with a comparison analysis. Finally, it outlines the limitations, conclusions, and potential future directions for this approach.

Chapter 7 conducts comprehensive comparison studies of three proposed fault detection algorithms (GAF-2DCNNs, 1D-CNNs, and RF-SVM), focusing on their characteristics, operation principles, complexities, and learning abilities. The aim is to evaluate and contrast their performance in detecting HVAC system faults based on their effectiveness in identifying different types of faults, efficiency, and adaptability to various operating conditions. Understanding the strengths and limitations of each algorithm is important for selecting the most suitable approach for practical fault detection applications in HVAC fault detection systems. The findings from these comparisons will be summarized to provide a clear overview of the results and their implications for future research and implementation strategies.

Chapter 8 summarizes the research findings and results, highlighting the effectiveness of the proposed methodologies in fault detection and diagnosis for HVAC systems. It emphasizes the practical implications of these methods, demonstrating their potential for real-world applications in improving HVAC system reliability and performance. Additionally, it addresses the limitations encountered during the study and suggests future research directions, outlining opportunities for further exploration and advancement in the field of HVAC fault detection and diagnosis. These include refining the algorithms, incorporating more diverse datasets, and exploring the integration of new technologies to enhance detection capabilities and system optimization.

Chapter 2

Literature Review

This chapter presents a comprehensive review of the literature related to fault detection and diagnosis (FDD) in Heating, Ventilation, and Air Conditioning (HVAC) systems. The review begins by outlining the key structural and functional components of HVAC systems, with emphasis on air handling units (AHUs), sensors, and control mechanisms that play a critical role in system performance and fault monitoring. It then examines the application of dynamic modelling and simulation techniques used to replicate HVAC system behaviours and generate representative fault scenarios. The chapter further explores a range of FDD methodologies, encompassing controller-based strategies, statistical analysis, and data-driven approaches, including recent advancements in machine learning and artificial intelligence. By critically analysing the strengths and limitations of existing studies, this review identifies current research gaps and opportunities for improvement. These insights form the basis for the methodological framework proposed in the subsequent chapters of this thesis.

2.1 Background Studies

HVAC systems comprise key components such as boilers, chillers, pumps, and air handling units (AHUs), which are integrated with automation and energy management systems to enhance operational efficiency. Among these, the AHU plays a central role in circulating and conditioning air within buildings through filtering, heating, cooling, humidifying, and dehumidifying processes [Basavaraja et al., 2019]. Sensors and controllers are also fundamental to HVAC operations, providing real-time data on parameters such as temperature, humidity, pressure, and air quality, thereby enabling precise monitoring and control. Faults in these components or processes, such as sensor drift, actuator failure, or control logic errors can result in incorrect system responses, leading to over-conditioning or inefficient cycling of equipment, which ultimately causes unnecessary energy consumption and reduced system performance. Consequently, improving fault detection capabilities is essential to support efficient system operation and minimize the impact of undetected faults on energy use.

In response to these challenges, recent studies have proposed strategies aimed at reducing energy consumption and improving economic performance without compromising indoor environmental quality [Asim et al., 2022]. For example, the concept of zero-investment HVAC operation focuses on optimising system schedules and control parameters to improve performance without requiring additional hardware upgrades [Fasiuddin et al., 2009]. In parallel, intelligent control approaches, such as fuzzy logic and neural network-based controllers, have been explored to manage dynamic operational conditions and improve fault resilience [Guo et al., 2007, Khan et al., 2020].

To support analysis and design of these strategies, dynamic simulation tools have been widely used to model system behaviour under a range of scenarios, including fault conditions [Aibing et al., 2020, Laith and Miklos, 2021, Yuan et al., 2018]. These tools provide detailed insights into thermal dynamics and airflow, but their reliance on extensive calibration and validation can limit scalability and real-time applicability. Complementing these efforts, data-driven and artificial intelligence-based FDD techniques have been proposed to detect faults directly from operational data, particularly within AHU systems [Yuan et al., 2018]. Despite these advancements, challenges remain in effectively integrating simulation-based methods with online fault detection tools. This highlights the need for simulation datasets that are not only cost-effective and scalable but also reliably capture the complexity of real-world operations. In this context, reliability refers the consistency, relevance, and practical usability of the data across a wide range of operating and fault conditions.

This chapter provides a structured review of literature related to fault detection and diagnosis (FDD) in HVAC systems. It begins by outlining the key system components in Section 2.2, with a particular focus on the functional roles of air handling units (AHUs) and the integration of sensors and controllers, further detailed in Subsections 2.2.1 and 2.2.2. Section 2.3 examines dynamic modelling approaches and simulation platforms used to analyse system performance and emulate fault conditions. A detailed review of existing FDD methodologies is then presented in Section 2.4, which categorises prior work into controller-based, statistical, and artificial intelligence-driven approaches, as discussed in Subsections 2.4.1, 2.4.2, and 2.4.3, respectively. As summarised in Section 2.5, this review provides a comprehensive understanding of HVAC system operation, dynamic modelling, fault simulation, and existing diagnostic approaches, working as a foundation for the development of more advanced and intelligent fault detection and diagnosis (FDD) frameworks.

2.2 HVAC System Components

The Heating, Ventilating, and Air-Conditioning (HVAC) system is a complex network designed to regulate indoor environmental conditions effectively, ensuring both comfort and air quality for building occupants. Central to this network is the Air Handling Unit (AHU), a critical component that integrates various essential parts such as Variable Air Volume (VAV) systems, fans, dampers, coils, and valves. The VAV systems, widely used in commercial buildings, offer significant flexibility and energy efficiency by allowing the HVAC system to adjust airflow and temperature based on the specific needs of different zones within the building [Pang et al., 2017]. The primary function of AHU is to control and maintain the temperature, humidity, and airflow, which it achieves through the coordinated operation of its internal components. Fans circulate the air, while dampers control the air volume and direction. Coils are used for heating or cooling the air, and valves regulate the flow of refrigerant or water through the coils [Wang et al., 2020].

The integration of VAV systems within AHUs allows for precise modulation of airflow and temperature, significantly optimizing energy consumption and enhancing occupant comfort [Goodman et al., 2016]. For example, during peak occupancy or varying thermal loads, VAV systems can adjust the air supply to different zones, thereby maintaining desired environmental conditions without wasting energy. This dynamic adjustment is important in modern buildings, where energy efficiency and sustainability are increasingly prioritized. Additionally, the ability of AHU to work with sensors and controllers further enhances its functionality, enabling real-time data acquisition and system optimization [Duarte et al., 2020]. This advanced control capability helps in maintaining a balanced indoor environment and contributes to the overall effectiveness and efficiency of the HVAC system.

In the following, Subsections 2.2.1 and 2.2.2 examine two critical components of HVAC systems such as the AHU, and the control infrastructure. Subsection 2.2.1 discusses the internal configuration, highlighting how components such as fans, dampers, coils, and valves function together to regulate airflow, temperature, and humidity. Subsection 2.2.2 focuses on the role of sensors and controllers in maintaining system stability and operational efficiency. Through continuous monitoring and adjustment, these elements support reliable performance and contribute to effective fault detection within the overall HVAC framework.

2.2.1 Air Handling Unit

This section focuses on the AHU, a key component of HVAC systems that plays a vital role in reconditioning and circulating air to ensure indoor air quality and occupant comfort. Its operation relies on the coordinated function of various elements, including fans, dampers, coils, and valves [Lee, 2020b, Vidhya et al., 2022]. As illustrated in Figure 2.1, the operation starts by drawing in fresh ambient air, which is first filtered to remove dust and ensuring the cleanliness of the processed air. The filtered air then passes over heating or cooling coils, which use hot water, steam, or refrigerant to adjust the air temperature to meet the energy demand of building.

As illustrated in Figure 2.1, the return air and supply air fans are crucial for moving air through the unit and ductwork, enabling efficient distribution throughout the building. The AHU also incorporates dampers, adjustable plates that control airflow volume and direction within the duct system, ensuring precise air distribution to various zones. Valves regulate the flow of heating or cooling fluids to the coils, allowing for fine-tuned temperature control. Humidifiers may be included to add moisture to the air when necessary, maintaining a comfortable indoor environment. In addition, sensors and controllers are essential for monitoring and adjusting the operation of systems, ensuring optimal conditions for temperature, humidity, and air quality. Typically, these integrated components, as detailed below, work together to ensure the AHU operates effectively, providing consistent and comfortable indoor conditions while optimizing energy use.

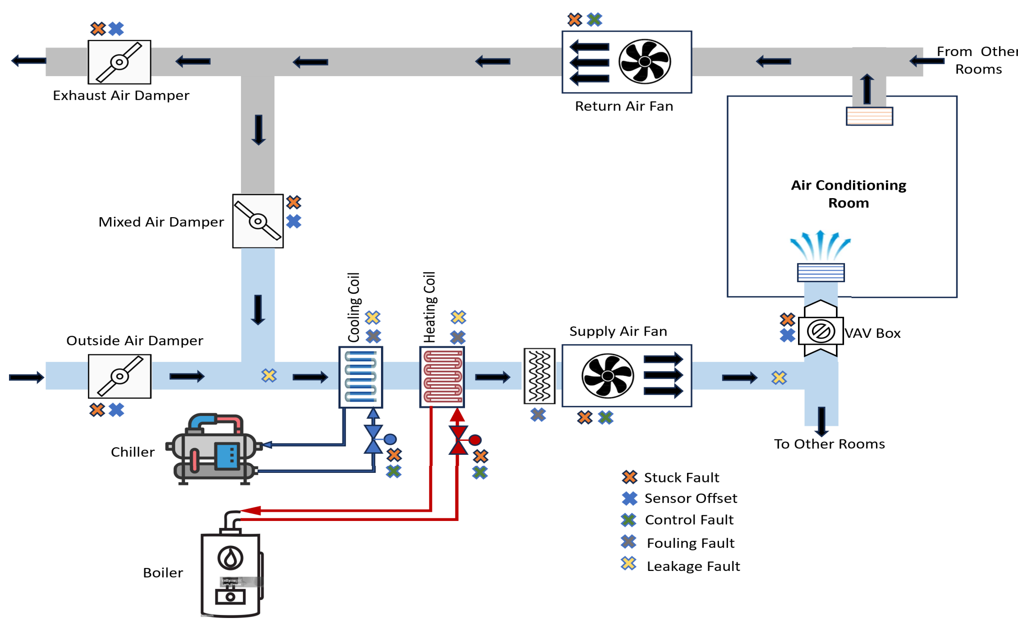


Figure 2.1: HVAC System with AHU and Components

Cooling Coil: To provide further details of the AHU, it starts with the cooling coil, one of its major components. It is working as the evaporator coil, and plays a critical role in maintaining indoor comfort by removing heat from the air passing through it. This process involves transferring heat to the refrigerant circulating within the coil, thereby cooling the air before it is distributed throughout the building [Vakiloroaya, 2012]. The effectiveness of the cooling coil can be quantitatively described by the heat transfer equation, which models its performance and efficiency (2.1).

$$Q_c = \dot{m} \times Cp \times (T_{in} - T_{out}) \tag{2.1}$$

where Q_c is the heat transfer in the cooling coil, $\dot{m}$ is the mass flow rate of air, Cp is the specific heat capacity of air, T_{in} is the inlet air temperature, and T_{out} is the outlet air temperature [Solgi et al., 2016].

Heating Coil: On the other hand, exploring the role of the heating coil, or reheat coil, reveals its critical function in achieving the desired indoor temperature by adding heat to the air. Typically, hot water, steam, or electric resistance is used to generate this heat. As air passes over the coil, it absorbs heat, raising its temperature before distribution. This process ensures indoor spaces remain warm during colder periods or when additional heating is required in specific zones. The performance of the heating coil can be mathematically described by equation (2.2) which quantifies its efficiency and heating capacity.

$$Q_h = \dot{m} \times Cp \times (T_{\text{out}} - T_{\text{in}}) \tag{2.2}$$

where Q_h is the heat transfer in the heating coil, $\dot{m}$ is the mass flow rate of air, Cp is the specific heat capacity of air, T_{out} is the outlet air temperature, and T_{in} is the inlet air temperature [Vakiloroaya, 2012]. Proper operation and control of the cooling and heating coils are essential for maintaining thermal comfort and energy efficiency within the HVAC system. In practice, the efficiency and performance of both the cooling coil and heating coil are affected by various factors including design, size, and operational parameters. Therefore, regular maintenance and cleaning are essential to ensure these coils operate optimally and maintain the energy efficiency of the HVAC system [Wang et al., 2009].

Three-Way Valve: It is essential for controlling the flow of cooling or heating fluids to optimize thermal comfort within buildings [Wen and Li, 2011a]. As illustrated in Figure 2.2, four types of water flow resistances are considered: coil flow resistance ($\mathrm{R_{coil}}$), bypass pipe flow resistance ($\mathrm{R_{bypass}}$), valve resistance for controlling coil water flow ($\mathrm{R_{v1}}$), and valve resistance for controlling bypass water flow ($\mathrm{R_{v2}}$). By adjusting the opening position of valve, the flow of fluids to the cooling coil or heating coil can be precisely managed. This allows for dynamic temperature adjustments according to the specific needs of different zones within the building, ensuring optimal occupant comfort while minimizing energy consumption. The integration of three-way valves in AHUs enhances the overall energy efficiency of HVAC systems. Mathematically, the valve resistances are calculated using equation 2.3 based on the position and characteristics of valve.

$$R_V = 1296 K_V^{-2} f^{-2} \tag{2.3}$$

Where R_v is R_{v1} or R_{v2}, K_v is valve capacity ($\mathrm{m^3/hr}$) and f is fractional flow (%). f is a function of the valve position x, with x ranging from 0 for fully closed to 1 for fully opened. The two regions, cut-off region, and liner region, in the three-way valves are used to determine the relationship between f and x and can be calculated by equations (2.4) and (2.5). For Cut-off region ($0 \leq \mathrm{x} \leq \mathrm{x}_l$) and Linear region

($x_l \leq x \leq 1$):

$$f = \left(\frac{\frac{1}{S_V} - C_L}{x_l} \right) x + C_L \tag{2.4}$$

$$f = \left(\frac{1 - \frac{1}{S_V}}{1 - x_l} \right) (x - x_l) + \frac{1}{S_V} \tag{2.5}$$

where C_L is fractional leakage (%) and S_V is valve rangeability (%).

The water flow rate through the coil or bypass path is determined using equation (2.6), which relates the flow rate to the pressure drop across the valve and the total flow resistance:

$$W = \sqrt{\frac{\Delta P}{R}} \tag{2.6}$$

where W represents the coil or by-pass water flow rate (kg/s), ΔP is the pressure drop across the coil and valve (KPa), and R is the total flow resistance (0.001 kg-m).

Supply and Return Fans: Another integral component of the AHU is the supply and return fans [Doe, 2015]. These fans are crucial for maintaining the desired indoor environmental conditions by ensuring adequate airflow and pressure within the system. The supply fan delivers conditioned air from the AHU to the occupied spaces, maintaining the designed airflow and pressure levels. This ensures consistent air distribution throughout the building, meeting both thermal and ventilation requirements. The performance of a supply fan can be mathematically represented by equation (2.7).

$$P_f = \eta_f \times \dot{m} \times \Delta P \tag{2.7}$$

where P_f is the power of the fan, η_f is the fan efficiency, $\dot{m}$ is the mass flow rate of air, and ΔP is the pressure difference across the fan .

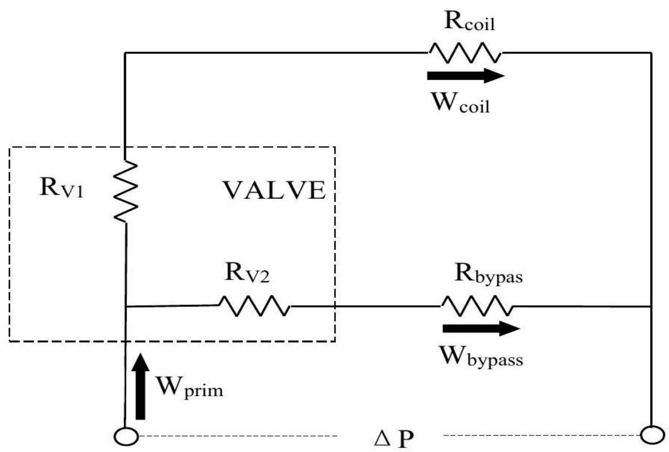


Figure 2.2: Diagram of a three-way valve model

On the other hand, return fans draw air back from the occupied spaces to the AHU for reconditioning or exhaust purposes [Smith, 2018a]. These fans maintain balanced air pressure within the building, preventing issues related to pressurization or depressurization. The operation of return fans ensures the building's ventilation system functions efficiently, contributing to energy savings and improved indoor air quality. The airflow rate of a return fan can be calculated using equation (2.8).

$$\dot{m}_{\text{return}} = \rho \times A \times V \tag{2.8}$$

where $\dot{m}_{\text{return}}$ is the mass flow rate of the return air, ρ is the air density, A is the cross-sectional area of the duct, and V is the air velocity.

In operation, proper coordination between supply and return fans is crucial for the efficient operation of an AHU. Without this balance, issues such as increased energy consumption, inadequate ventilation, and discomfort for building occupants can arise. Advanced control strategies, including the use of variable speed drives (VSDs), can optimize the performance of both supply and return fans by adjusting their speeds based on real-time demand. This not only enhances energy efficiency but also ensures that the indoor environment remains comfortable and healthy. The efficiency improvements achieved through VSDs can be quantified using the affinity laws, which relate fan speed to airflow and power consumption as described in equation (2.9).

$$Q \propto N \quad \text{and} \quad P \propto N^3 \tag{2.9}$$

where Q represents the volumetric flow rate, P denotes the power consumption, and N is the fan speed [Brown, 2017]. These relationships and control strategies highlight the critical role of supply and return fans in the performance and efficiency of AHU systems in modern HVAC applications. Proper design, selection, and control of these fans are essential to achieving optimal indoor air quality, energy efficiency, and occupant comfort.

Dampers: Functionally, the AHU employs various dampers, including Outside Air (OA), Exhaust Air (EA), and Mixed Air (MA) dampers, to regulate airflow and facilitate air exchange within buildings [Johnson, 2019a]. Outside Air Dampers (OADMPR) control the intake of fresh outdoor air into the AHU system, acting to dilute indoor pollutants and replenish oxygen levels. The mass flow rate of outside air ($\dot{m}_{oa}$) through OADs depends on the damper opening area (A_{oa}) and the velocity of the outside air (V_{oa}), as indicated in (2.10). Properly sized and adjusted OADMPR are essential for meeting ventilation requirements while minimizing energy consumption.

$$\dot{m}_{oa} = A_{oa} \times V_{oa} \tag{2.10}$$

The exhaust air dampers (EADMPR) regulate the discharge of indoor air contaminants and excess moisture, contributing to indoor air quality management [Lee, 2020a]. As shown in (2.11), the mass flow rate of exhaust air ($\dot{m}_{ea}$) through EADs is determined by the damper opening area (A_{ea}) and the velocity of the exhaust air (V_{ea}) . Effective positioning and control of EADs are critical for optimizing ventilation efficiency.

$$\dot{m}_{ea} = A_{ea} \times V_{ea} \tag{2.11}$$

Furthermore, Mixed Air Dampers (MADMPR) modulate the mixture of outside air and return air to achieve the desired mixed air temperature within the AHU [Smith, 2018b]. By mixing the outside air and return air, MADMPR contributes to optimize energy efficiency by reducing the need for mechanical heating or cooling. The mixed air temperature (T_{mix}) is calculated by (2.12), based on the mass flow rates ($\dot{m}_{oa}$ and $\dot{m}_{ra}$) and temperatures (T_{oa} and T_{ra}) of outside air and return air, respectively.

$$T_{mix} = \frac{\dot{m}_{oa} \times T_{oa} + \dot{m}_{ra} \times T_{ra}}{\dot{m}_{oa} + \dot{m}_{ra}} \tag{2.12}$$

Ducting System: For the distribution of conditioned air throughout the building, the ducting system is also considered a major component in the AHU. The airflow dynamics within the duct system can be mathematically modeled to optimize system performance. The airflow through ducts can be described by considering factors such as duct size, pressure drop, and airflow rates as shown in equation (2.13).

$$Q = \frac{\Delta P \times A}{R \times \rho} \tag{2.13}$$

where, Q represents the volumetric flow rate of air, P denotes the pressure differential across the duct, A signifies the cross-sectional area of the duct, V indicates the mean velocity of the air, and ρ denotes the density of the air. In (2.14), the airflow dynamics in ducts is derived from the principles of fluid mechanics and conservation of mass:

$$\dot{m} = \rho \times A \times V \tag{2.14}$$

where, $\dot{m}$ represents the mass flow rate of air, ρ denotes the air density, A is the cross-sectional area of the duct, and V signifies the airflow velocity [Munson et al., 2009]. The pressure drop (ΔP) along the length of the duct is given by (2.15).

$$\Delta P = f \times \frac{L}{D} \times \frac{1}{2} \times \rho \times V^2 \tag{2.15}$$

where, f is the Darcy friction factor, L is the length of the duct, D is the hydraulic diameter, ρ is the air density, and V is the airflow velocity [Incropera et al., 2006]. These equations provide a fundamental understanding of airflow dynamics in ducting systems to predict airflow rates based on duct geometry and airflow velocities.

2.2.2 Sensors and Controllers

This section emphasizes the significant advancement brought by integrating sensors into HVAC systems, enhancing the efficiency, reliability, and overall performance of building environmental controls [Dong et al., 2019, Smith and Doe, 2021]. These sensors are crucial for monitoring various parameters, including temperature, humidity, air quality, and airflow, which are essential for precise regulation and the implementation of advanced control strategies. By providing real-time data on these parameters, sensors enable the effective monitoring and management of maintaining optimal indoor conditions, improving occupant comfort, and increasing energy efficiency. With the incorporation of sensors, HVAC system can operate more intelligently, adjusting their performance based on current environmental conditions and occupancy levels.

The most fundamental sensors in an AHU are temperature sensors, which monitor and regulate air temperature at various stages, including supply air, return air, and mixed air streams. These sensors work by continuously measuring the temperature of the air at different points in the AHU [Johnson, 2019b]. For example, supply air temperature sensors ensure that the air being distributed to the occupied spaces is at the desired temperature, while return air sensors monitor the temperature of the air being cycled back into the system. Mixed air sensors, on the other hand, measure the temperature of the air that has been blended from outside and return air before it undergoes further conditioning.

The integration of advanced temperature sensors in AHUs has demonstrated improved precision in temperature control, leading to reduced energy consumption and enhanced occupant comfort [Pereira et al., 2020]. These sensors provide real-time data to the AHU's control system, which adjusts the operation of heating and cooling coils to maintain the set temperature. This precise control minimizes the energy required for heating and cooling by avoiding over-conditioning of the air. Additionally, by maintaining the optimal temperature, these sensors help create a comfortable indoor environment for building occupants.

In Tsai et al. [2016], it is noted that humidity sensors are essential for maintaining indoor air quality and preventing issues such as mold growth and occupant discomfort due to excessive moisture. These sensors measure the relative humidity of air and provide real-time feedback to the control system, which adjusts the operation of humidifiers and dehumidifiers within the AHU accordingly. When the humidity levels are too high, the control system activates the dehumidifiers to remove excess moisture from the air, preventing conditions that promote mold growth and discomfort. Conversely, when humidity levels are too low, the system engages humidifiers to add moisture to the air, ensuring a comfortable and healthy indoor environment. Accurate control of humidity levels has been shown to enhance indoor air quality significantly and mitigate health risks associated with improper humidity.

Furthermore, pressure sensors within HVAC systems play a pivotal role in monitoring and controlling air pressure across ductwork and essential components such as filters and coils. These sensors detect variations in air pressure and transmit real-time data to the control system, which then adjusts the operation of fans and other components accordingly. By maintaining optimal pressure levels, pressure sensors ensure efficient airflow distribution within the HVAC system. This capability is essential for preventing issues such as inadequate ventilation or excessive energy consumption due to overworked components.

Research highlighted in Kim et al. [2014] demonstrates that pressure sensors contribute significantly to system optimization. By enabling precise control over fan speeds based on real-time pressure data, these sensors help reduce energy consumption while enhancing overall system performance. This optimization not only improves operational efficiency but also extends the lifespan of HVAC system by minimizing wear and tear associated with improper airflow and pressure imbalances.

Therefore, pressure sensors are indispensable for achieving energy savings and maintaining the long-term reliability of HVAC systems.

The integration of diverse sensors into AHU systems facilitates the application of advanced control methodologies such as model predictive control (MPC) and adaptive control, by leveraging real-time data to support informed decision-making. Through continuous monitoring, HVAC systems can respond effectively to fluctuations in environmental conditions and occupancy patterns, thereby improving energy efficiency and indoor comfort. For example, studies have explored the use of sensor data combined with machine learning algorithms to forecast and optimise HVAC operations, demonstrating significant potential in reducing energy consumption and enhancing system management [Serale et al., 2018]. In addition, rule-based (RB) approaches remain widely adopted in HVAC fault detection due to their straightforward logic and ease of implementation [Katipamula and Brambley, 2005a], whereas reinforcement learning (RL) has gained attention for its ability to handle complex control and fault scenarios through continuous learning and adaptation [Wei et al., 2017].

Moreover, controllers within AHUs play a critical role in coordinating responses based on sensor inputs, facilitating accurate adjustments to environmental conditions to achieve optimal performance and efficiency. According to research Yan et al. [2018], valve control, actuator management, fan speed regulation, and other control strategies are essential for optimizing HVAC system performance, reducing energy consumption. The valve controller governs the flow of fluids through pipes and coils to regulate temperature and humidity levels, providing precise adjustments based on feedback signals from sensors [Hu and Smith, 2018]. These controllers maintain setpoint conditions by modulating valve positions in response to changes in environmental conditions. In addition, actuator control extends beyond the valves regulation to control a broader range of HVAC system, including dampers and VAV system. These actuators adjust the position, angle, or speed of mechanical components to modulate airflow and ventilation in buildings.

Besides, the fan speed controller is essential for efficiently managing airflow rates and minimizing energy usage. Variable Speed Drives (VSDs) are frequently employed to adjust fan speeds precisely in response to varying load conditions [Li and Zhang, 2019]. Control algorithms play a key role in this process by regulating fan speed based on temperature and pressure differentials across ducts and filters [Weber and Davis, 2017]. Moreover, current research investigates the application of artificial intelligence methods like neural networks and fuzzy logic for adaptive fan speed control, enabling autonomous adjustments according to real-time data [Fumo and Garcia, 2019].

In addition to regulating valve, actuator, and fan speeds, HVAC systems also focus on advancing other control aspects. These include zone control strategies for multi-zone buildings, algorithms for demand response to manage loads, and techniques for detecting and diagnosing faults to monitor system health [Haberl and Fischer, 2016]. Integration with Building Energy Management Systems (BEMS) and Smart Grid technologies further enhances HVAC control capabilities, allowing for demand-side management and grid integration [Jin and Li, 2017]. Consequently, controllers are pivotal in optimizing HVAC system performance, energy efficiency, and occupant comfort. They encompass valve, actuator, fan speed control, and other strategies that drive advancements in adaptive control algorithms, wireless communication technologies, and artificial intelligence methods. Ongoing research in this domain continues to advance HVAC control, creating smarter, more efficient, and sustainable building environments.

2.3 Dynamic Modeling of HVAC Systems

In the context of fault simulation, dynamic simulation modeling using tools such as TRNSYS [Tran and Nguyen, 2021], EnergyPlus [Crawley et al., 2001], and HVAC-SIM+ [Luo et al., 2004] is utilized for gaining deep insights into HVAC systems and enhancing their performance. These advanced tools enable comprehensive analysis of how HVAC systems behave across diverse operational scenarios, encompassing normal operation and various fault conditions. By employing these simulations, accurate predictions can be made regarding system responses to changing environmental conditions, occupant behaviors, and operational parameters such as setpoints and schedules. Additionally, various faults that can occur within HVAC systems, including sensor failures, actuator malfunctions, or component degradation, can be simulated and studied using these tools. Through fault simulation, fault detection and diagnostic algorithms can be developed and validated, ensuring early detection and timely responses to system anomalies.

In Aibing et al. [2020] and Laith and Miklos [2021], TRNSYS is recognized for its adaptability in modeling intricate HVAC systems, integrating components like fans, coils, and valves to simulate system dynamics with precision. It excels in simulating diverse faults by enabling detailed component-level modeling, making it suitable for in-depth fault analysis and scenario testing. This capability allows engineers to predict how HVAC systems will perform under normal operating conditions as well as during fault events, such as sensor failures or component degradation. However, due to its complexity and steep learning curve, TRNSYS may pose challenges for beginners or those new to dynamic simulation tools. Its detailed analytical capabilities require expertise to harness effectively, but its ability to provide comprehensive insights into HVAC system performance and fault behavior makes it a valuable tool for optimizing system design and operation.

On top of that, EnergyPlus [Gunay et al., 2016] becomes famous as a robust software tool renowned for its comprehensive building energy simulation capabilities. It excels in modeling detailed thermal dynamics within buildings and HVAC systems, making it particularly effective for assessing thermal performance and energy consumption under various conditions. Its user-friendly interface and extensive documentation support its widespread adoption in both research and practical applications. However, EnergyPlus can be resource-intensive, requiring significant computational power to execute detailed simulations accurately. In addition, it may not offer the same level of dynamic simulation capabilities or real-time feedback as given in HVAC Simulation Plus (HVACSIM+), which are crucial for applications requiring immediate predictive insights or advanced control strategy development in HVAC systems. Therefore, while it is powerful for detailed energy simulations, its limitations in real-time dynamics and responsiveness may make it less suitable for certain advanced HVAC applications.

In Galler [2020] and Bushby et al. [2001], HVACSIM+ is recognized for its robust capabilities in dynamic modeling and fault simulation within HVAC systems. This software tool allows engineers and researchers to simulate complex system behaviors under varying operational conditions, including normal operations and fault scenarios. By integrating detailed component-level modeling of HVAC systems, such as fans, valves, and control algorithms, HVACSIM+ enables accurate predictions of system responses to environmental changes and component failures. This capability is crucial for developing and validating advanced fault detection and diagnostic algorithms, thereby enhancing system reliability and efficiency. Compared to other simulation tools, HVACSIM+ offers a user-friendly interface and extensive customization options, making it a preferred choice for comprehensive HVAC system analysis and optimization.

Moreover, accurate selection of system parameter setpoints is essential in HVAC dynamic modeling, as these values directly influence thermal performance, energy consumption, and fault behavior. Previous studies have reported typical ranges for parameters such as supply air temperature, chilled water temperature, duct static pressure, and zone setpoints, which are widely adopted in simulation frameworks. For instance, the ASHRAE RP-1312 project maintained a supply air temperature of 55°F (12.77°C), room temperature at 70°F (21°C) during occupancy, and regulated duct static pressure at 1.4 PSI by controlling the supply fan speed [Wen and Li, 2011b]. Gao et al. [2023] used a chilled water supply-return temperature difference of 5°C and set the return fan to operate at 80% of the supply fan speed. Similarly, Zhang and Hong [2016, 2017] implemented chiller setpoints between 6°C and 8°C and enabled economizer control below 18°C outdoor air temperature. The parameter values selected in this study for HVACSIM+, as presented in Chapter 3, follow similar ranges and are aligned with these commonly used standards. This supports the validity of the chosen setpoints in Tables 3.1 and 3.2, ensuring consistency with previous work while meeting the specific objectives of dynamic simulation and operational fault analysis.

2.4 HVAC Faults Detection System

This section provides an overview of current methods for fault detection and diagnosis (FDD) in HVAC systems. It covers three main approaches such as controller-based methods (2.4.1), statistical methodologies (2.4.2), and artificial intelligence (AI)-based techniques (2.4.3). The controller-based methods utilize built-in AHU capabilities and advanced sensors to monitor and regulate key parameters. Statistical methodologies rely on historical data and apply models such as regression analysis and principal component analysis (PCA) to identify anomalies. Meanwhile, AI-based techniques employ machine learning and deep learning algorithms, including neural networks, convolutional neural networks, and support vector machines (SVM), for detecting complex fault patterns. These approaches collectively represent the forefront of HVAC fault detection systems.

2.4.1 AHU Controller Approaches

Extensive research has been dedicated to analyzing HVAC operational faults through controller-based approaches [Lymperopoulos et al., 2020]. These methods utilize advanced control strategies and systems to enhance HVAC performance by leveraging real-time data for continuous monitoring. Feedback control mechanisms dynamically adjust system operations, ensuring both efficiency and comfort. This continuous adjustment helps in maintaining optimal performance levels under varying conditions. However, despite these advancements, challenges such as sensor inaccuracies, control command errors, damper malfunctions, and coil valve blockages remain prevalent due to environmental conditions and unforeseen system interactions [Moradi et al., 2016]. Such faults can drastically reduce energy efficiency, resulting in significant energy waste.

In Venkatasubramanian et al. [2003], another controller-based fault detection method is introduced, which employs control algorithms and sensors to monitor and diagnose faults in HVAC systems by comparing real-time data against expected system behavior. This method also utilizes feedback from system controllers to identify deviations that indicate faults, thereby enabling real-time monitoring and prompt fault detection. A notable advantage of this approach is its ability to leverage existing control infrastructure, minimizing the need for additional hardware. However, the effectiveness of controller-based fault detection is highly dependent on the quality and reliability of the sensors used. Additionally, the implementation and maintenance of these systems can be complex, especially in environments with intricate control strategies.

Different from the previously mentioned approaches, in Venkatasubramanian et al. [2003], a controller-based fault detection and diagnosis (FDD) method is introduced, utilizing control algorithms and sensors to monitor system performance and identify deviations from expected behavior to detect potential faults. This method leverages the control logic embedded within AHU controllers to detect and diagnose faults in real-time. By analyzing control signals, setpoints, and feedback from sensors, these systems can identify issues such as actuator failures, control loop oscillations, or abnormal system behavior. The primary advantage of this approach is its ability to integrate with existing control infrastructure, thereby minimizing the need for additional hardware and facilitating immediate fault detection. However, the effectiveness of controller-based FDD is heavily reliant on the quality and accuracy of the sensors used. Additionally, the complexity of implementing and maintaining these systems can be significant, particularly in environments with intricate control strategies.

Furthermore, the implementation of advanced control strategies, such as fuzzy logic controllers and neural network-assisted systems, has demonstrated significant potential in enhancing HVAC system efficiency and performance [Guo et al., 2007]. These advanced strategies are critical for ensuring that HVAC systems not only operate effectively but also meet the dual objectives of comfort and energy efficiency [Khan et al., 2020]. However, despite their benefits, these advanced control strategies present notable challenges in the area of fault detection. Fuzzy logic controllers, for instance, are often complex to design and scale, relying heavily on accurate input data. Additionally, the setup and maintenance of these systems demand specialized expertise, and as the system expands, managing the fuzzy rules becomes increasingly burdensome. In practice, these controllers do not inherently adapt to new data, necessitating manual updates to maintain their effectiveness.

Moreover, advanced control algorithms such as adaptive control and predictive control can further enhance the sensitivity and specificity of fault detection by dynamically adjusting controller parameters in response to changing system dynamics [Ahmad et al., 2020]. It adjusts system parameters in real-time to maintain optimal performance despite variations in the system or environment, whereas predictive control algorithms use models to predict future system behavior and adjust controls proactively to minimize faults. These algorithms can significantly improve fault detection capabilities by anticipating and mitigating issues before they become critical. However, they also come with disadvantages such as high computational requirements and the need for accurate models of the system dynamics. The complexity of implementing these algorithms and ensuring their robustness in the face of real-world uncertainties can also pose significant challenges.

Besides, model-based fault detection and diagnosis (FDD) methods, which utilize mathematical models to represent the expected behavior of system components under normal operating conditions, are proposed in Cui et al. [2019]. By continuously comparing real-time data from the HVAC system with these model predictions, discrepancies can be identified that indicate potential faults. This approach allows for precise fault identification and diagnosis, enabling timely interventions to maintain system performance and reliability. One of the main advantages of these methods is their ability to detect faults early and accurately, thereby reducing downtime. Additionally, they can be tailored to specific HVAC systems, improving effectiveness in diverse operational environments. However, developing and calibrating accurate models can be time-consuming and require significant expertise. Moreover, the performance of model-based FDD methods is highly dependent on the quality of input data, which may necessitate frequent updates and maintenance to ensure ongoing accuracy and reliability.

2.4.2 Statistical Methodologies

Through extensive research and development over time, statistical methods are often preferred over controller-based methods for fault detection in HVAC systems because they can analyze large datasets to identify patterns and anomalies without relying on pre-defined control logic, making them more adaptable to different systems and capable of detecting a wider range of faults. Statistical process monitoring (SPM) methods have been extensively applied in the field of HVAC systems to enhance fault detection and diagnostics [Holland and Howell, 2018]. These methods involve the use of statistical techniques to analyze historical and real-time data, identifying patterns and anomalies that may indicate the presence of faults.

By leveraging techniques such as regression analysis [Lee et al., 2014], principal component analysis (PCA) [Jiang et al., 2009], and control charts, it can effectively monitor the performance of HVAC systems and detect deviations from normal operating conditions. One significant advantage of SPM is its ability to handle large datasets, enabling comprehensive analysis and robust fault detection without relying on pre-defined control logic. Additionally, SPM methods are relatively straightforward to implement and do not require extensive modifications to existing control systems. However, its effectiveness is heavily dependent on the quality and quantity of the available data. While it can identify that a fault has occurred, it may not always provide specific insights into the root cause of the fault, necessitating further investigation.

In Ahn et al. [2020], time-series analysis is a powerful method for detecting and diagnosing faults in HVAC systems by analyzing data points collected over time. This method leverages techniques such as autoregressive models, moving averages, and seasonal decomposition to identify patterns, trends, and anomalies in the operational data. One key advantage of time-series analysis is its ability to model temporal dependencies and predict future system behavior based on historical data. This capability allows for early fault detection and proactive maintenance, thereby improving system reliability and efficiency. However, the effectiveness of time-series analysis depends on the quality and granularity of the data. High-quality, high-frequency data is essential for accurate modeling and fault detection. Additionally, it requires explicit modeling of temporal dependencies and may not capture complex, nonlinear relationships in the data effectively.

In addition, Bayesian Fault Diagnosis for HVAC systems which uses Bayesian inference to assess fault presence probabilistically by updating likelihoods based on real-time sensor data is proposed [Li et al., 2019]. This method integrates prior knowledge with current observations, providing a flexible and robust approach to fault detection and diagnosis. Its ability to handle uncertainty and incorporate prior information enhances fault detection accuracy, although it requires significant computational resources and intricate model development. However, challenges still remain, such as accurately specifying prior distributions and obtaining sufficient data for reliable fault diagnosis in environments with limited data availability.

2.4.3 Artificial Intelligence Based Techniques

In recent years, researchers have increasingly turned to machine learning to enhance fault detection and diagnosis in HVAC systems. Supervised learning algorithms have been effectively applied to classify sensor data and diagnose faults [Liu et al., 2019]. These algorithms leverage labeled training data to learn the relationships between sensor readings and specific fault conditions, enabling accurate and efficient fault classification. On the other hand, unsupervised learning methods, including clustering and anomaly detection algorithms, have been employed to identify patterns and anomalies in sensor data without the need for labeled training data [Zhang et al., 2021]. These methods are particularly valuable in situations where labeled data is scarce or unavailable, allowing for the detection of novel or unexpected faults. The ability of machine learning algorithms to automatically learn from data and adapt to changing conditions makes them highly effective for fault detection and diagnosis in dynamic environments like HVAC systems.

In Lee et al. [1996], fault diagnosis of an air-handling unit (AHU) using artificial neural networks (ANNs) leverages machine learning techniques is proposed to effectively identify and diagnose faults by analyzing complex patterns in sensor data. In this method, the ANNs is trained on historical data to recognize normal and faulty operating conditions, enabling them to predict and detect faults in real-time. The primary advantage of using ANNs for fault diagnosis is their ability to model nonlinear relationships and interactions among various system components, which traditional statistical methods may fail to capture. This leads to improved accuracy in fault detection and the potential for early identification of issues, thereby enhancing system reliability and efficiency. However, the use of ANNs also has disadvantages, including the need for large amounts of labeled training data and significant computational resources for model training. Additionally, the black-box nature of ANNs can make it challenging to interpret the results and understand the underlying reasons for fault predictions.

Additionally, subsystem-level fault diagnosis of AHU using general regression neural networks (GRNN) is proposed to detect and diagnose faults within specific components. In Lee et al. [2004], GRNNs is designed to handle nonlinear relationships and can provide accurate predictions even with limited training data. A key benefit of using GRNNs for subsystem-level fault diagnosis is their ability to rapidly learn from data and deliver high precision in detecting faults. However, it also presents some disadvantages, such as the need for high-quality input data to achieve reliable performance. Moreover, the training process can be computationally intensive, and the results may be difficult to interpret due to the complexity of model.

In the domain AHU, an advanced fault detection and diagnosis (FDD) strategy integrates artificial neural networks (ANNs) with wavelet analysis to elevate fault detection precision and reliability [Fan and Guo, 2010]. In this hybrid method, wavelet analysis is employed initially to preprocess sensor data, extracting important features that enable ANNs to classify faults effectively. It offers notable advantages, including improved fault detection accuracy and the capacity to capture transient faults often overlooked by conventional methods. Nonetheless, its implementation demands substantial computational resources for both wavelet transformation and ANN training. Overall, in ANN-based fault detection, challenges such as the complexity of feature extraction, selection, and scaling from raw sensor data, as well as generalizing findings across different HVAC systems were encountered. Thus, ensuring appropriate feature extraction and scaling is essential for optimal performance in HVAC fault detection and classification using ANNs.

A novel approach for diagnosing multiple faults in bearings combines weighted permutation entropy (WPE) and an improved support vector machine (SVM) ensemble classifier is proposed in [Zhou et al., 2018]. This method uses WPE to extract features from vibration signals, capturing the complexity and irregularity of the signal data effectively. These features are then fed into an enhanced SVM ensemble classifier to improve fault classification accuracy. This method improves the reliability of fault diagnosis in bearings, leading to better maintenance decisions and reduced downtime. However, the process of calculating WPE can be computationally intensive, potentially requiring significant processing power and time. Most importantly, focusing on only a few common faults may not adequately capture the diversity of real-world HVAC faults, potentially compromising the robustness and comprehensiveness of the diagnosis system.

Another hybrid approach, utilizing random forest (RF) combined with extreme gradient boosting (XGBoost), has been applied in fault detection and diagnosis (FDD) systems [Chakraborty and Elzarka, 2019, Zhang et al., 2018]. In this system, RF prioritizes feature importance ranking, while XGBoost categorizes specific fault types. However, this method faces challenges, including high computational complexity due to the sequential construction of decision trees. During training, each subsequent tree is optimized to rectify errors from its predecessors, demanding significant processing power. Additionally, an FDD strategy based on Classification and Regression Trees (CART) with an automatic feature extraction method was proposed by Yan et al. [2016]. Compared to other data-driven ANNs and SVM models, it is valued for their interpretability, generating a series of if-then rules organized in a binary tree format. Despite their effectiveness, certain HVAC faults, such as heating coil valve leakage and exhaust air dampers stuck in a fully closed position, were not fully addressed by these optimized rules.

An unsupervised feature selection method for automatic fault detection and diagnosis (AFDD) in HVAC systems is proposed [Yuwono et al., 2015]. This approach addresses redundancies in sensory and control signals by employing Ensemble Rapid Centroid Estimation (ERCE) to identify key features based on the relative entropy between low- and high-frequency features. The ASHRAE-1312-RP dataset, containing 49 days of various faults, was used for experiments. Results indicated that the selected features had fewer redundancies compared to manual selection, but the lack of validation using simulated data is a significant limitation. It could impact the ability of model to generalize to new data, potentially resulting in incomplete representation of real-world variability and complexity. More importantly, inaccurate or inadequate feature selection can undermine the fault detection process, reducing the reliability and effectiveness of the FDD system.

In Yanab et al. [2022], a novel decentralized Boltzmann-machine-based approach for diagnosing faults in HVAC air handling units (AHUs) is introduced. This method addresses challenges related to correlated fault indicators and computational demands by leveraging less affected residuals as indicators and implementing a decentralized voting mechanism for efficient sensor fault localization. Experimental evaluations utilize ASHRAE Project 1312-RP data, comparing AHU-A with faults to AHU-B operating under normal conditions across multiple seasons. However, this study is limited in its ability to test performance on simulated HVAC operational data. In practice, conducting comprehensive testing across different datasets could substantially enhance fault detection robustness, providing deeper insights into performance under varied operating conditions and diverse fault scenarios.

The application of deep belief networks for detecting HVAC faults in air-conditioning systems, aimed at enhancing building energy conservation is introduced in recent research [Boureau and LeCun, 2008, Lee et al., 2019]. While these networks excel in learning intricate patterns through layer-wise training, they may encounter challenges in effectively capturing the complex spatial and temporal relationships inherent in HVAC data. Furthermore, this study focus on only five specific faults may not adequately represent the diverse spectrum of potential issues, including human errors, unexpected device malfunctions, and sensor drift. Therefore, there is a critical need for further investigation into a broader range of AHU faults to ensure that diagnostic models are robust and accurate across various real-world scenarios.

Recently, there has been a growing interest in using one-dimensional convolutional neural networks (1D-CNNs) to analyze raw sensor time series signals from HVAC systems. These networks are valued for their strong classification capabilities, automatic feature extraction, and computational efficiency [Li et al., 2021, Liao et al., 2021]. Validation typically involves using fault datasets from standard HVAC system configurations, such as the chiller dataset from ASHRAE research project 1043 (RP-1043). While 1D-CNNs excel in achieving high accuracy, their effectiveness is limited by their reliance on a single simulation dataset to evaluate model generalization. Moreover, the applicability of 1D-CNNs is reduced in scenarios involving multiple HVAC fault classifications, as they primarily focus on temporal patterns and may not fully capture the complex spatial interdependencies within HVAC systems.

Recent developments in HVAC fault detection have explored the use of techniques such as Gramian Angular Fields (GAF) to convert time-series data into spatial formats, thereby enhancing the representational power of input features for classification tasks. When combined with convolutional neural networks (CNNs), as demonstrated in the GAF-2DCNNs approach proposed by Gao et al. [2023], this methodology contributes to improved performance in deep learning-based fault diagnosis. The framework also incorporates parameter pruning to reduce model complexity and employs layer-wise relevance propagation (LRP) to improve interpretability of the decision-making process. The proposed model was evaluated using 31 fault scenarios simulated from real HVAC systems, and the results highlight its effectiveness in accurately identifying a wide range of fault conditions.

However, focusing solely on 47 AHU operational parameters may overlook certain complex system behaviours, and the added complexity introduced by pruning and layer-wise relevance propagation (LRP) during 24-hour training cycles warrants careful consideration. The selection of these 47 parameters was informed by prior literature and engineering relevance, with an emphasis on variables commonly used in AHU fault detection tasks, including temperature, pressure, flow rate, damper position, and actuator state. Although there is no universally established threshold for the optimal number of input features in this context, the selected set aims to strike a balance between comprehensive system representation and computational feasibility. In practise, the implementation requires rigorous evaluation across diverse fault conditions and standard operating modes to minimise false positives. Furthermore, assessing the generalisability of the proposed method through comparisons with alternative machine learning-based diagnostic frameworks and benchmark datasets is essential to ensure robustness and applicability. Despite ongoing challenges, continuous research continues to refine modelling, simulation, and detection methodologies to improve the reliability and accuracy of HVAC fault detection systems.

In addition, recent literature continues to expand on the role of AI in HVAC fault detection and diagnosis. A comprehensive review by Bi et al. [2024] systematically analyzed AI-based FDD methods, highlighting prevailing trends in supervised, unsupervised, and hybrid approaches, as well as emerging challenges such as data scarcity, generalizability of models. This work reinforces the need for robust and adaptable AI techniques that can operate effectively under diverse fault conditions, and supports the direction of this study in developing hybrid deep learning-based frameworks.

2.5 Summary

In summary, this chapter has reviewed the key components and operational characteristics of HVAC systems, with a particular focus on air handling units (AHUs), sensor and controller infrastructures, and their roles in maintaining indoor environmental conditions. It further examined dynamic modelling tools used for simulating HVAC operations and faults, as well as existing fault detection and diagnosis (FDD) methodologies, including controller-based, statistical, and artificial intelligence-driven approaches. Although prior studies have contributed substantially to the advancement of FDD techniques, many face limitations in their ability to simulate a wide range of fault conditions or assess diagnostic performance systematically. While real-world validation remains valuable, this work focuses on simulation-based development due to limited access to operational datasets with labelled fault scenarios, and the need for controlled environments to rigorously evaluate model performance. These considerations highlight the importance of simulation frameworks in advancing scalable and adaptable FDD methods. The insights gained from this review form the basis for the simulation-based fault detection framework developed in the subsequent chapters.

Chapter 3

HVAC Dynamic Modeling and Fault Simulation

This chapter introduces a dynamic modeling and fault simulation framework based on HVACSIM+ to support the development of data-driven fault detection and diagnosis (FDD) methods in HVAC systems. As a simulation environment, HVACSIM+ enables detailed representation of system behavior by capturing complex component interactions, control logic, and realistic fault conditions under both normal and faulty operations. The framework involves configuring system parameters, simulating a range of fault types, and generating labelled datasets suitable for training machine learning models. To ensure the validity of the simulated data, results are benchmarked against the ASHRAE RP-1312 dataset, confirming the accuracy of normal operating conditions. The model is then extended to simulate nine representative faults, enabling the generation of a comprehensive and reliable fault dataset. This foundation supports the data-driven approaches evaluated in later chapters and contributes to the development of effective FDD solutions.

3.1 Background Studies

Dynamic simulation models for HVAC systems play a crucial role in advancing fault detection and optimizing energy efficiency. These models allow for a thorough exploration of system behaviors across various operational scenarios, providing valuable insights into potential issues such as sensor inaccuracies and actuator malfunctions. According to Aibing et al. [2020], Laith and Miklos [2021], simulating these faults virtually refines early detection strategies, thereby enhancing system reliability and reducing downtime. Moreover, these simulations enable the prediction of energy consumption patterns, assessment of HVAC configurations, and implementation of effective energy-saving measures. Ultimately, the use of dynamic simulation models supports precise fault detection and strategic energy optimization in HVAC systems, contributing to enhanced operational performance and sustainability in building environments.

To study HVAC operational faults, EnergyPlus has been proposed as a building performance simulation tool [Gunay et al., 2016]. This platform facilitates the simulation and analysis of complex building energy systems, accurately predicting thermal comfort, energy consumption, and overall system performance. By focusing on aspects such as occupancy patterns and the utilization of building features like windows, blinds, lighting, and clothing in office settings, the study aims to inform decision-making and optimize design strategies. However, it currently lacks specific focus on operational faults within HVAC systems. Integrating these faults into simulations could provide crucial insights into energy usage patterns and opportunities for enhancing system reliability and efficiency.

Additionally, by harnessing the advanced features of EnergyPlus for building simulation and HVAC system modeling, a dynamic system modeling and fault simulation framework has been implemented [Zhang and Hong, 2016, 2017]. This framework enables accurate representation of various faults occurring in HVAC components, facilitating a thorough assessment of their impact on both building energy consumption and occupant comfort levels. While it does provide basic fault modeling capabilities, it lacks detailed analysis of operational HVAC faults, detection, and diagnosis. This presents a significant opportunity for enhancement, particularly through the integration of specialized features tailored for fault detection and diagnosis (FDD) systems. By augmenting these tools with comprehensive capabilities to gather precise operational fault data for detection and diagnosis, the effectiveness of fault detection systems in HVAC applications could be substantially improved.

In the domain of HVAC system simulation, HVACSIM+ [Bushby et al., 2001, Galler, 2020] offers distinct advantages for modeling dynamic system behaviors and simulating operational faults. Compared to TRNSYS [Gunay et al., 2016] and EnergyPlus [Zhang and Hong, 2016, 2017], which are more suited for whole-building energy analysis, it provides greater detail at the component level, including control systems. This capability supports the creation of varied fault scenarios in a controlled environment, enabling the development and testing of fault detection models using consistent and labelled datasets.

This Chapter presents a comprehensive analysis of HVAC systems, focusing on dynamic modeling and operational fault simulation using HVACSIM+, as discussed in Section 3.2. Additionally, Subsection 3.2.1 provides the pseudocode for the HVAC control algorithm based on predefined inputs. In Subsection 3.3, it explores nine major types of HVAC operational faults considered in this study, whereas Subsection 3.2.2 discusses the desired operational and building parameters. Furthermore, Section 3.2.4 presents a comprehensive validation process, comparing the dynamic behavior of HVAC system parameters, including time series data and fault scenarios generated by HVACSIM+, with benchmark ASHRAE experimental data. Finally, Subsection 3.4 assesses HVAC operational faults by analyzing "Normal" and "faulty" conditions, highlighting the importance of using simulated data for advanced fault detection and diagnosis systems developed in Chapters 4, 5, and 6.

3.2 HVAC System Dynamic Simulation Model

This section provides an in-depth exploration of the HVAC system dynamic model, emphasizing critical aspects including the step-by-step control algorithm pseudocode (3.2.1), simulation of HVAC operational faults (3.3), and considerations for design parameters (3.2.2). Firstly, the dynamic model configures an HVAC system within a single-story building using HVACSIM+, with four rooms each covering 400 square meters, as presented in Figure 3.1. This setup ensures comprehensive exposure to external heat loads, which is essential for conducting a detailed analysis of operational faults. Moreover, essential components such as coils, valves, dampers, and outlets are interconnected via ducts, detailed in Section 2.2 of Chapter 2. The embedded sensors continuously monitor critical parameters like pressure, temperature, humidity, and airflow, enabling a thorough exploration of HVAC system behaviors and fault detection mechanisms. With this setup, the dynamic model follows a step-by-step approach outlined in the following Section 3.2.1.

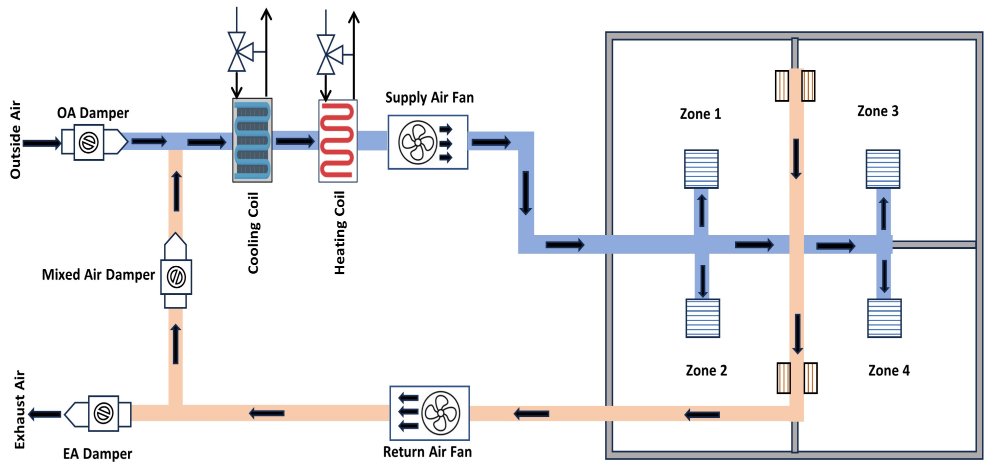


Figure 3.1: Block Diagram of Four Zone HVAC System

3.2.1 Control Algorithm Pseudocode

In this section, detailed insights into the operational procedures of the proposed integrated framework for HVAC system dynamic modeling, fault simulation, and detection are provided by the Pseudo algorithm 1.2 from Section 1.3. In this algorithm, key inputs are target zone temperature, maximum room occupancy, temperature tolerance range, and HVAC system capacities, which are crucial for decision-making. Firstly, it is initiated by setting these inputs, establishing the framework for subsequent processes. It then retrieves current environmental data through the *RetrieveCurrentTemperatureAndOccupancy* function [Tun et al., 2023b], ensuring real-time updates on zone conditions using temperature and occupancy sensors.

$$\begin{aligned} \text{COOLING\_POWER} = (&\text{current\_Temperature} - \text{ZONE\_TEMPERATURE}) \\ &\times \text{SET\_COOLING\_POWER} \end{aligned} \tag{3.1}$$

$$\begin{aligned}\text{HEATING\_POWER} = (&\text{ZONE\_TEMPERATURE} - \text{current\_Temperature}) \\ &\times \text{SET\_HEATING\_POWER}\end{aligned} \tag{3.2}$$

The core function of algorithm, *TemperatureControl*, starts HVAC system operations based on real-time temperature data. When the current temperature exceeds the desired setpoint plus the tolerance range, the algorithm calculates the necessary cooling power using the equation (3.1). This calculated power is then applied to lower the temperature. Conversely, if the current temperature drops below the setpoint minus the tolerance range, the algorithm computes the required heating power using the equation (3.2), which is then applied to raise the temperature. If the current temperature falls within the tolerance range of the setpoint, no additional heating or cooling is applied, ensuring efficient HVAC operation that maintains optimal comfort levels while conserving energy.

In application, understanding the HVAC control algorithm is crucial for optimizing HVAC system performance. It provides insights into how inputs such as desired temperature and occupancy impact system operation, enabling operators to make informed decisions that improve energy efficiency and ensure occupant comfort. Moreover, being familiar with the algorithm supports efficient troubleshooting and fine-tuning of HVAC systems, ultimately enhancing their overall reliability and functionality.

3.2.2 Key Parameters in Building HVAC Systems

To develop an accurate HVAC dynamic model, as described in Section 3.2, it is important to define detailed parameters that enhance system efficiency. As illustrated in Figure 3.1, The HVAC system setups firstly with components discussed details in Section 2.2, operates and refines through parameter adjustments outlined in 3.2.1. To effectively simulate HVAC systems, accurately defining parameters that determine building dimensions, thermal properties, and occupant-related factors is essential. These details directly influence heat transfer dynamics within the building, enabling realistic indoor environment simulations and optimizing energy efficiency strategies for heating, ventilation, and air conditioning. The key building parameters considered in the developed dynamic model is given in Table 3.1, offering insights into the physical and environmental characteristics of the simulated building.

In Table 3.1, it outlines dimensions such as the length and width of the building (40 m x 40 m) and each room (20 m x 20 m), emphasizing a single-story configuration with four rooms/zones. Key architectural features like floor-to-ceiling height (3.5 m) and window-to-floor ratio (35%) are specified, alongside occupant density (0.15 person/sqm), lighting power (20 W/sqm), and equipment power (12.5 W/sqm). Additionally, thermal properties crucial for energy performance, such as shading coefficient (SC=0.95) and U-values for windows (6.21 W/sqmK), roof (0.795 W/sqmK), and above-grade walls (3.778 W/sqmK), are detailed. These parameters collectively define the physical attributes and thermal characteristics necessary for accurate simulation and analysis of the building energy consumption and thermal comfort performance.

Description	Building Parameter
L x W of building	40 m x 40 m
Number of floor, rooms / zones	Single storey, 4
L x W of each room	20 m x 20 m
Floor to ceiling height	3.5 m
Window to floor ratio	35 %
Occupants	0.15 person/sqm
Lighting power	20 W/sqm
Equipment power	12.5 W/sqm
Shading coefficient and U value of the window	SC=0.95, U=6.21 W/sqmK
U value of the roof	0.795 W/sqmK
U value of the above grade wall	3.778 W/sqmK

Table 3.1: Building Design Parameter

Additionally, crucial aspects of HVAC system configuration and operation are outlined by the parameters detailed in Table 3.2. The ability of the developed dynamic system to meet thermal demands efficiently is governed by "HVAC System Capacity" and "Chiller Coefficient", ensuring optimal performance. Parameters such as "Chilled Water Temperature" and "Supply Air Temperature Set Point" define the internal thermal conditions, maintaining comfort and efficiency levels. Besides, Control settings, including AHU with VAV and VSD, dynamically regulate airflow and pressure, adapting to varying occupancy and environmental conditions. Energy efficiency benefits from the inclusion of Economizer, utilizing outdoor air when suitable, alongside specific temperature differentials for chilled and condensed water that ensure effective heat exchange. Thus, each parameter plays a pivotal role in shaping HVAC system performance, effectively balancing operational needs with energy conservation goals.

Therefore, the parameters presented in Tables 3.1 and 3.2 provide the essential foundation for developing a reliable and accurate dynamic model of HVAC systems. These parameters describe the key physical characteristics of the building and the operational settings of the HVAC system, including aspects such as building dimensions, thermal properties, occupancy levels, and control configurations. Accurately defining these parameters is critical for simulating realistic environmental conditions and system behavior.

Description	**System Parameter**
HVAC System Capacity	Auto Sizing
Chiller coefficient	4.45
Chilled water temperature	7 deg C
Supply/return chilled water temperature different	5 deg C
Supply condensed water temperature	30 deg C
Supply/return condensed water temperature different	5 deg C
AHU fan power	0.000826 W/cfm
Supply air temperature set point	12.77 deg C
Supply air duct static pressure	348.5 pa
Zone heating and cooling point	21 deg C and 22 deg C
Control	AHU with VAV, VSD
Cooling coil	Used
Heating Coil	Not used
Economizer	Enable, 18.32 deg C

Table 3.2: HVAC System Parameter

The selection of approximately 25 building and system parameters represents a focused and practical approach to dynamic modeling. These parameters were chosen based on their relevance and direct impact on thermal comfort, energy consumption, and overall system performance, as supported by existing literature. Rather than attempting to include all possible variables, the study concentrates on those that are measurable, meaningful, and aligned with the objectives of fault simulation and detection. This approach maintains a balance between model accuracy and computational efficiency, ensuring that the simulation framework can effectively support the generation of high-quality data for fault analysis. As a result, the model provides a suitable basis for evaluating HVAC performance, detecting operational faults, and informing strategies for improved system efficiency and building sustainability.

3.2.3 Execution of Dynamic Simulation Model

After completing the HVAC system setup and parameter configuration in Section 3.2.2, the next step, as shown in the proposed fault simulation and detection framework in Figures 1.1 and 1.2 of Section 1.3, is to initialize the simulation environment in HVACSIM+. This includes accurately setting indoor and outdoor temperatures, accounting for solar heat gains, and adjusting humidity levels. Furthermore, ventilation was ensured by implementing a minimum outdoor air damper opening of 40%. The economizer control activated when the outdoor air temperature fell below 18°C, maintaining a supply air temperature of 12.77°C. The fan speeds were adjusted to sustain duct pressure, with the return fan operating at 80% of the supply fan speed. These parameters are fundamental as they provide the initial conditions necessary for the HVAC system simulation to accurately model real-world conditions.

Following the initialization phase, the baseline simulation runs continuously for 24-hour periods, aligned with occupancy schedules from 6:00 AM to 6:00 PM in summer conditions. Throughout occupied hours, the target room temperature was maintained at 21°C, with airflow adjustments ranging from 200 to 1000 CFM across various zones. Data are sampled from various type of sensors at one-minute intervals, generating 1440 data points per sensor across 194 sensor locations. Throughout the simulation, the system calculates heat transfer characteristics, including heat exchange through components such as walls, windows, and internal sources (Q_{wall}, Q_{window}, Q_{internal}).

These parameters collectively contribute to the total heat load (Q_{total}) affecting the indoor environment. By adjusting the indoor temperature (T_{indoor}) based on these computed heat flows, the simulation provides insights into the dynamic thermal behavior within the simulated space. Essentially, the process of initializing the simulation environment and conducting the baseline simulation is important for developing an accurate HVAC dynamic system model. It facilitates a comprehensive analysis of thermal dynamics, thereby generating a reliable dataset cost-effectively, optimizing energy efficiency through the use of dataset, and improving overall system performance in various environmental conditions.

In this study, sensor inaccuracies refer exclusively to faults introduced within the HVACSIM+ simulation environment. As the dataset was entirely generated through simulation, no physical sensors were involved. Faults such as signal bias, drift, and measurement failure were systematically embedded to reflect realistic anomalies commonly encountered in HVAC systems. This controlled setup enabled detailed analysis of system responses to sensor faults without the complexities associated with hardware deployment or calibration.

3.2.4 ASHRAE Benchmark Validation

This section presents a detailed validation of the HVACSIM+ simulation model, which forms a key contribution of this study and is described in Section 3.2.3. The validation is carried out through a comparative analysis with the ASHRAE RP-1312 experimental dataset, a well-established benchmark widely recognised in the HVAC domain for accurately representing real-world system behaviour [Wen and Li, 2011a].

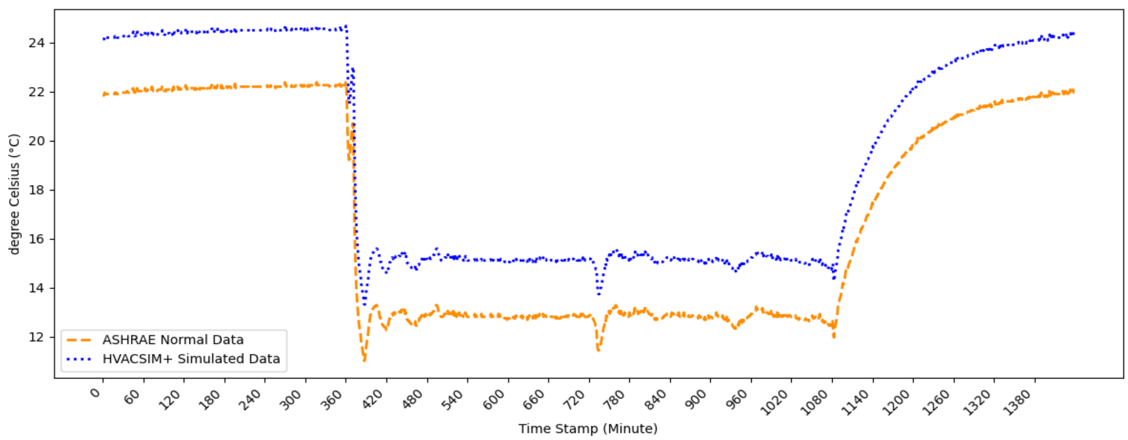


Figure 3.2: Supply Air Temperature (ASHRAE vs Simulation)

In this study, the ASHRAE dataset is used specifically to validate the HVACSIM+ model under normal operating conditions, ensuring consistency with industry standards and confirming the ability of model to reproduce realistic system dynamics. While the ASHRAE data provides a strong reference for normal performance, it does not account for the full range of fault conditions encountered in practical applications. To address this limitation, the validated HVACSIM+ model is extended to simulate nine representative operational fault scenarios. This approach enables the development of a reliable and comprehensive dataset, supporting fault detection research while overcoming the cost, complexity, and practical limitations associated with collecting large-scale real-world data, as discussed in Section 2.4.3 of Chapter 2.

Furthermore, the validation process plays a key role in confirming that the design parameters outlined in Section 3.2.2 are representative of real-world operating conditions. As part of the parameter optimization process illustrated in Figure 1.1 and guided by the pseudocode presented in 1.2 of Section 1.3, the initial parameter values are refined through an iterative approach. Adjustments are made when discrepancies are observed between the simulated results and benchmark data, ensuring improved alignment with expected system behaviour. By iteratively refining these parameters based on validation outcome, the ability of HVACSIM+ model and reliability in simulating dynamic system behavior under various conditions are progressively enhanced. This approach leads to a more robust and accurate representation of HVAC system performance, thereby improving the overall effectiveness of the simulation framework.

For validation, key parameters including supply air temperature, cooling coil temperature, supply and return air flow rates, fan speed, and power consumption are selected due to their significant influence on HVAC system performance and efficiency. As shown in Figures 3.2 and 3.3, comparisons are carried out between the simulated supply air and cooling coil temperatures in HVACSIM+ and the corresponding ASHRAE experimental data. The temporal variations showed significant similarities, with peaks and troughs closely aligned in both datasets, indicating the accurate representation of temperature dynamics by the simulation model.

Moreover, the evaluation of supply air flow rate, as shown in Figure 3.4, was conducted continuously due to its significant influence on overall HVAC system performance. The simulation results generated in Section 3.2.3 demonstrated consistent patterns of oscillation that closely matched those observed in the ASHRAE benchmark data [Wen and Li, 2011a], particularly during periods of system regulation or changes in environmental conditions. This close alignment underscores the capability of the simulation model to accurately replicate supply air flow dynamics, which are essential for ensuring adequate ventilation and maintaining thermal comfort in occupied zones.

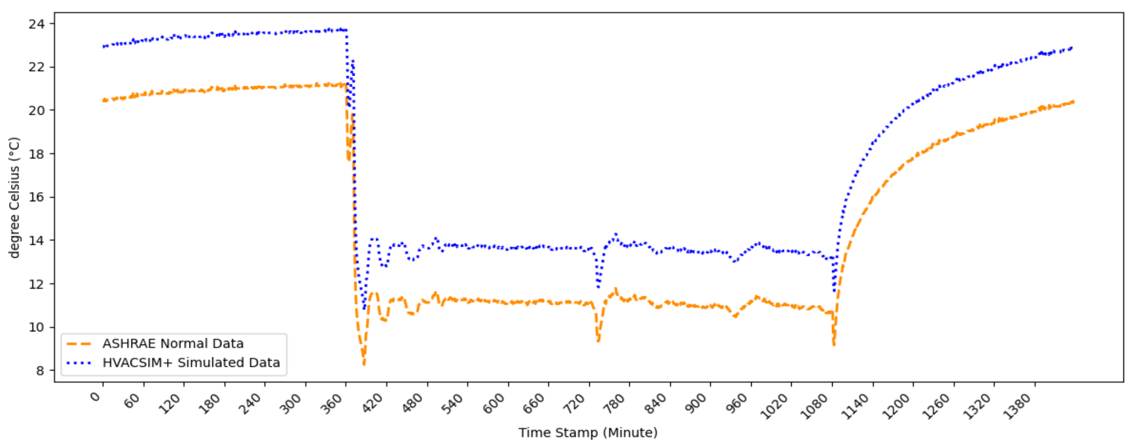


Figure 3.3: Cooling Coil Temperature (ASHRAE vs Simulation)

Additionally, the evaluation also considered fan speed, as shown in Figure 3.5, due to its critical impact on system efficiency and airflow distribution. The simulation accurately replicates the fan speed response to variations in system load and operating conditions, demonstrating the accuracy of the fan model. Although minor Variations are present, the model accurately captures fan speed fluctuations, maintaining airflow rates and system performance that align closely with both simulated and benchmark data. Besides, the validation extended to fan power consumption, as illustrated in Figure 3.6. Results indicate that simulated fan power consumption closely reflects the actual data from ASHRAE, reinforcing the capability of simulation model to provide reliable energy requirement.

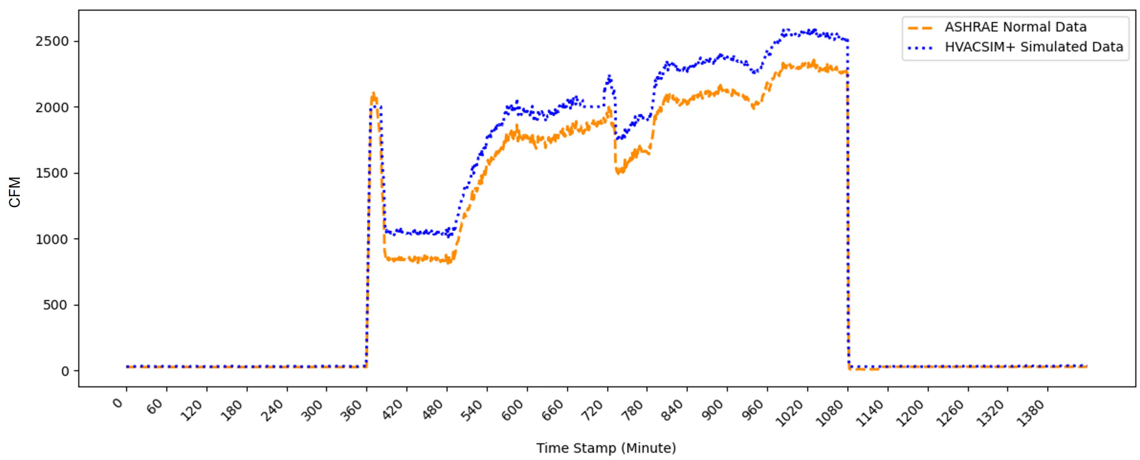


Figure 3.4: Supply Fan Flow Rate (ASHRAE vs Simulation)

In addition to the comparison studies discussed earlier, a detailed statistical evaluation was performed using mean absolute error (MAE) and correlation coefficients, as summarised in Table 3.3. These quantitative metrics were used to assess the accuracy and consistency of the HVACSIM+ simulation results, as described in Section 3.2.3, in relation to real-world system behaviour represented by the ASHRAE benchmark data. The results show a mean absolute error of 2.3 for supply air temperature and 2.5 for cooling coil temperature, with both parameters achieving a correlation coefficient of 1. These findings indicate that the simulation model closely replicates actual temperature dynamics.

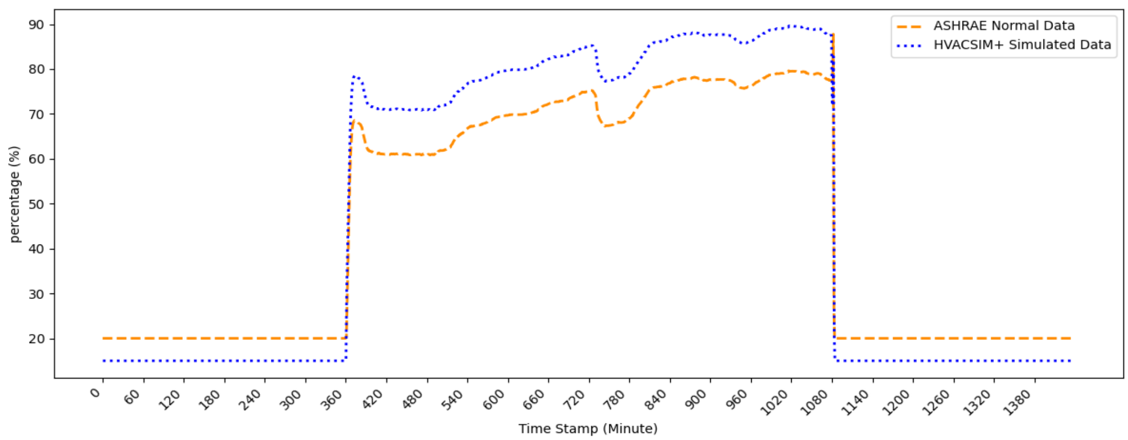


Figure 3.5: Supply Fan Speed (ASHRAE vs Simulation)

In this study, the correlation coefficients for supply air temperature and cooling coil temperature reached 1, indicating a strong alignment between the HVACSIM+ simulation outputs and the ASHRAE benchmark data under normal operating conditions. These values were derived from a controlled simulation environment specifically configured to replicate real-world HVAC system behaviour, using high-resolution time-series data and precisely calibrated input parameters. The perfect correlation reflects the model's capability to accurately reproduce expected system responses, rather than any duplication of variables. This clarification has been provided to avoid potential misinterpretation of the results.

Additionally, the mean absolute errors for supply air flow rate, fan speed, and fan power are 5.98, 7.49, and 6.02, respectively, with a high correlation coefficient of 0.99 for each. This thorough validation confirms that the simulation in Section 3.2.3 closely model real-world dynamics, providing strong confidence in its reliability and accuracy. As a result, this validation deepens the understanding of HVAC system behavior and establishes the applicability of model for practical applications.

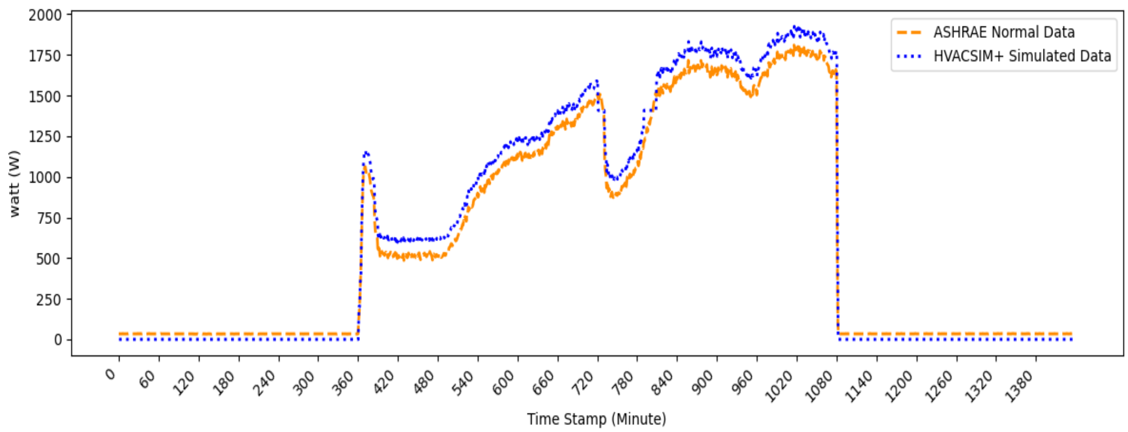


Figure 3.6: Supply Fan Power (ASHRAE vs Simulation)

Sensor Data	Mean Absolute Error	Correlation Coefficient
Supply Air Temperature	2.3	1
Cooling Coil Temperature	2.5	1
Supply Air Flow Rate	5.98	0.99
Fan Speed	7.49	0.99
Fan Power	6.02	0.99

Table 3.3: Comparative Analysis: Simulation vs ASHRAE Result Validation

In summary, the comparison with ASHRAE benchmarks achieves a standardized metric for assessing the performance of the simulation model. It offers a solid framework for evaluating the alignment between simulated responses and real-world benchmark observation, thereby identifying variations and areas for improvement. This process is important for refining the HVACSIM+ model in Section 3.2.3 to ensure its accurate representation of the complex HVAC systems dynamics, providing informed decision-making in practical applications. Overall, the validation against ASHRAE data [Wen and Li, 2011a] emphasizes the credibility of the simulation model, demonstrating its effectiveness in advancing HVAC fault detection systems and operational strategies aimed at achieving optimal performance and energy efficiency.

3.3 Operational Faults Configuration

With the comprehensive validation presented in Section 3.3, it is confirmed that the dynamic modeling of the HVAC system closely matches real-world scenarios. The next step in this section involves the cost-effective simulation and analysis of operational faults. In practice, HVAC systems can experience multiple faults simultaneously (as depicted in Figure 3.1), but this study specifically focuses on nine major faults to provide a targeted analysis and to enhance the understanding of their individual impacts on system performance. Additionally, the "Normal" operating condition is used as a baseline reference for comparative analysis. A detailed discussion of each fault is provided below:

Control Coil Fault: The initial focus is directed towards cooling coils, given their frequent occurrence and substantial influence on system performance. This fault scenario commonly occurs when the coil is either fully opened (CCV100%OP) or fully closed (CCV100%CL), leading to notable disruptions in HVAC system operation and efficiency. In operational scenario, when the cooling coil is set to 100% opened, it triggers the heating coil to adjust the supply air temperature, sometimes causing unintended control strategy faults such as the malfunction of outdoor air dampers during operation. Conversely, a 100% closed cooling coil valve can result in either excessive cooling or inadequate temperature regulation, leading to deviations in supply air temperature. In such scenarios, potential actions may include opening dampers, increasing supply airflow, or adjusting fan speeds. These observations highlight the critical need for thorough fault diagnosis and effective mitigation strategies in HVAC systems. The effect of faults occurring in the cooling coil, both when fully opened and closed is given by (3.3) and (3.4):

$$\frac{dT_{\text{coil}}}{dt} = -k_1 \cdot (T_{\text{coil}} - T_{\text{ambient}}) \tag{3.3}$$

$$\frac{dT_{\text{coil}}}{dt} = -k_2 \cdot (T_{\text{coil}} - T_{\text{ambient}}) + k_3 \cdot N_{\text{SF}} \tag{3.4}$$

where T_{coil} represents the cooling coil temperature, T_{ambient} is the surrounding ambient temperature, N_{SF} denotes the speed of the supply air fan, and k_1 and k_2 are coefficients that indicate the heat conduction properties of the coil. Additionally, k_3 accounts for the combined effect of airflow restriction and fan speed influence. Understanding these equations is crucial for diagnosing faults and implementing effective corrective measures in HVAC systems.

These equations (3.3) and (3.4) provide insights into the dynamic behavior of the cooling coil within an HVAC system, The first equation outlines the cooling coil response when fully open, indicating a gradual decrease in temperature regulated by the constant k_1, which dictates the rate of heat dissipation to the ambient air T_{ambient}. Conversely, the second equation elucidates the coil behavior when fully closed, accounting for heat loss (k_2) alongside the influence of supply air fan speed (N_{SF}) on temperature dynamics, encapsulated by the coefficient k_3. Ultimately, these mathematical expressions serve as invaluable tools for predicting and optimizing HVAC system performance, ensuring efficient climate control within indoor environments.

Cooling Coil Valve Reverse Action Fault: Additionally, faults related to the cooling coil valve operating in reverse, where it behaves opposite to its intended function, can disrupt the thermal balance within the system, leading to inefficiencies and discomfort. In cases of reverse action faults ($CCVREV$), a manual override introduces a fault scenario where the cooling coil valve is set to open when it should be closed, or vice versa, disturbing the thermal balance within the HVAC system. For example, if the valve is manually adjusted to open when it should be closed, it can cause excessive cooling or insufficient temperature control. Conversely, if the valve is manually adjusted to close when it should be open, it can lead to reduced cooling capacity and compromised temperature control.

Duct Leakage After Supply Fan Fault: Another significant fault in HVAC systems is duct leaks occurring after the supply air fan ($DLAFTSF$), which can considerably affect system performance by diminishing airflow rates and compromising pressure conditions. This fault generally allows air to escape from the duct work, leading to reduced airflow rates and compromised pressure conditions. The $DLAFTSF$ fault were introduced manually by adjusting the flow resistance of the duct, resulting in reduced airflow rates and pressure. Equation ((3.5)) provides a mathematical representation of the impact of duct leakage occurring downstream of the supply air fan ($DLAFTSF$) in HVAC systems. Here, Q_{leak} denotes the airflow rate through the leak, with C_d representing the discharge coefficient governing airflow behavior. The term A_{leak} signifies the area of the leak, influencing the magnitude of airflow. Additionally, ρ corresponds to the air density, a key factor affecting airflow dynamics. The pressure difference driving airflow through the leak is captured by $\Delta P_{\text{leak}} = P_{\text{fan}} - P_{\text{leak}}$, where P_{fan} represents the pressure at the fan and P_{leak} denotes the pressure at the leak point.

$$Q_{\text{leak}} = C_d A_{\text{leak}} \sqrt{2\rho \Delta P_{\text{leak}}} \tag{3.5}$$

Understanding this equation is important for assessing the impact of duct leaks in HVAC systems. The equation quantifies the airflow rate through the leak, denoted by Q_{leak}, which directly affects system performance and efficiency. By incorporating parameters such as the discharge coefficient C_d, leak area A_{leak}, air density ρ, and pressure difference ΔP_{leak}, the equation provides insights into how duct leaks influence airflow and pressure conditions within the system.

Exhaust Air Damper Fault: Malfunctions in exhaust or outside air dampers can disturb airflow balance, leading to inefficiencies and discomfort. These problems occur when dampers do not react to control signals, staying either fully open or fully closed. The inclusion of faults related to exhaust air dampers, such as fully opened ($EADAMPOP$) and fully closed ($EADAMPCL$) faults, is crucial in the model as they directly impact ventilation and air circulation in HVAC systems. These faults can compromise indoor air quality, energy efficiency, and proper temperature regulation. In addition, this study examines faults related to outside air dampers, such as 45% opened ($OADAMP$ $45\%OP$) and fully closed ($OADAMPCL$) faults, as they impact the proportion of recirculated air due to simulated stuck damper positions. The effect of these faults were represented in (3.6) in which θ_{damper} is the position of the damper, θ_{setpoint} is the desired position, and k is a coefficient representing the responsiveness of damper.

$$\frac{d\theta_{\text{damper}}}{dt} = -k \cdot (\theta_{\text{damper}} - \theta_{\text{setpoint}}) \tag{3.6}$$

Heating Coil Leakage Fault: In another significant HVAC fault investigation, attention is directed to stages of heating coil leakage($HCVLSTG1$, $HCVLSTG2$, $HCVLSTG3$). Under typical HVAC operating conditions, these faults cause the supply air temperature to exceed the setpoint, leading to increased opening of the cooling coil valve and higher fan speeds. Heating coil valve leakage in HVAC systems can result in inefficient heating and energy loss. This fault allows hot water or steam to escape from the heating coil valve, reducing heating efficiency and potentially creating temperature variations in the system. In the HVACSIM+ dynamic simulation model, the $HCVLSTG2$ fault was implemented by partially opening the heating coil bypass valve to allow hot water flow. Mathematically, the impact of heating coil valve leakage is represented by equation (3.7), where Q_{leak} denotes the leakage rate, T_{hcoil} is the heating coil temperature, T_{ambient} is the ambient temperature, and k is a coefficient indicating the thermal conductivity of the valve.

$$\frac{dQ_{\text{leak}}}{dt} = -k \cdot (T_{\text{hcoil}} - T_{\text{ambient}}) \tag{3.7}$$

Equation ((3.7)) describes the rate of leakage from a heating coil valve in an HVAC system. The equation represents how this leakage rate changes over time, as indicated by the derivative $\frac{dQ_{\text{leak}}}{dt}$. The leakage rate Q_{leak} is influenced by several factors, including the temperature difference between the heating coil (T_{hcoil}) and the ambient temperature (T_{ambient}). A higher temperature difference leads to a greater leakage rate. Additionally, the coefficient k reflects the thermal conductivity of the valve, indicating how easily heat transfers through it. A higher thermal conductivity results in a higher leakage rate for a given temperature difference. Hence, equations (3.3) to (3.7) are important for understanding and predicting the impact of major operational faults in HVAC systems. This understanding helps to ensure optimal system operation, energy efficiency, and minimizing potential issues and associated costs.

Therefore, using HVACSIM+ dynamic simulation models, understanding these nine faults is crucial because they significantly impact HVAC system performance and energy efficiency. This understanding helps to optimize system reliability and efficiency, ensuring effective HVAC operation under various conditions. Furthermore, in-depth analysis of these faults enables cost-effective generation of reliable datasets, essential for the development of advanced fault detection systems. This approach promotes proactive maintenance practices, minimizing operational disruptions and enhancing overall building performance.

3.4 Evaluating Faulty and Normal Operations

This section presents the evaluation of the HVAC dynamic simulation model under both fault-free ("Normal") and "Faulty" operating conditions, as outlined in Section 3.3. Each simulation scenario was run over a 24-hour period, with a specific focus on the occupied hours from 6:00 AM to 6:00 PM to reflect realistic building usage and HVAC system demand. Data were recorded at one-minute intervals, resulting in 1440 samples per sensor across 194 sensor points. This high-resolution sampling was essential for capturing rapid system fluctuations and enabling accurate fault detection. For the baseline reference (F0: NORMAL), the simulation was extended across three consecutive days under normal conditions.

During each day, data were collected only during the 12-hour occupied period, producing 720 samples per day and a total of 2160 samples. The occupied period was selected because HVAC systems are actively controlled during these hours to maintain thermal comfort and respond to internal heat gains, occupancy levels, and ventilation requirements. In contrast, system activity is significantly reduced during unoccupied hours, leading to minimal variation in sensor readings. Focusing on the occupied period ensures that the dataset reflects realistic operating conditions, which are most relevant for detecting and analysing faults.

Fault	**Abbreviation**	**Description**	**Fault Implementation**	**Sample**
F0	NORMAL	Normal Condition	normal	2160
F1	CCV100%OP	Control Coil Valve fully opened	manually control valve at 100% opened position	1440
F2	CCV100%CL	Control Coil Valve fully closed	manually control valve at 100% closed position	1440
F3	CCVREV	Cooling Coil Valve Reverse Action	overwrite cooling coil valve scaling factor	1440
F4	DLAFTSF	Duct Leakage After Supply Fan	manually changing duct flow resistance	1440
F5	EADAMPOP	Exhaust Air Damper opened	manually control damper at 100% opened position	1440
F6	EADAMPCL	Exhaust Air Damper closed	manually control damper at 100% closed position	1440
F7	OADAMPCL	Outside Air Damper closed	manually control damper at 100% closed position	1440
F8	OADAMP45%OP	Outside Air Damper 45% opened	manually control damper at 45% closed position	1440
F9	HCVLSTG2	Heating Coil Valve Leak	manually open heating coil bypass valve	1440

Table 3.4: Summary of HVAC Faults Considered in the Simulated HVACSIM+ Model

Table 3.4 provides a comprehensive overview of the various AHU faults examined in this study. Each fault is denoted by an abbreviation and described in detail, indicating deviations from standard operating conditions. For example, faults such as the cooling coil valve being fully open (F1: CCV100%OP) or fully closed (F2: CCV100%CL) can significantly disrupt the HVAC system's balance, resulting in inefficient energy use and occupant discomfort. Other faults, such as Cooling Coil Valve Reverse Action (F3: CCVREV) and Duct Leakage After Supply Fan (F4: DLAFTSF), are also highlighted, with each affecting system performance differently by altering airflow and thermal regulation.

Other faults considered in this experiment involve adjustments to damper positions, including fully opening the Exhaust Air Damper (F5: EADAMPOP) or completely closing it (F6: EADAMPCL), as well as fully closing the Outside Air Damper (F7: OADAMPCL) or partially opening it to 45% (F8: OADAMP45%OP). Each of these faults introduces specific challenges to the system, highlighting the requirement of precise detection and response mechanisms for optimal performance. Finally, the presence of Heating Coil Valve Leak (F9: HCVLSTG2) is noted. Each fault scenario is accompanied by a sample count, indicating the number of instances considered for analysis and simulation. In addition, the normal operating condition (F0: NORMAL) works as the baseline reference for system performance evaluation, with 2160 samples collected for analysis.

Furthermore, the analysis is carried out to compare the "Normal" and "Faulty" scenarios using statistical analyses as summarized in Table 3.5. One significant example from the Table 3.5-(a) is the fault "CCV100%OP" with a p-value of 3.2300×10^{-3} for OA-CFM (Outdoor Air-Cubic Feet per Minute). The low p-value for OA-CFM suggests a significant deviation from normal operation, indicating potential issues with outdoor air intake. The high p-values for MA-TEMP (Mixed Air Temperature), HC-TEMP (Heating Coil Temperature), and SF-TEMP (Supply Air Temperature) also highlight pronounced impacts on these parameters, underscoring the significance of the fault.

Besides, "HCVSTG2L" with a p-value of 5.0571×10^{-3} for HC-TEMP suggests leakage in the second-stage heating coil valve, which can cause deviations in heating coil temperature, disrupting heating efficiency and potentially leading to energy wastage. Additionally, "DLAFTSF" with a p-value of 1.1476×10^{-16} for CC-TEMP (Cooling Coil Temperature) signifies duct leakage occurring after the supply air fan, resulting in reduced airflow rates and compromised pressure conditions, thereby impacting cooling efficiency and occupant comfort.

Another notable example from the Table 3.5-(b) is the fault "CCV100%OP" with a p-value of 4.2078×10^{-48} for OA-HUMD (Outdoor Air Humidity). This low p-value suggests a significant deviation from normal operation, indicating potential issues with outdoor air humidity control. The high p-values for MA-HUMD (Mixed Air Humidity), RA-HUMD (Return Air Humidity), and CHWPHT (Chilled Water Pump Heat) also indicate pronounced impacts on these parameters, highlighting the significance of the fault. Additionally, "HCVSTG2L" with a p-value of 0.0000×10^{0} for RA-HUMD signifies leakage in the second-stage heating coil valve, which can cause deviations in return air humidity, disrupting humidity control and potentially affecting indoor air quality.

Fault	OA-CFM	OA-TEMP	MA-TEMP	HC-TEMP	CC-TEMP	SF-TEMP
EADAMPOP	3.1609E-13	2.0458E-251	1.2512E-235	2.0021E-225	1.2919E-95	1.7729E-118
CCV100%OP	3.2300E-03	5.5109E-01	8.8561E-01	7.4872E-01	1.9404E-03	3.9243E-04
EADAMPCL	3.1609E-13	1.9614E-216	5.1873E-206	8.2651E-202	3.7227E-67	4.8491E-86
CCVREV	1.8388E-05	1.2261E-137	4.2831E-108	4.4038E-109	1.0391E-18	1.8377E-23
OADAMP45%OP	3.1609E-13	6.0663E-232	2.1543E-209	8.6525E-209	5.1097E-65	8.5073E-84
CCV100%CL	3.1609E-13	1.7996E-306	7.8212E-264	2.9108E-252	1.7081E-93	9.7191E-117
OADAMPCL	2.0601E-03	1.0884E-18	3.5194E-18	2.0365E-16	1.3785E-10	1.8622E-13
HCVSTG2L	3.1609E-13	5.0571E-03	1.0953E-17	7.1502E-17	2.1576E-11	6.6490E-15
DLAFTSF	3.1609E-13	1.1476E-16	1.3458E-31	1.1382E-30	1.8090E-06	3.0163E-08

(a) Normal vs Faults of p-Values Analysis

Fault	OA-HUMD	MA-HUMD	RA-HUMD	CHWPHT	OA-DMPR	RA-DMPR
EADAMPOP	0.0000E+00	0.0000E+00	0.0000E+00	1.1581E-19	4.8291E-08	4.8290E-08
CCV100%OP	4.2078E-48	1.5115E-42	5.2151E-25	6.0155E-02	1.7073E-02	1.7073E-02
EADAMPCL	0.0000E+00	0.0000E+00	0.0000E+00	2.9218E-15	4.8291E-08	4.8290E-08
CCVREV	8.8147E-113	4.8414E-69	2.5691E-71	5.7111E-07	8.8395E-04	8.8394E-04
OADAMP45%OP	0.0000E+00	0.0000E+00	0.0000E+00	5.7963E-13	4.8291E-08	4.8290E-08
CCV100%CL	0.0000E+00	0.0000E+00	0.0000E+00	1.5478E-18	4.8291E-08	4.8290E-08
OADAMPCL	2.5155E-298	4.6574E-210	6.0164E-175	2.7957E-01	1.4914E-02	1.4914E-02
HCVSTG2L	0.0000E+00	0.0000E+00	2.3218E-308	5.3359E-05	4.8291E-08	4.8290E-08
DLAFTSF	4.8150E-197	9.3625E-140	2.4542E-89	4.0260E-05	4.8291E-08	4.8290E-08

(b) Normal vs Faults of p-Values Analysis - Continue

Fault	EA-DMPR	CHWC-VLV	EA-TEMP	RA-TEMP	HCS-TEMP	CHWP-EWT
EADAMPOP	4.8291E-08	5.1652E-04	6.1022E-170	8.0906E-162	1.7865E-225	4.5280E-66
CCV100%OP	1.7073E-02	4.0907E-01	5.7623E-13	3.9121E-12	7.4927E-01	8.3172E-03
EADAMPCL	4.8291E-08	3.3626E-04	2.6485E-144	2.7056E-148	7.6027E-202	2.9733E-46
CCVREV	8.8395E-04	1.2652E-02	4.5810E-82	1.7874E-76	4.5486E-109	1.3202E-15
OADAMP45%OP	4.8291E-08	4.6079E-04	4.7245E-135	1.3824E-124	8.4146E-209	7.6453E-47
CCV100%CL	4.8291E-08	4.6805E-04	2.2556E-145	2.6494E-136	2.5049E-252	7.1733E-66
OADAMPCL	1.4914E-02	6.6100E-02	2.9826E-37	1.9461E-34	1.9917E-16	3.8809E-07
HCVSTG2L	4.8291E-08	7.8488E-04	1.0332E-30	2.7590E-28	6.9542E-17	1.0633E-06
DLAFTSF	4.8291E-08	3.1460E-04	2.3345E-38	2.2334E-34	1.0893E-30	2.8691E-04

(c) Normal vs Faults of p-Values Analysis - Continue

Table 3.5: Comparison of 9 Faults versus Normal Conditions: Analysis of p-Values

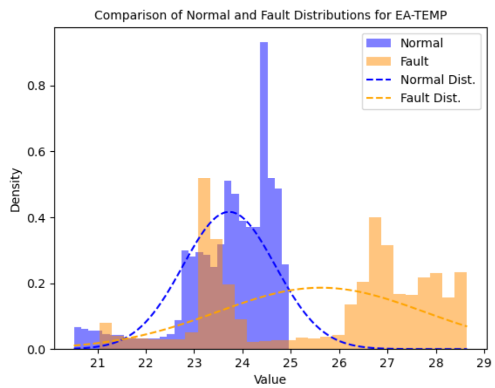
Besides, "DLAFTSF" with a p-value of 4.8150×10^{-197} for OA-HUMD represents duct leakage occurring after the supply air fan, resulting in compromised humidity control and potentially leading to discomfort for building occupants. In Table 3.5-(c), it also provides more significant examples like "CCV100%OP" with a p-value of 1.7073×10^{-2} for EA-DMPR (Exhaust Air Damper). This relatively high p-value suggests a notable deviation from normal operation, indicating potential issues with the exhaust air damper. Additionally, the low p-values for CHWC-VLV (Chilled Water Coil Valve) and CHWP-EWT (Chilled Water Pump Entering Water Temperature) highlight pronounced impacts on these parameters.

For instance, a fault in the chilled water coil valve ("CCV100%OP") can disrupt the flow of chilled water, affecting the cooling capacity of the system and potentially leading to inadequate temperature control. Similarly, "OADAMPCL" with a p-value of 1.4914×10^{-2} for CHWP-EWT signifies a fault in the outdoor air damper, which could result in improper regulation of the chilled water pump entering water temperature, impacting the overall efficiency of the cooling system. Overall, these findings highlight the importance of monitoring and addressing faults in various components of the HVAC system to ensure optimal performance and energy efficiency.

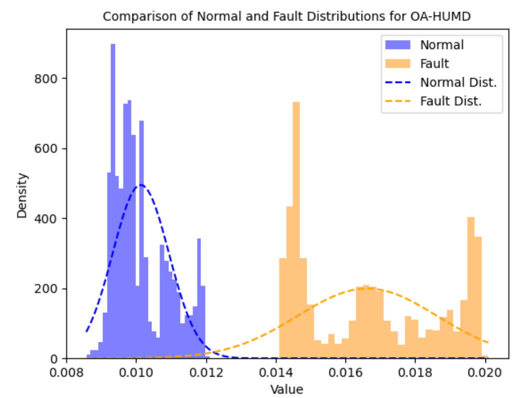
Another comparison study was conducted as presented in Figure 3.7. In Figure 3.7-(a), the distribution of Exhaust Air Temperature (EA TEMP) and its corresponding density function are presented. Under normal conditions, the distribution exhibits a left-skewed pattern, with the majority of values concentrated between 21 to 24 degrees Celsius. This skewness reflects the expected temperature readings typical of standard operational circumstances. Conversely, during fault conditions, the distribution shifts towards higher values, specifically ranging between 26 to 29 degrees Celsius. This notable shift in distribution, with temperatures skewed towards the higher end of the scale, works as a significant indicator of deviations from normal operation. These differences in distribution patterns between "Normal" and faulty conditions offer valuable insights for detecting faults due to temperature variations.

In Figure 3.7-(b), the density function for Outside Air Humidity (OA-HUMD) are illustrated. The plot distinctly shows the separation between normal and faulty conditions, with the normal condition ranging from 0.008 to 0.012, while the faulty condition from 0.014 to 0.020. This clear separation between the two sets of data highlights the effectiveness of the analysis on humidity levels as it is important for diagnosing potential faults within the HVAC system. In addition, Figures 3.7-(c) and (d), the analysis for Mixed Air Humidity (MA-HUMD) and Return Air Humidity (RA-HUMD) give a clear separation between normal and faulty conditions, with distinct ranges of values observed for each operational state. By leveraging the distinct distribution patterns between "Normal" and faulty conditions, robust algorithms can be developed for automated fault detection.

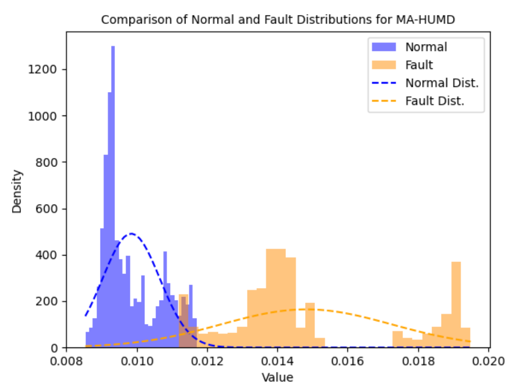
In summary, the results presented in Table 3.5 underscore the significant importance of data-driven approaches in HVAC fault detection, as discussed in Chapter 2. Bedies, conducting statistical analysis techniques in this study shows the extraction of meaningful insights from complex datasets, thereby advancing the development of effective fault detection and diagnosis strategies in a cost-effective manner. As HVAC systems grow in complexity, these methodologies become increasingly important for improving system resilience, sustainability, and operational efficiency. Visualizing distinctions between "Normal" and "Faulty" conditions, as shown in Figure 3.7, enhances understanding of critical fault indicators. It highlights the value of data-driven analysis in fault detection and diagnosis, supporting proactive maintenance and ensuring system reliability.



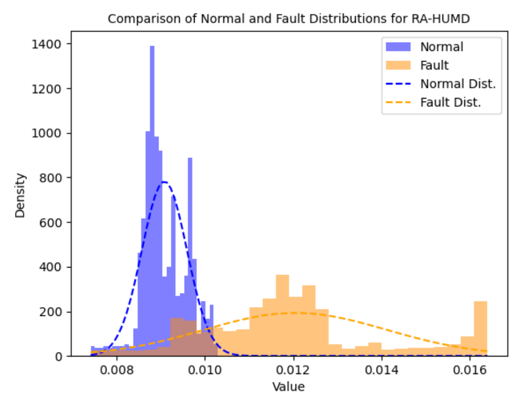
(a)



(b)



(c)



(d)

Figure 3.7: Comparison of Fault vs. Normal Data Distribution

3.5 Dataset Preparation

Through comprehensive validation of dynamic simulation data (Section 3.2.3) against ASHRAE benchmark data in Section 3.2.4, along with validation between faulty and normal conditions in Section 3.4, the simulated data has proven to be highly accurate and reliable. In practice, high-quality data of this nature is important for developing a robust fault detection system, as discussed in Chapters 4, 5, and 6. In this Section, both the simulation and benchmark datasets are used to prepare the training, testing, and validation datasets for the proposed advanced fault detection approaches using machine learning and deep learning techniques, which are further discussed in the following Chapters 4, 5, and 6.

3.5.1 HVACSIM+ Simulated Data

To effectively train the proposed fault detection systems discussed in Chapters 4, 5, and 6, the simulated dataset generated from HVACSIM+ (Table 3.4) was carefully selected to include only data corresponding to the occupancy period (6 AM to 6 PM). This focused approach reduced the samples for each fault type from 1440 to 720 data points over a 12-hour period, as shown in Table 3.6. During non-occupancy hours, sensor readings showed minimal fluctuations, as presented in Section 3.2.4, Figures 3.2 to 3.6, making them unsuitable for modeling decision-making patterns effectively.

In addition, focusing on this specific occupied period allows the dataset to closely reflect real-world conditions, thereby improving fault detection accuracy. Under this consideration, the 720 fault samples were collected for each fault type as listed in Table 3.6. In the real world scenario, this targeted approach enhances accuracy while also simplifying the architecture of the fault detection system, maintaining efficiency without getting the complexity of 24-hour training [Gao et al., 2023] period. This methodology aligns effectively with HVAC fault detection requirements, ensuring accuracy, simplicity, and efficiency.

Fault	Abbreviation	Description	Sample
F0	NORMAL	Normal Condition	2160
F1	CCV100%OP	Control Coil Valve fully opened	720
F2	CCV100%CL	Control Coil Valve fully closed	720
F3	CCVREV	Cooling Coil Valve Reverse Action	720
F4	DLAFTSF	Duct Leak After Supply Fan	720
F5	EADAMPOP	Exhaust Air Damper opened	720
F6	EADAMPCL	Exhaust Air Damper closed	720
F7	OADAMPCL	Outside Air Damper closed	720
F8	OADAMP45%OP	Outside Air Damper 45% opened	720
F9	HCVLSTG2	Heating Coil Valve Leak—Stg 2	720

Table 3.6: Simulated Dataset of HVAC Faults and Normal Conditions for Fault Detection

3.5.2 ASHRAE RP-1312 Benchmark Data

This section focuses to explain on the dataset sourced from the publicly available ASHRAE RP-1312 [Wen and Li, 2011a]. The dataset includes both fault-free ("Normal") and operational HVAC faults conducted under various severity levels during the summer season. The experimental setup closely matches the HVACSIM+ configuration as proposed in Section 3.4 in Chapter 3, considering different AHU configurations, zone setups, and heating and cooling plant arrangements.

In this setup, the outdoor air damper maintained a minimum opening of 40% to meet ventilation requirements, enabling economizer control when the outdoor air temperature dropped below 65°F. The supply air temperature was set at 55°F, and duct static pressure was maintained at 1.4 PSI by controlling the supply fan speed, with the return fan operating at 80% of the supply fan speed. Room temperature was set at 70°F during occupied periods. The maximum airflow rates were 1000 CFM for exterior zones and 400 CFM for interior zones, with a minimum airflow rate of 200 CFM for all zones.

The ASHRAE dataset considered in this study includes "Normal" conditions and nine different types of HVAC operational faults over several days, with data sampled every minute. This results in 1440 samples collected from 160 sensor sources over a 24-hour period. However, as briefly described in Section 3.5.1, the dataset was selected to include only the subset of data corresponding to the occupancy period, reducing the number of samples for each faults, from 1440 to 720 data points over a 12-hour span (6 AM to 6 PM). As clearly explained in Figure Figures 3.2 to 3.6, outside this time-frame, sensor readings shows minimal variability, rendering them unsuitable for modeling and decision-making purposes.

3.6 Summary

This study presents an improved method for modeling HVAC operational faults within the HVACSIM+ dynamic simulation system, offering a comprehensive solution for identifying major faults in a single-story, four-room building. By assessing the effects of faults on building energy consumption and occupant comfort during the summer season, this advancement streamlines timely fault detection. The case study also demonstrates the significant impact of faults on both occupant comfort and HVAC system efficiency, filling a critical gap in obtaining real-world fault data by integrating dynamic system modeling and fault simulation. A rigorous validation process compared HVAC system parameters, including normal and faulty scenarios, from the simulation model with benchmark ASHRAE experimental data, and ensures the accuracy and reliability of the simulation model.

Chapter 4

Hybrid Random Forest and SVM for Advancing HVAC Fault Detection

This chapter presents a hybrid machine learning framework that combines Random Forest (RF) and Support Vector Machine (SVM) algorithms for fault detection and diagnosis (FDD) in HVAC systems. The approach is motivated by the limitations of conventional methods, including rule-based and model-based diagnostics, as well as standalone machine learning techniques such as neural networks, fuzzy systems, and probabilistic models. These methods often face challenges related to scalability, interpretability, and adaptability in complex, dynamic environments. The proposed RF-SVM framework leverages the feature selection capability of RF and the classification strength of SVM to enhance diagnostic accuracy while reducing false positive rates. The chapter begins by outlining the methodological background of RF and

SVM, followed by the formulation of the hybrid approach. The training procedures are described using both simulated data and publicly available benchmark datasets. Key design parameters, feature selection strategies, and performance evaluation metrics are also discussed. The chapter concludes with a presentation of experimental results, demonstrating the model's effectiveness in identifying various fault types and its potential for generalisation across different data sources.

4.1 Background Studies

Through the application of HVAC system dynamic modeling tools, fault simulation, and data generation, substantial advancements have been made in data-driven fault detection and diagnosis (FDD) for HVAC systems, as outlined briefly in Chapter 3. Traditional methods for fault detection, including rule-based thresholds and physical models, have historically offered valuable insights but are limited in adapting to the complex and diverse behaviors of HVAC systems, as discussed in the literature review in Chapter 2. Furthermore, recent research has explored data-driven fault detection techniques such as principal component analysis (PCA) [Jiang et al., 2009] and diagnostic Bayesian networks (DBNs) [Li et al., 2019] for capturing fault dependencies. Despite their contributions, these methods may face challenges in identifying non-linear relationships among variables, potentially impacting diagnostic accuracy. Additionally, they often rely on domain experts for rule development and interpretation, which may restrict their scalability and practical implementation in real-world settings.

Moreover, rule-based control (RBC) is one of the earliest and most widely implemented approaches in HVAC fault detection and diagnosis. It operates based on predefined if-then rules developed by domain experts, using threshold values or logical conditions to identify abnormal system behaviour [Katipamula and Brambley, 2005a]. While RBC is simple to implement and highly interpretable, its effectiveness heavily depends on expert knowledge, and it often lacks the flexibility to adapt to changing system dynamics or unforeseen conditions. Another conventional approach is model-based control (MCP), which relies on physics-based models or analytical redundancy to detect deviations from expected system performance [Isermann, 2006]. These methods can deliver accurate fault detection when the system is thoroughly characterized and the model is properly calibrated. However, they are often limited by their sensitivity to modelling inaccuracies, the need for extensive system knowledge, and their reduced effectiveness in complex or evolving environments. Due to these limitations, both RBC and MCP face challenges in scalability and generalisation, especially in modern, data-rich HVAC systems.

Overcoming the limitations of rule-based approaches, significant efforts have been devoted to developing FDD systems using artificial neural networks (ANNs), adaptive fuzzy neural networks (AFNNs) and the integration of an extended Kalman filter with a recursive one-class SVM (EKF-OCSVM) [Du et al., 2010a, Lee et al., 1996, Yan et al., 2017]. Despite their potential, techniques like ANNs and AFNNs often require substantial amount of training data and computational resources, making them unsuitable for real-time HVAC fault detection. Moreover, the chance of overfitting, lack of interpretability and performance degradation in unseen scenarios may limit their application in dynamic environments. Furthermore, the EKF-OCSVM approach faces challenges related to precise parameter tuning and generalizability across different HVAC configurations, which significantly limit its scalability. Therefore, overcoming these challenges is crucial for the successful deployment of advanced fault detection systems in complex HVAC environments.

Intensive research aims to improve further by exploring probabilistic models such as Hidden Markov Models (HMMs) [West et al., 2011] to address the challenges of detecting complex HVAC faults. This approach uses HMMs to capture probabilistic relationships among data points during both normal and faulty conditions, enabling accurate passive inference of similar patterns in future data. However, the non-deterministic nature of the HMMs training process often leads to local optima, resulting in inconsistent likelihood estimates and challenges in establishing a robust fault detection threshold. Furthermore, it uses publicly available datasets from the standard ASHRAE 1020 which may limit the generalizability of the model to HVAC systems with different configurations and settings. In Yan et al. [2019], an integrated method combining the extended Kalman filter with cost-sensitive dissimilar ELM (EKF-CD-ELM) was proposed to achieve faster training and accurate fault diagnosis. However, this approach is computationally demanding and challenging to implement, particularly when handling high-dimensional data and multiple hidden states.

While the above-discussed methods have been widely used for HVAC fault detection [Jiang et al., 2009, Yan et al., 2019], each methods has their own limitations, such as lack of adaptability to dynamic system changes and challenges with interpretability. Conversely, SVM has been proposed for machine condition monitoring and fault diagnosis due to its robust generalization abilities and achieving high classification accuracy [Widodo and Yang, 2007]. However, the SVM itself may struggle with effective feature selection and is highly sensitive to parameter tuning which can limit its generalizability across different datasets under varying operational conditions. To address these challenges, an improved hybrid approach combining SVM with RF has been proposed [Kumar and Gopal, 2010], whereas leveraging RF for effective feature selection and SVM for accurate classification. This method aims to improve generalization ability, reduce computational complexity, and enhance overall performance. Nevertheless, while this method has demonstrated significant advantages in protein type identification [Saifur et al., 2017], oral cancer screening [Singh et al., 2008], it has not yet been applied to HVAC fault detection.

Motivated by these considerations, this chapter presents a comprehensive exploration of the methodological background of Random Forest (RF) and Support Vector Machine (SVM) methods, discussed in Sections 4.2.1 and 4.2.2, with a focus on their theoretical foundations and operational principles. Subsequently, Section 4.3 introduces the Hybrid RF-SVM approach for HVAC fault detection, emphasizing its innovative integration of RF for effective feature selection and SVM for accurate classification. This hybrid approach aims to enhance the accuracy of HVAC fault detection by reducing false positive rates, making it particularly effective in HVAC complex and dynamic environments. Furthermore, Section 4.4 provides an overview of the training procedures and performance evaluation using both simulated data (Section 3.5.1) and ASHRAE RP-1312 public data (Section 3.5.2). In addition, key design parameters, feature selection methods, and performance metrics are briefly discussed in Sections 4.4.1, 4.4.2, and 4.4.3 respectively. Finally, Section 4.5 presents the experimental findings, giving a comprehensive analysis of the various faults outcomes and demonstrating their generalizability using both simulated data and the benchmark public dataset, with concluding remarks presented in Section 4.6.

4.2 Methodological Background

In this section, the fundamental concepts and operational principles of the Random Forest (RF) classifier (Section 4.2.1) and the Support Vector Machine (SVM) (Section 4.2.2) are explored. Both algorithms have gained significant attention in the fields of machine learning and artificial intelligence due to their effectiveness in classification tasks across a wide range of applications, as introduced in Section 4.1.

4.2.1 Random Forest (RF)

The Random Forest (RF) classifier introduced in this Section is an ensemble machine learning algorithm that effectively addresses the limitations of traditional decision trees [Breiman, 1996]. More specifically, the RF starts its training process by building multiple decision trees on differentt subsets of the original training dataset. In this method, bootstrap sampling is used to randomly select samples with replacement, which ensures that each decision tree receives a unique subset of data, and introduce variability among the trees, thereby reducing overfitting problem. Additionally, at each node split within a decision tree, a random subset of features is selected rather than considering all available features, which promotes diversity among the individual models. This randomness at both the data and feature levels allows the ensemble to learn different data patterns, ultimately contributing to the robustness and accuracy of the overall model.

Another significant feature of the RF algorithm is its capacity to provide insights into feature importance [Genuer et al., 2010]. During the training process, each decision tree independently makes predictions, and the final output of the RF is derived by averaging the individual predictions in regression tasks (or) by majority voting in classification tasks. This ensemble-based decision-making mechanism contributes to greater stability and robustness against noise in the data. Moreover, RF models are less occurred to overfitting compared to individual decision trees, particularly when hyperparameters such as the number of trees and the maximum depth of each tree are appropriately optimized. Additionally, it can effectively manage a large number of input features and remains proficient in capturing complex, nonlinear relationships between variables, making it an adaptable and powerful tool in the field of machine learning.

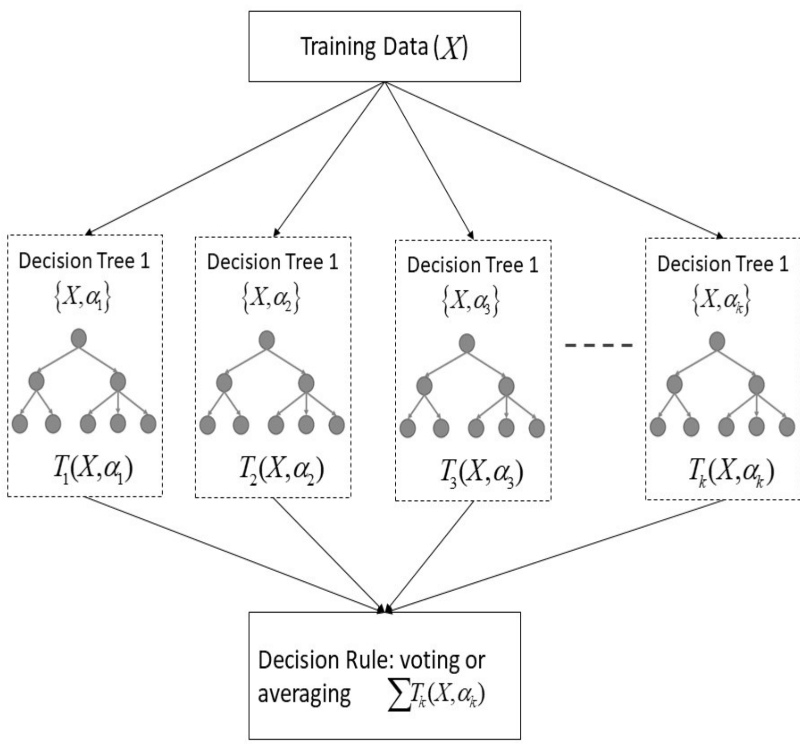


Figure 4.1: The structure of Random Forest (RF) [Aldrich and Auret, 2010, Zhang et al., 2018]

Furthermore, the RF classifier enhances model interpretability. Upon completion of the training phase, the ensemble of decision trees produces a set of optimized if-then rules, which can be leveraged to explain the predictions [Breiman, 2001]. This level of interpretability is particularly advantageous in domains where understanding the decision-making process is important, such as medical diagnosis and financial forecasting. The flowchart given in Figure 4.1 visually represents a clear overview of the RF algorithm, while the step-by-step training and implementation process is given in the algorithm 4.2.1.

As denoted in the algorithm 4.2.1, the dataset $X = \{x_1, x_2, \ldots, x_n\}$ and their corresponding responses $Y = \{y_1, y_2, \ldots, y_n\}$ process iteratively to derive a tree predictor T_b. Each tree T_b, ranging from 1 to B, is constructed with a slightly varied subset of observations to ensure model diversity, while nodes within each tree are partitioned based on a limited set of features. During the implementation phase, several critical parameters require careful consideration, such as the number of trees (B), the maximum allowable depth for each tree, and the criteria for node splitting. Additionally, the "Gini" impurity is considered as another important parameters as it commonly used as a measure of homogeneity within decision trees, helping in determining optimal split points [Aldrich and Auret, 2010, Zhang et al., 2018].

1. For $b = 1$ to B:

   1.1 Draw a bootstrap sample X_b of size N from the training data.

   1.2 Grow a random forest (RF) tree T_b to the bootstrapped data by recursively repeating the following steps for each terminal node of the tree until the minimum node size n_{min} is reached:

      i. Select m variables at random from the p variables.

ii. Pick the best variable/split-point among the m selected variables.

iii. Split the node into two daughter nodes.

2. Output the ensemble of trees $\{T_b\}_{b=1}^{B}$:

   - To make a regression prediction at new points x, use:

   $$\hat{f}_{\mathrm{rf}}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x),$$

   where $T_b(x)$ is the prediction of the b^{th} RF tree.

   - To make a classification prediction at new points x, use:

   $$\hat{C}_{\mathrm{rf}}^{B}(x) = \text{majority vote}\left\{\hat{C}_b(x)\right\}_{b=1}^{B},$$

   where $\hat{C}_b(x)$ is the class prediction of the b^{th} RF tree.

As discussed above, although RF is highly effective for feature selection, it can face several challenges in the presence of noisy data and shows a notable bias towards the majority class in imbalanced datasets, which limits their applicability in scenarios involving rare but critical faults. By employing RF as a feature selector followed by SVM for final classification, the RF-SVM framework effectively reduces dimensionality, mitigates noise, and allows for more sophisticated decision boundaries. The use of SVM enables the model to overcome limitations of RF by maximizing the margin between classes, thereby enhancing generalizability and addressing overfitting concerns. Consequently, RF-SVM emerges as a compelling strategy for fault detection and classification, particularly in complex and high-dimensional environments. The following Section 4.2.2 will examine the ways in which SVM addresses these challenges and ensures precise fault classification in HVAC systems.

4.2.2 Support Vector Machine (SVM)

This section introduces Support Vector Machine (SVM), a supervised learning algorithm extensively utilized for both classification and regression. SVM works by identifying an optimal hyperplane that maximizes the margin between classes, thus enhancing its ability to classify new data points accurately [Jan et al., 2017, Liang and Du, 2007]. By employing kernel functions, SVM effectively handles both linear and nonlinear classification by transforming input data into higher-dimensional spaces, where complex relationships become more separable. The flexibility of SVM, particularly with the soft-margin approach, allows it to achieve a balance between maximizing margin width and accommodating minor classification errors, thereby improving model robustness and generalization in complex datasets.

As outlined in Equation 4.1, the primary goal of the Support Vector Machine (SVM) algorithm is to optimize a cost function by maximizing the margin between classes. The parameters α_i and γ_i serve as Lagrange multipliers, while the parameter C controls the penalty term, balancing margin width against classification error. The kernel function $K(x_i, x)$, as defined in Equation 4.2, is a spectral kernel that can take various forms, including linear, polynomial, or Gaussian radial basis function (RBF) kernels, which measure the similarity between input data points x_i and training samples x. The SVM output, detailed in Equation 4.3, determines the decision boundary by aggregating weighted kernel evaluations and applying the signum function, where b is an offset parameter learned during training. This formulation enables SVM to classify data effectively by maximizing class separation and minimizing classification errors.

$$\min_{\alpha_i \gamma_i} \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K\left(x_i, x\right) - \sum_{i=1}^{N} \alpha_i \tag{4.1}$$

where $\sum\limits_{i=1}^{N} \alpha_i y_i = 0$ and $0 \leq \alpha_i \leq C$ for $i = 1, 2, \ldots, L$, α_i is Lagrange multiplier which was controlled by the penalty factor C, $K\left(x_i, x\right)$ is spectral kernel, which was expressed by linear, polynomial, and Gaussian radial basis function kernels as follows:

$$K\left(x_i, x\right) = \begin{cases} x_i^T x \\ \left(x_i^T x + b\right)^P, & b > 0 \\ \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right), & \sigma \neq 0 \end{cases} \tag{4.2}$$

Finally, the output of SVM was calculated by:

$$f\left(x\right) = \operatorname{sgn}\left(\sum_{i \notin \vartheta} \alpha_i y_i K\left(x_i, x\right) + b\right) \tag{4.3}$$

where $K\left(x_i, x\right)$ is a polynomial kernel function that measures the similarity between input pattern x_i and training sample x, α is the weight parameter, sgn is a signum function and b is the parameter of SVM obtained at the end of the training process.

In summary, the hybrid approach that combines Random Forest (RF), as described in Section 4.2.1, with Support Vector Machine (SVM), as outlined in Section 4.2.2, demonstrates significant potential for HVAC fault detection and diagnosis [Singh et al., 2008]. This approach is particularly effective due to the capacity of RF for feature selection, isolating the most influential parameters affecting system behavior. By focusing the SVM classifier on these key features, diagnostic accuracy is enhanced. Additionally, the robust classification capabilities and adaptability of SVM through various kernel functions help address the overfitting and computational demands often associated with RF. As detailed in Section 4.3, this hybrid system presents an efficient and reliable method for identifying and diagnosing HVAC faults. The following part, Section 4.4, will discuss model training, implementation, and the benefits of this RF-SVM hybrid approach in achieving optimal HVAC system performance.

4.3 Hybrid RF-SVM HVAC Fault Detection System

This section introduces the proposed hybrid RF-SVM framework for enhancing HVAC system diagnostics, combining Random Forest (RF) and Support Vector Machine (SVM) methodologies. As shown in Figure 4.2, the RF-SVM framework is specifically designed to leverage the strengths of both algorithms to improve the accuracy and reliability of HVAC system diagnostics. The framework begins with data preprocessing, where operational parameters and diagnostic indicators are collected and refined, as outlined in Section 3.5 of Chapter 3.

Following this, the RF component is employed for feature selection, identifying the most impactful parameters that influence diagnostic outcomes. This selection process reduces data dimensionality, thereby increasing the efficiency and accuracy of the subsequent classification stage. After feature selection, the SVM as detailed in Subsection 4.2.2, is applied to refine the classification boundaries using the selected features. The final fault classification is obtained by integrating the outputs from both the RF and SVM components.

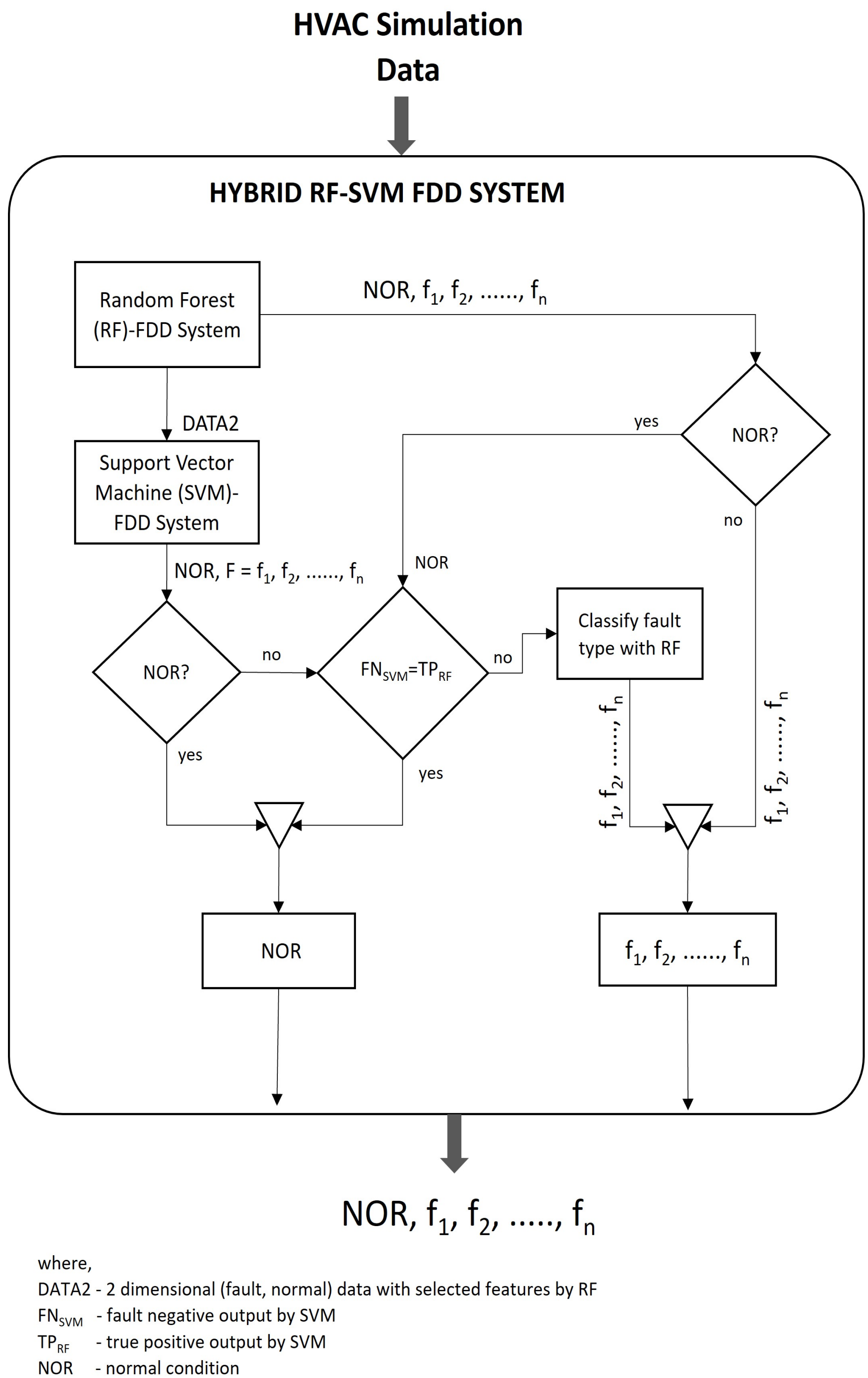


Figure 4.2: Overview of the Proposed Hybrid RF-SVM Fault Detection and Diagnosis (FDD) System

By leveraging the effective feature selection of RF and the precise classification capabilities of SVM, this hybrid approach results in enhanced accuracy, robustness, and efficiency in system diagnostics. Moreover, the integration of these two algorithms allows the hybrid RF-SVM framework to effectively address challenges such as noisy and imbalanced data, which are prevalent in HVAC systems. The feature selection step reduces computational complexity, thereby improving classification efficiency, while the combined use of both components ensures reliable fault detection. Consequently, this comprehensive approach enhances overall diagnostic accuracy and reliability, contributing to optimal HVAC system performance.

To enhance the efficiency of the hybrid approach, as illustrated in Figure 4.2, the proposed methodology unifies multiple identified faults in the HVAC system into a single fault category. Specifically, in the dataset ($DATA2$), individual faults labeled as $f_1, f_2, \ldots, f_n$ are aggregated into a composite fault category denoted as ($F = f_1, f_2, \ldots, f_n$). This aggregation significantly reduces the complexity involved in classifying faults by treating multiple individual fault types as a single entity, thus streamlining the fault diagnosis process and enhancing the overall computational efficiency of the hybrid model.

The hybrid RF-SVM output, comprising normal and fault states ($NOR, f_1, f_2, \ldots, f_n$), is then consolidated. It is achieved through a multi-step process where the predicted faults $f_1, f_2, \ldots, f_n$ from the first sub-RF system are combined with the predicted normal state (NOR) from the second sub-SVM system. Additionally, the methodology includes integrating votes from the RF system against the normal state (NOR) for the minority fault negative samples (FN_{SVM}). This comprehensive voting mechanism ensures that the most accurate classification is achieved by cross-validating the outputs of both the RF and SVM subsystems.

The proposed hybrid RF-SVM (Figure 4.2 method for HVAC faults detection can make several significant contributions, as outlined below:

1. **Integration of RF and SVM Classifiers**: The integration of RF and SVM classifiers in the proposed method represents a strategic combination of two potent machine learning techniques. Utilizing the simulated data from Section 3.5.1 and the benchmark ASHARE data from Section 3.5.2 in Chapter 3, the method leverages the extensive and varied information provided by these simulations. This integration exploits the robustness and flexibility of RF for feature selection and fault classification, while also utilizing the capability of SVM to manage complex data patterns and refine classification boundaries. Consequently, the hybrid approach benefits from the complementary strengths of both algorithms, leading to a more comprehensive and effective fault detection and diagnosis system for HVAC systems.

2. **Efficient Feature Selection**: The pre-processing phase of the proposed HRF-SVM framework involves feature selection, which reduces the original 160 features to the 15 most important ones. This reduction not only significantly decreases computational costs but also enhances classification accuracy. Furthermore, the streamlined feature set allows for efficient fault identification using only 15 sensors, making the approach practical for real-world applications. Additionally, it enables the interpretation of which top features are important for decision making

3. **Handling Imbalanced Data**: HVAC system operational data typically shows imbalance, with normal conditions being more prevalent than faulty ones. To

address this issue, the proposed HRF-SVM method employs RF as a multi-class classifier for fault type classification and SVM as a binary classifier to identify normal conditions. Different from other hybrid SVM based decision trees [Demidova et al., 2019, Kumar and Gopal, 2010, Saifur et al., 2017, Singh et al., 2008], the proposed hybrid system effectively manages imbalanced input data, improving the system robustness and accuracy.

4. **Validation and Performance Improvement**: To illustrate the effectiveness and generalizability of the proposed hybrid RF-SVM approach, it is validated using ASHRAE RP-1312 dataset as briefly described in Section 3.5.2. Additionally, it is compared and analyzed using Linear-FDD system, standalone SVM and RF alternative methods. The experimental results consistently highlight the superior performance of the proposed approach, achieving higher classification accuracy across nine distinct types of HVAC operational faults. This validation confirms the effectiveness of the hybrid RF-SVM method in enhancing fault detection and diagnosis within HVAC systems.

The proposed system and its contributions lead to the next phase, training the hybrid RF-SVM fault detection system (Section 4.4). Following this, the selection of model parameters is addressed in Section 4.4.1.

4.4 Training and Performance Evaluation

This section examines the training process of the hybrid RF-SVM fault detection system. The training procedure consists of several key steps, starting with the preparation of a dataset containing both "Faulty" and "Normal" operational data, as briefly outlined in Section 3.5, the HVACSIM+ simulation dataset in Subsection 3.5.1, and the benchmark ASHRAE-RP1312 dataset in Subsection 3.5.2 of Chapter 3. Using these datasets, the process initiates with training the RF classifier, which involves extracting significant features to be used as input for the subsequent SVM algorithm.

In the training phase of the Random Forest (RF) model, multiple decision trees are built using random subsets of the training data and feature sets. Each decision tree is developed independently, while the entire ensemble collaboratively assesses the relevance of features by analyzing their importance across all trees. This collective approach helps in identifying the most critical features contributing to the predictive capabilities of RF model. Subsequently, the extracted significant features are used as input for the SVM algorithm, which is trained to classify normal and faulty conditions accurately. This step is important for optimizing HVAC system performance across different fault scenarios, as discussed in Section 4.4.1. To further ensure generalization, the proposed model was trained on the benchmark ASHRAE-RP1312 dataset, as described in Subsection 3.5.2 of 3.5.

4.4.1 Design Parameters

Upon completion of the training process, the optimized parameters are determined and analyzed in this section. In the proposed hybrid RF-SVM system in Figure 4.2, the RF component was first fine-tuned by adjusting key parameters. These parameters include the number of decision trees, the maximum depth allowed for each tree, and the number of features considered at each node split. For example, configuring the model with 100 trees, a maximum depth of 10, and selecting 15 features at each split can significantly improve the generalization capability of model and ability to capture complex data patterns.

Conversely, in the hybrid fault detection system, the SVM model was configured with an RBF kernel, a regularization parameter of $C = 10$, and specific kernel parameters, such as gamma set to 50 for the radial basis function. These parameters influence the flexibility of the decision boundary and the margin between classes, affecting the model's effectiveness in separating data points in high-dimensional feature spaces. By carefully tuning these design parameters, both RF and SVM can be adapted to the unique characteristics of the dataset during the training process, ultimately improving the accuracy and reliability of the fault detection and classification system.

4.4.2 Feature Selection

In this Section, the dataset comprised 195 features gathered from various sensor types. The methodology employed the Random Forest (RF) classifier for feature selection, ultimately identifying the 15 most significant features. This selection process effectively removed approximately 92% of the less relevant features, significantly improving the generalization capability of the proposed hybrid system. Moreover, the reduction in unnecessary features contributes to lower sensor installation costs. Upon completion of the training process, using the optimized parameters detailed in Section 4.4.1, the ranking of the top selected features based on their relative "Gini" scores is depicted in Figure 4.3.

Notably, as presented in Figure 4.3, the model identified several key features as crucial for HVAC fault detection, each contributing significantly to the performance and reliability of system. The "Outdoor Air Humidity Sensor (OA-HUMD-SEN)" was considered critical for maintaining indoor air quality and comfort since fluctuations in outdoor humidity directly impact the efficiency of HVAC system. Additionally, the Zone Return Humidity Control - Dew Point (Z3RHC-DP) plays an essential role in preventing condensation and managing humidity levels, thus indicating potential issues in the dehumidification process when faults occur.

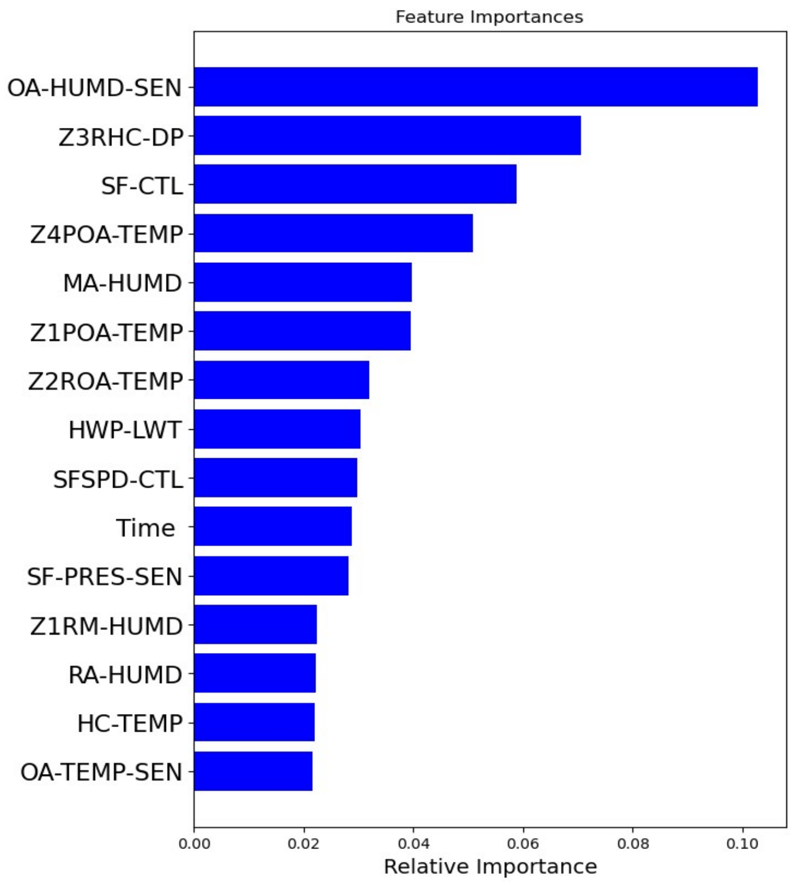


Figure 4.3: Feature Ranking by RF Model

Furthermore, “Supply Fan Control (SF-CTL)” ensures proper air circulation and ventilation; faults in this control can lead to problems with air distribution and pressure control. Monitoring the “Zone Primary Outdoor Air Temperature (Z4POA-TEMP)” is also crucial for optimizing heating and cooling loads, which is vital for effective temperature control strategies. Similarly, the “Mixed Air Humidity (MA-HUMD)” sensor, by monitoring the humidity of mixed air, is important for maintaining appropriate indoor humidity levels.

In addition, the “Zone 1 Primary Outdoor Air Temperature (Z1POA-TEMP)” sensor affects heating and cooling efficiency by tracking outdoor air temperature in specific zones, while the “Zone Return Outdoor Air Temperature (Z2ROA-TEMP)” influences energy efficiency and thermal comfort by measuring the return outdoor air temperature. The “Heat Water Pump - Leaving Water Temperature (HWP-LWT)” is also important, as it ensures efficient heat transfer by monitoring the water temperature leaving the heat pump.

Besides, the “Supply Fan Speed Control (SFSPD-CTL)” is essential for maintaining desired airflow and pressure levels, faults in this control can cause air distribution inefficiencies. The inclusion of “Time” as a feature captures periodic patterns and time-dependent behaviors in the HVAC system, such as daily or seasonal variations. Next, the “Supply Fan Pressure Sensor (SF-PRES-SEN)“ is crucial for ensuring the correct pressure levels within the supply fan system.

Furthermore, the “Zone Room Humidity (Z1RM-HUMD)” and “Return Air Humidity (RA-HUMD)” sensors are essential for maintaining indoor air quality and comfort by monitoring humidity levels in specific zones and the return air, respectively. Finally, the “Heating Coil Temperature (HC-TEMP)” sensor is critical for controlling the heating process, with faults potentially affecting heating efficiency and comfort levels. Similarly, the “Outdoor Air Temperature Sensor (OA-TEMP-SEN)”, by measuring the overall outdoor air temperature, plays a key role in determining the necessary heating and cooling loads. In summary, these features were identified as important by the model due to their direct influence on the ability of HVAC system to maintain desired environmental conditions, detect anomalies, and ensure efficient and reliable operation. The selection of these features highlights the importance of comprehensive monitoring and control in achieving optimal performance and fault detection in HVAC systems.

4.4.3 Performance Metrics

For a comprehensive analysis and evaluation of the proposed HRF-SVM fault detection system, precision (4.4), recall (4.5), and F1-score (4.6) are essential metrics for assessing the performance of classification models. Theoretically, precision (4.4) quantifies the accuracy of positive predictions by measuring the ratio of true positive predictions to all positive predictions. It offers insights into the ability of model to avoid false positives.

$$Precision = \frac{TP}{[TP + FP]} \times 100 \tag{4.4}$$

$$Recall = \frac{TP}{[TP + FN]} \times 100 \tag{4.5}$$

$$F1 - score = 2 \times [\frac{Precision \times Recall}{Precision + Recall}] \times 100 \tag{4.6}$$

In contrast, recall, as defined in 4.5, measures the ability of model to identify all positive instances by calculating the ratio of true positives to the total number of actual positive cases in the dataset. This metric emphasizes how effectively the model detects relevant instances. The F1-score, as represented in 4.6, is the harmonic mean of precision and recall, offering a balanced metric that accounts for both false positives and false negatives. This score provides a singular value to reflect the model's overall performance in terms of both precision and recall. Collectively, these metrics provide a comprehensive evaluation of the model's classification performance, enabling the identification of strengths and weaknesses and guiding subsequent refinement efforts.

4.5 Experimental Result and Discussion

In this Section, the efficiency of proposed hybrid RF-SVM fault detection system(Figure 4.2) was assessed using the dataset delineated in Subsection 3.5.1. The dataset detailed in Table 3.6, was divided randomly, allocating 80% of samples for model training and reserving the remaining 20% for testing. The 80/20 split used in this study follows a common practice in machine learning, offering a balanced compromise between providing enough data to effectively train the model and retaining a representative portion for assessing its generalization performance on unseen data. Therefore, the model was trained with 6912 samples and tested with 1728 samples. Initially, the training starts the RF classifier, identified the most significant 15 features from the original set of 195, subsequently feeding them into the SVM classification layer for final faults classification.

The effectiveness of the proposed RF-SVM fault detection system is presented in Table 4.1. Based on the overall model accuracy of 91%, the proposed hybrid RF-SVM fault detection system demonstrates strong performance, particularly in detecting faults such as “CCVREV”, “EADAMPCL”, and “HCVSTG2L” where precision, recall, and F1-scores are exceptionally high (98% or above in Recall). However, the model shows slightly lower accuracy for the “CCV100%CL” and “OADAMP45%OP” faults, with lower precision and F1-scores, highlighting areas where model performance could be further improved. Besides, the "NORMAL" condition shows a relatively lower recall (74%) compared to other categories, but its precision remains high at 97%, resulting in an F1-score of 84%. This suggests that while some misclassifications may occur, the detection of normal operating conditions remains sufficiently reliable for practical applications.

DataSet	Fault Code	Precision (%)	Recall (%)	F1-score (%)
HVACSIM+	NORMAL	97	74	84
	CCV100%CL	65	94	77
	CCV100%OP	93	99	96
	CCVREV	97	100	98
	DLAFTSF	97	97	97
	EADAMPCL	100	99	100
	EADAMPOP	99	90	94
	HCVSTG2L	96	98	97
	OADAMP45%OP	73	94	82
	OADAMPCL	98	96	97
	Overall Model Accuracy		91	
ASHRAE-RP1312	NORMAL	91	76	83
	CCV100%CL	99	99	99
	CCV100%OP	100	85	92
	CCVREV	93	100	97
	DLAFTSF	88	98	93
	EADAMPCL	99	99	99
	EADAMPOP	95	100	98
	HCVSTG2L	87	99	93
	OADAMP45%OP	63	92	75
	OADAMPCL	98	86	92
	Overall Model Accuracy		90	

Table 4.1: Classification Reports for Hybrid RF-SVM Using HVACSIM+ Simulation and ASHRAE-RP1312 Datasets

Furthermore, the benchmark ASHRAE dataset from Section 3.5.2 in Chapter 3 was used to evaluate the generalization capability of the proposed RF-SVM model. As shown in the second half of Table 4.1, an overall accuracy of 90% was achieved, with varying performance levels across different fault types. More specifically, fault codes such as "CCVREV", "EADAMPOP", "CCV100%CL","EADAMPCL", and "HCVSTG2L", demonstrate high precision values of 100%, 100%, 99%, 99%, and 99%, respectively.

These values from Table 4.1 suggest the system accuracy in minimizing false positives when identifying these faults. Conversely, fault codes like "CCV100%OP" and "OADAMPCL" exhibit lower recall values of 85% and 86%, respectively, indicating a higher false negative rate for these faults. Additionally, while some fault codes achieve relatively high F1-score values, such as "CCV100%CL," "CCVREV," and "EADAMPCL," and "EADAMPOP,", others show lower scores, highlighting potential trade-offs between precision and recall. Ultimately, the system achieves an overall accuracy of 90%, reflecting its accuracy in identifying across all fault types and normal conditions.

Upon further examination of the confusion matrix shown in Figure 4.4, while the overall performance appears satisfactory, some misclassifications are evident, especially involving the "EADAMPOP" and "NORMAL" fault types. Moreover, the misclassification of "EADAMPOP" as "OADAMP45%OP" can be attributed to their similar fault symptoms within the dynamic nature of HVAC systems. Both "EADAMPOP" and "OADAMP45%OP" may shows overlapping patterns in sensor data or system responses due to factors like airflow disruptions or pressure differentials, leading to make difficult for the fault detection system.

In addition, the misclassification of "NORMAL" as "CCV100%CL" within the HVAC system could be influenced by the inherent complexity of HVAC operations. In HVAC systems, the "NORMAL" state represents the system standard operating condition without any faults. However, certain fault conditions, such as "CCV100%CL" (potentially related to cooling coil valve closed at 100% position), might exhibit data patterns similar to those observed during normal operation. The complexity of HVAC systems, where similar sensor readings or system responses can occur under both normal and fault conditions, poses challenges for accurate fault detection. Additionally, factors like the interaction of system components and environmental influences further complicate detection, leading to misclassifications. Therefore, enhancing the HVAC fault detection model to consider these complexities and integrating more contextual information about HVAC behavior could enhance reliability.

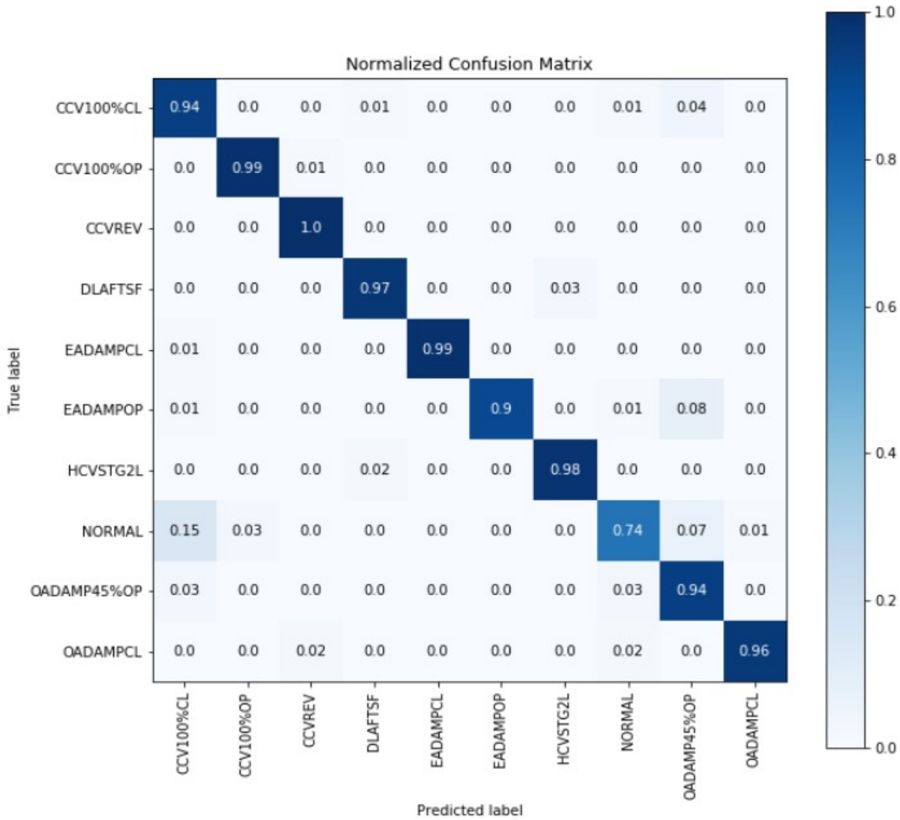


Figure 4.4: Confusion Matrix: the Hybrid RF-SVM Performance on HVACSIM+ Simulation Data

In summary, testing the proposed fault detection system with two datasets, “ASHRAE-RP1312” and “HVACSIM+” highlights its potential to generalize across varied environments and fault scenarios. While the overall accuracy is satisfactory, a detailed examination of individual metrics such as precision and recall is vital for comprehensively assessing the performance. This analysis provides insights into both strengths and areas needing improvement, ultimately enhancing the capability of the fault detection system and ensuring HVAC system reliability. Further experiment in this studies involve exploring alternative approaches such as RF, SVM, and One vs Rest-SVM (OvR-SVM), across nine distinct types of summer fault scenarios, as briefly discussed in Chapter 7.

4.6 Summary

A novel approach for HVAC fault detection is presetned in this section. Leveraging the strengths of both RF and SVM classifiers, the model efficiently extracts relevant features through RF feature importance ranking and achieves better classification using SVM. The generalization of model was evaluated using simulated data and publicly available ASHRAE-RP 1312 data. Comparative studies with various existing methods, including RF, SVM, and OvR-SVM, demonstrate the superior performance of the hybrid approach. Experimental findings show that the hybrid RF-SVM approach achieves a notable 91% accuracy in diagnosing nine distinct HVAC faults. Despite its effectiveness, the hybrid RF-SVM system has certain limitations, including longer processing times due to the two-step classification process and potential suboptimal performance due to irrelevant feature selection by RF and the need for extensive tuning of SVM. Therefore, improvements could streamline the feature selection process and reduce processing time, thereby improving the overall efficiency and performance of detection system.

Chapter 5

Enhancing HVAC Fault Detection Using One-Dimensional Convolutional Neural Networks

This chapter investigates the application of one-dimensional convolutional neural networks (1D-CNNs) for fault detection and diagnosis in heating, ventilation, and air conditioning (HVAC) systems. Building upon the hybrid RF-SVM approach presented earlier, which demonstrated strengths in feature selection but encountered limitations in capturing complex temporal patterns and handling high-dimensional sensor data, this chapter introduces a deep learning framework capable of learning directly from raw time-series inputs. Unlike traditional machine learning models that rely on manual feature engineering, 1D-CNNs offer automated hierarchical feature extraction, enabling more accurate and scalable detection of subtle anomalies in dynamic system behaviour. The growing complexity of HVAC systems and the demand for real-time monitoring further necessitate methods that are both adaptive and generalisable across diverse operational scenarios. To this end, the chapter presents a fault detection system trained using high-resolution simulation data and validated against industry-standard benchmarks. It details the theoretical foundations, architectural design, training methodology, and evaluation metrics of the proposed 1D-CNN model, culminating in a comparative analysis with conventional fault detection techniques. The framework aims to enhance diagnostic accuracy and support generalisation of fault detection across typical HVAC operational scenarios.

5.1 Background Studies

A hybrid RF-SVM approach was investigated for fault detection in HVAC systems as presented in Chapter 4. While the RF-SVM method demonstrated its strengths in feature extraction and selection, it faced challenges in handling high-dimensional data and effectively capturing the complex temporal patterns characteristic of HVAC systems. The reliance on manual feature extraction and selection made it difficult for the SVM to identify intricate relationships within the data, thereby limiting its overall performance. These challenges highlight the need for a more advanced fault detection and diagnosis (FDD) system that can leverage the temporal variations in the data.

To address these limitations, this Chapter presents a deep learning framework based on one-dimensional convolutional neural networks (1D-CNNs). Unlike RF-SVM, which depends on manual feature engineering, 1D-CNNs can automatically learn features directly from raw time-series data, using convolutional layers to effectively capture temporal dependencies. Compared to conventional machine learning techniques such as artificial neural networks (ANNs) [Afefy and El-Refaie, 2017, Du et al., 2010b], general regression neural networks (GRNN) [Lee et al., 2004], and wavelet-based neural networks [Fan and Guo, 2010], 1D-CNNs excel at learning hierarchical features, making them particularly effective for handling sequential data and detecting faults in HVAC systems.

Extending this research, a continuous studies have explored a hybrid approach for fault diagnosis by integrating rule-based methods with one-dimensional convolutional neural networks (1D-CNNs) [Liao et al., 2021]. In this approach, potential sensor faults are initially identified through a rule-based component, using threshold values derived from prior operational data. This initial identification is followed by a more detailed analysis performed by 1D-CNNs, which leverage historical data from the building management system to accurately detect and classify faults. The experimental validation conducted on the AHU confirmed the high accuracy of the proposed method, although the study was focused on detecting only four specific types of fault. For practical applications, there is potential to encounter the detection to a wider range of fault types as well as enhance the generalization of the model by validating it against industry-standard benchmark data.

Furthermore, a deep learning-based approach was introduced in Li et al. [2021], incorporating three distinctive features such as the elimination of the pooling layer, the application of a convolution filter kernel of size one, and the use of the "softsign" activation function. This approach aims to maintain the spatial resolution of the input data while ensuring that the operational characteristics of HVAC systems are preserved. In this approach, validation was performed using a dataset that included seven chiller faults from the ASHRAE research project 1043 (RP-1043). Although the model showed its effectiveness in certain situations, the generalization ability may be limited due to its reliance only on ASHRAE data. In this scenario, using a more diverse dataset and performing a comprehensive analysis of system dynamics and fault simulation with advanced simulation tools could provide an effective and alternative approach.

Apart from HVAC faults detection, 1D-CNNs have been widely applied in various fields, including fault diagnosis in rotating machinery [Long et al., 2019] and electric power systems [Fahim et al., 2020]. Time-series data were analyzed to classify bearing faults, rotor imbalances, and misalignments effectively. This method also considered the use of knowledge graphs to enhance model interpretability, and improving diagnostic accuracy. Similarly, the study in [Fahim et al., 2020] showed the effectiveness of 1D-CNNs in electric power systems by classifying faults in power transmission lines, highlighting the ability of model to detect anomalies in complex scenarios.

With their superior feature extraction, automatic learning capabilities, and robust classification performance, 1D-CNNs offer considerable potential for further exploration in HVAC fault detection. Although it has been widely applied, there is still considerable room for improvement through the development of an integrated approach that considers HVAC system modeling, fault simulation, validation, and advanced fault detection methods. This approach could subsequently overcome the limitations of manual feature extraction and selection discussed in Chapter 4, while also ensuring effective handling of complex temporal patterns.

To achieve this, the Chapter focuses on advancing HVAC fault detection by integrating dynamic system modeling, fault simulation, and 1D-CNNs detection frameworks, utilizing dynamic fault simulation data. In Section 5.3, a 1D-CNNs-based fault detection system is introduced, with its theoretical advantages detailed in Section 5.2. The training process of the proposed method, using optimized parameters, is discussed in Sections 5.4 and 5.4.2, where the model is trained on simulated data from Section 5.4.1 to enable automatic feature extraction from time-series data and effective classification of both "normal" and "faulty" conditions. Moreover, Section 5.5 examines the effectiveness of the proposed approach, including an evaluation of its generalization performance using both HVACSIM+ simulated data (Section 3.5.1) and industry-standard data (Section 3.5.2), thereby addressing an aspect commonly neglected by existing methods. Finally, Section 5.6 summarizes conclusions, limitations and future research directions, highlighting the potential for further exploration.

5.2 Methodological Background

This Section presents the theoretical foundations of one-dimensional convolutional neural networks (1D-CNNs) and explores their application in HVAC fault detection. A thorough understanding of CNN fundamentals is essential for developing an effective fault detection system, as it provides a clear explanation of their architecture, functionality, and learning mechanisms [Yamashita et al., 2018]. Furthermore, this methodological background highlights how CNNs can be efficiently utilized for fault detection purposes. Considering these aspects, the next Section 5.2.1 provides a detailed description of the CNN structure, along with its mathematical formulation.

5.2.1 Convolutional Neural Networks (CNNs)

This Section provides an overview of the typical architecture of a one-dimensional Convolutional Neural Networks (1D-CNNs), outlining its key components, which include convolutional, pooling, and fully connected layers. As shown in Figure 5.1, CNN architectures typically consist of two primary components. The first component employs convolutional operations to extract feature maps from the raw input signal using an appropriate kernel size, while the second component utilizes a multi-layer perceptron (MLP) to identify fault characteristics [Mehta et al., 2019]. Specifically, the input layer is characterized by dimensions of $N \times k$, where k represents the number of input time series, and N represents the length of each univariate series. The convolution layer, which is the second layer, performs convolution operations using m filters, a stride of s, and a filter size of $y \times y$. Additionally, a non-linear activation function f is also applied in this layer.

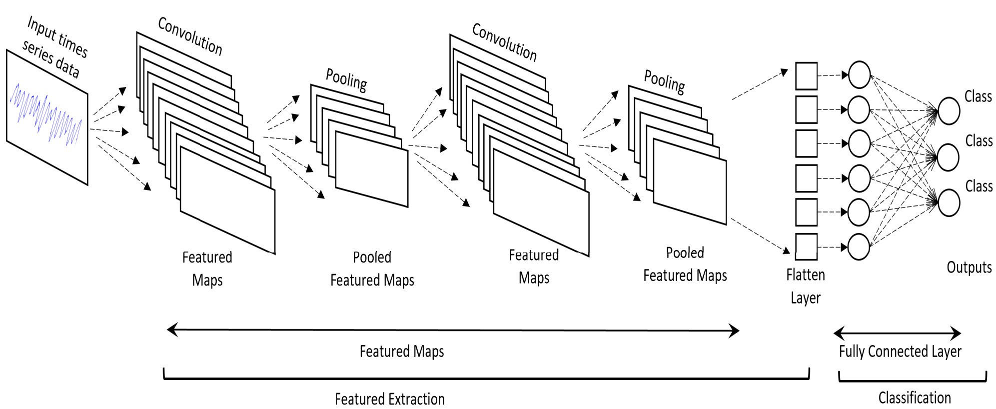


Figure 5.1: Architecture of 1D-CNNs

The next step in the process is the pooling procedure, which involves splitting a feature map into N equal-length segments and representing each segment by its average or maximum value. By downsampling the output bands of the convolutions, the pooling procedure has the advantage of reducing the hidden activation's variability. A set of feature mappings that link to final output layers with n classes after various convolution and pooling processes represent the initial time series. A sequence of training examples which is used to perform is given by: $(x_1, y_1), (x_2, y_2), .., (x_{Nsample}, y_{Nsample})$ with $(x_t \in R^{N \times k}, y_t \in R^n for 1 \leq t \leq N_{sample}$. The multivariate or uni-variate time series x_t is given as input to the network, while the vector y_t denotes the target output. The network is trained using the multiple steps as detailed in the following steps:

Step 1: Determine the CNN architecture with the required number of convolutional and pooling layers, initialize parameters such as weights, biases, and the number of hidden neurons with random number, choose a learning rate η and activation function f. The most commonly used activation function is the ReLU function $f(x)$ which is defined as:

$$f(x) = \max(0, x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.1}$$

Step 2: Do the following calculations for each convolution layer's output using the provided training set:

$$C_r(t) = f(\sum_{i=1}^{t} \sum_{j=1}^{k} x(i + s(t-1), j)\omega_r(i, j) + b(r)) \tag{5.2}$$

where $x \in R^{N \times k}$ is the time series input (or) the output of the preceding layer, s is the convolution stride, $C_r(t)$ refers to the t^{th} component of the r^{th} feature map, $\omega_r \in R^{l \times k}$ and $b(r)$ refer to the weights and bias of the r^{th} convolution filter.

Step 3: After the convolution step, the pooling step is performed by:

$$P_r(t) = g(C_r((t-1)l+1), C_r((t-1)l+2), ..., C_r(tl)) \tag{5.3}$$

where the function g represents the most popular used is averaging (or) max pooling. It is clear that point data reduction is achieved by the pooling operation without changing the number of feature maps.

Step 4: Finally, the output of CNN layer is calculated by:

$$O_j = f(\sum_{i=1}^{M} z(i)\omega_f(i,j) + b_f(j)), j = 1, 2, ..., n \tag{5.4}$$

where z denotes the final feature map in the feature layer, b_f is the bias of the output layer and $\omega_f \in R^{M \times n}$ refers to the connection weights between the feature layer and the output layer. Thus, the mean-square error is written as:

$$E = \frac{1}{2}\sum_{k=1}^{n} e(k)^2 = \frac{1}{2}\sum_{k=1}^{n}(O(k) - y(k))^2 \tag{5.5}$$

Step 5: The gradient descent algorithm is used to update the weights and bias in order to minimise the error (E):

$$p = p - \eta\frac{\partial E}{\partial p} \tag{5.6}$$

where p is the value of the parameter, η is the learning rate and p refers to ω_r, ω_f, b or b_f in this CNN.

Step 6: Once the algorithm has reached the maximum number of iterations, it stops the iteration process. If not, it continues **Step 3** instead. In this study, the maximum number of training iterations was fixed at 40 epochs. This decision aligns with established practices in time series classification using one-dimensional convolutional neural networks (1D-CNNs), where the number of training epochs typically ranges from 30 to 100, depending on model complexity and dataset characteristics [Fawaz et al., 2019]. It was conducted with an early stopping configuration set at 100 epochs, and a patience of 5. However, the convergence was consistently achieved within 40 epochs. Therefore, 40 epochs was selected as a suitable and efficient training limit.

As described by equations 5.1 to 5.6, the fundamental operations of a 1D-CNN are important for understanding the underlying principles and practical implementation of the model. These operations form the foundation of the ability of network to effectively extract, distinguish, and classify meaningful patterns from sequential data. Such capabilities are particularly important for HVAC fault detection, where the identification of complex temporal relationships is important for accurate fault detection.

5.3 HVAC Fault Detection with 1D-CNNs

This Section introduces a method for identifying HVAC faults using one-dimensional convolutional neural networks (1D-CNNs). The proposed framework, as illustrated in Figure 5.2, consists of three key components: dataset preparation as input data, the 1D-CNNs architecture for fault detection, and evaluation of model performance. Each component plays a critical role in ensuring the precise detection of “nine” major HVAC faults and normal operating condition.

The proposed system, as illustrated in Figure 5.2, starts by generating operational data that includes both “faulty” and “normal” conditions using the HVACSIM+ dynamic simulation model, as detailed in Section 3.5.1 of Chapter 3. Following this, a 1D-CNNs-based fault detection system is trained on time-series sensor signals collected from various HVAC components, enabling the classification of "nine" major HVAC faults and "normal" conditions without manual feature extraction. During training, convolutional operations are performed to extract relevant features from the sequential input data (Section 3.5), using filters to detect important temporal patterns over time. The network parameters are optimized through backpropagation, which iteratively adjusts the weights to minimize the difference between predicted and actual outputs, ultimately achieving optimal model performance for faults classification.

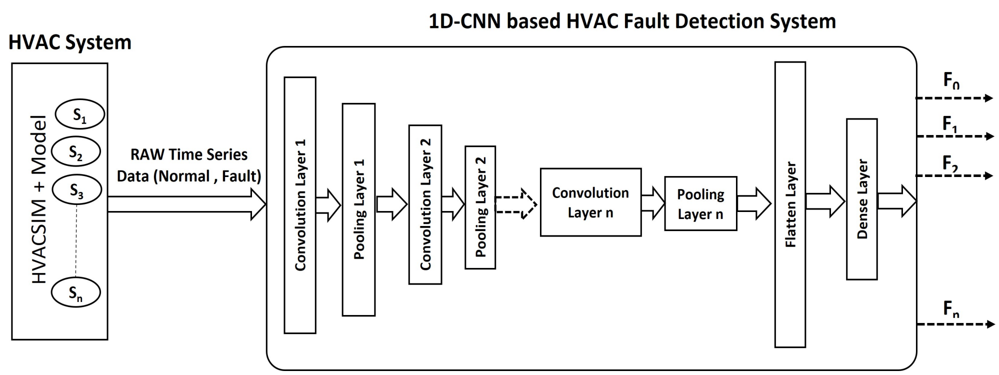


Figure 5.2: Proposed 1D-CNN HVAC Operational Fault Detection System

On the other hand, the proposed system leverages the capability of CNNs to automatically learn and recognize meaningful temporal patterns within the data, thereby addressing the limitations highlighted in Chapter 4, which relies on manual feature engineering and lacks the ability to effectively capture the dynamic and nonlinear characteristics of HVAC time-series data. Finally, the effectiveness of the proposed framework is evaluated by conducting comparison studies with other data-driven fault detection methods, while the generalization capability of the model is validated using both the ASHRAE-RP1312 dataset, as discussed in Section 3.5.2, and the simulated data presented in Section 5.4.1. This approach eliminates the need for domain-specific expertise in feature extraction, demonstrating the effectiveness of 1D-CNNs for HVAC fault detection.

5.4 Training 1D-CNNs Fault Diagnosis System

This Section provides a comprehensive overview of the training process for the 1D CNNs-based fault detection system (Figure 5.2). In Section 5.4.1, it describes the dataset used for training and testing, which includes both simulated HVAC operational data (Section 3.5.1) and industry-standard benchmark data, ASHARE (RP-1312) detailed in Section 3.5.2. A comprehensive discussion of this dataset preparation is provided in Sections 3.5 of Chapter 3.

Following data preparation, Section 5.4.2 addresses the careful selection of design parameters for 1D-CNNs, such as network architecture, layer configurations, learning rate, and batch size, which are essential for attaining optimal performance in detecting HVAC operational faults. Additionally, it emphasizes the importance of choosing suitable activation functions to reduce overfitting and improve model generalization. The section also highlights the use of hyperparameter tuning and cross-validation processes to ensure the robustness and accuracy of the model. Finally, the performance of the model is evaluated, showing its effectiveness in robust fault detection as well as its generalization ability in different dataset.

5.4.1 Dataset Preparation

This Section provides a comprehensive description of the dataset used to train the proposed 1D-CNN fault detection system, as illustrated in Figure 5.2. The dataset, described in Section 3.5 of Chapter 3, was employed in this study, ensuring consistency with the dataset used in Section 4.5 of Chapter 4 for comparison analysis to evaluate the effectiveness of the proposed methods. The dataset used in this study considers both “normal” and “fault” scenarios. The normal operating condition (denoted as F0) represents the baseline where no faults are present, with a total of 2160 samples. The faulty scenarios are represented by nine distinct conditions, each with 720 samples. These faults include “Control Coil Valve fully opened (F1)”, “Control Coil Valve fully closed (F2)”, and “Cooling Coil Valve Reverse Action (F3)”, “Duct Leak After Supply Fan (F4)”, “Exhaust Air Damper opened (F5)”, and “Exhaust Air Damper closed (F6)”. The “Outside Air Damper closed (F7)” and “Outside Air Damper 45% opened (F8)” are also considered, along with “Heating Coil Valve Leak—Stage 2 (F9)”.

In real-world HVAC systems, conditions such as a fully opened control coil valve or specific damper positions can occur during normal operation, particularly under high cooling loads or specific ventilation requirements. However, in this study, these conditions are classified as faults when they remain in a fixed position and do not respond to changes in system demand or control input. For example, “Control Coil Valve Fully Opened (F1)” and “Fully Closed (F2)” are considered fault conditions when the valve fails to adjust dynamically as required by the system. Similarly, damper-related cases such as “Exhaust Air Damper Opened/Closed (F5 and F6)” and “Outside Air Damper Closed or 45% Opened (F7 and F8)” are regarded as faults when the dampers do not change position in response to environmental or control signals. This interpretation is consistent with standard practices in HVAC fault detection, where a lack of actuator response such as a valve or damper stuck in position is considered a sign of mechanical failure or control malfunction [Katipamula and Brambley, 2005b]. To capture these behaviours, the faults were intentionally introduced in the HVACSIM+ environment as persistent and unintended states, allowing the fault detection model to learn from clearly defined abnormal patterns that degrade system performance.

As outlined in Section 4.5, the dataset described in Table 3.6 was randomly divided, with 80% of the samples used for training and 20% reserved for testing. Therefore, for training the fault detection model in the proposed 1D-CNNs framework, it uses 6,912 samples for training and 1,728 samples for testing. This distribution, considering a wide range of scenarios, ensures a comprehensive evaluation of the performance, contributing to its robustness and reliability in fault detection. Additionally, the "ASHRAE-RP1312" benchmark, as detailed in Section 3.5.2, was used to assess the adaptability of the proposed fault detection system across varying conditions. Finally, the performance of the proposed 1D-CNNs fault detection system was evaluated by comparing it with alternative FDD models, including RF, SVM, and One vs Rest-SVM (OvR-SVM), across nine distinct summer fault scenarios as further explains in Section 5.5.

5.4.2 Design Parameters of 1D-CNNs

This Section explores the design parameters of the proposed 1D-CNNs model for HVAC fault detection. The system was developed and validated using data gathered during occupancy, which provided 2,160 normal and 720 fault data points over a 12-hour period, as detailed in Section 5.4.1.

Layer	Filters	Kernel	Output	Parameters
Input Layer	-	-	(194,1)	-
Conv1D	32	6×6	(194, 32)	224
Batch Normalization	-	-	(194, 32)	128
ReLU	-	-	(194, 32)	-
Conv1D	32	6×6	(194, 32)	6176
Batch Normalization	-	-	(194, 32)	128
ReLU	-	-	(194, 32)	-
Conv1D	64	6×6	(194, 64)	12352
Batch Normalization	-	-	(194, 64)	256
ReLU	-	-	(194, 64)	-
Conv1D	64	6×6	(194, 64)	24640
Batch Normalization	-	-	(194, 64)	256
ReLU	-	-	(194, 64)	-
Conv1D	128	6×6	(194, 128)	49280
Batch Normalization	-	-	(194, 128)	512
ReLU	-	-	(194, 128)	-
Global Average Pooling	-	-	128	-
Classification	-	-	10	1290

Table 5.1: 1D-CNN HVAC Fault Detection System: Network Architecture and Parameters

Using these data insights, the model was trained using training and testing phases with 6,900 and 1,740 samples. During the training process, the 1D-CNN model was built incrementally, employing a sequential approach in Keras. Its architecture consisted of seven convolutional layers [32-32-64-64-128-128-10], each followed by a pooling layer, culminating in a fully connected classification layer. For each layer, it employed kernel filters of size 6×6 with a stride of 1. The optimized parameters for the 1D-CNNs HVAC fault detection system are detailed in Table 5.1. The "SoftMax" was used for final classification, while rectified linear units ("ReLU") were applied as activation functions in all convolutional layers. Furthermore, the adaptive moment estimation ("Adam") optimizer was utilized to achieve optimal parameter tuning, ensuring effective learning and high accuracy in fault detection.

Ultimately, the effectiveness of fault detection in the system depends on carefully optimizing design parameters. By adjusting settings like filters and layers, the system improves its ability to interpret data accurately, thereby enhancing its reliability in detecting anomalies. These refinements are crucial in improving the performance of system to operate smoothly in real-world environments, where accurate fault detection is essential. As a result of these improvements, the fault detection system is expected to provide increased reliability and effectiveness, ensuring consistent performance across different conditions and applications.

5.5 Experimental Result and Discussion

This section provides a brief overview of the experimental results obtained from the proposed 1D-CNNs based fault detection system, presented in Figure 5.2. The effectiveness of this system is validated using precision, recall, and F1 score metrics, as discussed in Section 4.4.3 of Chapter 4. These metrics are important in fault detection and diagnosis, as they assess the capability system to accurately identify and categorize faults while reducing false positives and negatives. In Table 5.2, the proposed 1D-CNNs demonstrates impressive accuracy in detecting a range of summer HVAC operational faults and normal conditions, achieving an overall accuracy rate of 94%.

Furthermore, another outstanding result is for the “EADAMPOP” fault, which achieved near-perfect performance with precision, recall, and F1-score of 100%, 95%, and 98%. This exceptional performance indicates that every instance classified as “EADAMPOP” by the system was perfectly correct, demonstrating its remarkable accuracy in identifying this specific fault. Another notable result is for the fault type “CCV100%CL”, which showed high precision, recall, and F1-score values of 94%, 100%, and 97% respectively. These scores indicate that the system correctly identified the closure of cooling coil valves in the majority of instances, while also minimizing false positives and negatives. This suggests that the system is effective in detecting this specific fault with a high degree of accuracy.

DataSet	Fault Code	Precision (%)	Recall (%)	F1-score (%)
HVACSIM+	NORMAL	96	96	96
	CCV100%CL	95	99	97
	CCV100%OP	92	98	95
	CCVREV	98	95	96
	DLAFTSF	82	94	88
	EADAMPCL	91	89	90
	EADAMPOP	100	95	98
	HCVSTG2L	99	82	90
	OADAMP45%OP	91	98	95
	OADAMPCL	98	95	97
	Overall Model Accuracy	94		
ASHRAE-RP1312	NORMAL	98	89	93
	CCV100%CL	94	100	97
	CCV100%OP	100	92	96
	CCVREV	100	99	99
	DLAFTSF	98	92	95
	EADAMPCL	94	100	97
	EADAMPOP	92	99	96
	HCVSTG2L	100	83	93
	OADAMP45%OP	67	99	80
	OADAMPCL	100	98	99
	Overall Model Accuracy	94		

Table 5.2: Classification Reports for 1D-CNNs Using HVACSIM+ and ASHRAE-RP1312 Data

The results for other fault types also show high performance. For instance, CCV100%OP achieved an F1-score of 95%, OADAMPCL demonstrated an F1-score of 97%, and CCVREV exhibited a strong F1-score of 96%. These results highlight the robustness of the system in accurately detecting faults across a wide range of operational conditions. On the other hand, the fault type "DLAFTSF" showed comparatively lower precision of 82%. While the recall and F1-score were 94% and 88% respectively, indicating a relatively high level of true positive identification and overall performance, the lower precision suggests that there were instances where other faults were mistakenly classified as “DLAFTSF”. This indicates a potential area for improvement in the FDD ability to get better accuracy.

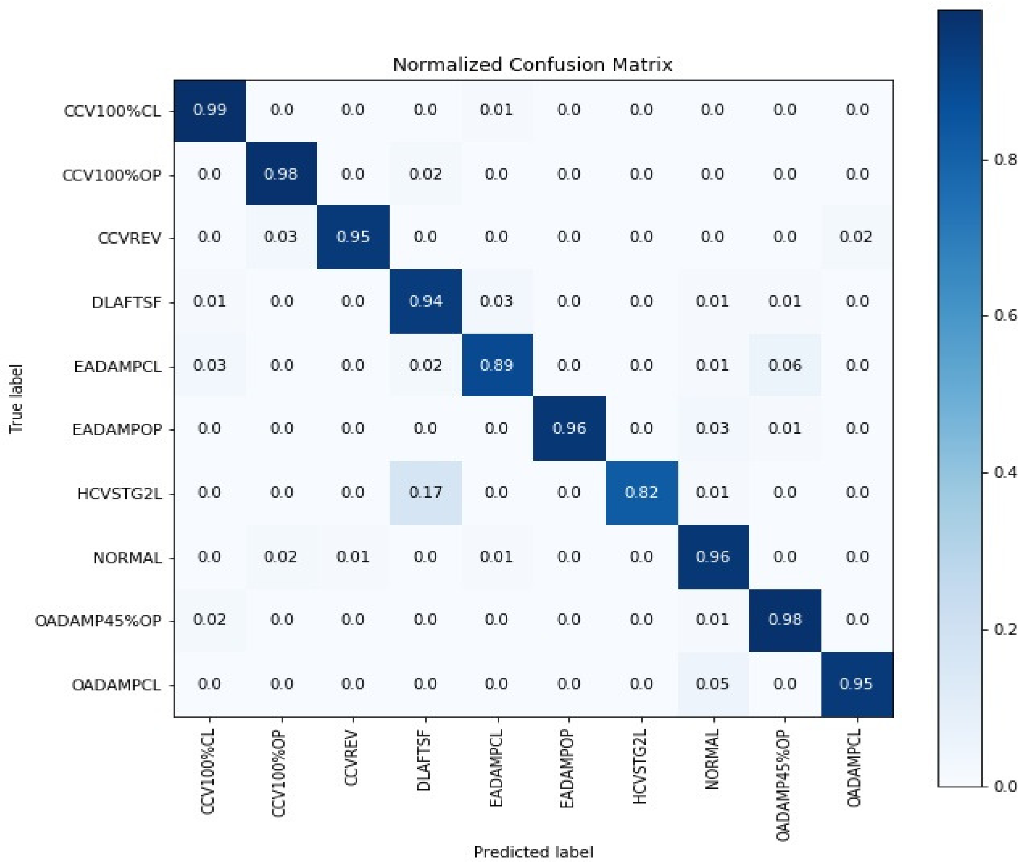


Figure 5.3: Confusion Matrix: Evaluating 1D-CNNs Performance using HVACSIM+ Simulation Data

In the “ASHRAE-RP1312” dataset evaluation (Section 3.5.2, the proposed fault detection system demonstrates exceptional performance in identifying faults such as “CCVREV” and “CCV100%OP,” achieving perfect precision and high recall. These results highlight the reliability of proposed FDD system in accurately detecting specific fault types without significant misclassifications. However, it encounters challenges with the "OADAMP45%OP" fault, exhibiting lower precision, which indicates potential misclassifications or false alarms. Despite this, the overall model accuracy remains commendable at 94%, confirming the effectiveness of the system in real-world fault detection scenarios.

In addition, the analysis of the confusion matrix presented in Figure 5.3 reveals consistently high diagnosis accuracy for the majority of fault types, surpassing 89%, with the exception of heating coil valve leaks ("HCVSTG2L"), which achieved approximately 90 to 99 % accuracy. Particularly, the ability model to classify cooling coil valve (fully opened and closed) and outside air damper fault ("OADAMP45%OP") with accuracy consistently achieves above 98%. The fault detection system slightly misclassified "HCVSTF2L" as "DLAFTSF" with an 82% accuracy, indicating some difficulty in distinguishing between these faults. This discrepancy may arise from similarities in operational characteristics or sensor data patterns. However, overall system performance remains effective, given by high accuracy rates across other fault types. These findings highlight the effectiveness of the proposed fault detection system in accurately identifying various HVAC operational faults. In addition, its performance will be further validated through comparisons with other state-of-the-art techniques in Chapter 7.

5.6 Summary

In conclusion, this study presents an innovative fault diagnostic system for HVAC systems using one-dimensional Convolutional Neural Networks (1D-CNNs). By leveraging simulated fault data generated through the HVACSIM+ building energy model, the proposed system accurately detects nine different HVAC fault types and normal conditions, achieving a classification accuracy of 94%. The 1D-CNNs effectively extracts high-level temporal features from raw sensor signals, supporting real-time fault detection and improving system reliability, energy efficiency, and overall performance. However, 1D-CNNs primarily focus on time-based patterns and may not fully capture the relationships between different sensor signals that are functionally linked across the system. These spatial dependencies, such as the influence of airflow or temperature across connected zones, are better addressed using methods like GAF-2DCNNs. This approach transforms time series into 2D images, enabling the model to learn both spatial and temporal patterns. These findings suggest opportunities for future research to further enhance fault detection through multidimensional feature learning.

Chapter 6

Advancing Fault Detection in HVAC Systems: Unifying Gramian Angular Field with 2D-Convolutional Neural Networks

This chapter introduces an advanced fault detection framework for HVAC systems that integrates Gramian Angular Field (GAF) encoding with two-dimensional convolutional neural networks (2D-CNNs). The proposed approach transforms multivariate time-series sensor data into image-based representations, allowing both temporal dynamics and spatial relationships between sensor signals to be effectively captured. This enables the model to learn complex patterns associated with various fault conditions, including those that are difficult to distinguish using conventional feature extraction methods. By leveraging the expressive power of 2D-CNNs on GAF-encoded inputs, the framework enhances classification performance and supports early, accurate detection of faults under diverse HVAC operating scenarios. The method is evaluated using simulated data generated from HVACSIM+ and benchmark data from ASHRAE RP-1312, ensuring comprehensive validation across controlled and real-world-like environments.

6.1 Background Studies

Recent advancements in one-dimensional convolutional neural networks (1D-CNNs) have proven effective in HVAC system fault detection and diagnosis by accurately classifying faults through automatic feature extraction and temporal dependency, thereby minimizing the need for extensive preprocessing. As discussed in Chapter 5, during the training process, features are automatically extracted by applying convolutional filters to the input dataset, identifying patterns through local dependencies and relationships within the raw time-series sensor data. However, this approach has notable limitations, especially in capturing both spatial and temporal patterns. In 1D-CNNs, it primarily captures temporal patterns, focusing on changes in data over time, rather than spatial patterns, which involve relationships between different sensor locations or spatially distributed data points. This limitation can reduce their effectiveness in applications where spatial context is important, These challenges highlight the need for developing more advanced fault detection systems that can overcome these limitations.

To address these challenges, a decentralized Boltzmann-machine-based approach for HVAC air handling unit (AHU) fault diagnosis is proposed in Yanab et al. [2022]. This method uses less affected residuals as indicators and employs a decentralized voting mechanism to localize sensor faults effectively. Although the approach shows high accuracy in diagnosing sensor faults, its reliability depends on the quality of residual data. Experimental evaluations, using data from ASHRAE Project 1312-RP, compare AHU-A with induced faults to AHU-B under normal conditions across various seasons to assess robustness and accuracy. However, the study lacks simulated HVAC operational data, which limits the scope of comprehensive testing and validation of the fault detection and diagnosis methodologies. This absence of simulated data restricts the ability to fully understand the performance of systems under diverse operating conditions and fault scenarios, potentially hindering the development of more generalizable fault detection systems.

In the context of enhancing fault detection, the utilization of deep belief networks (DBNs) for detecting various HVAC faults is introduced [Boureau and LeCun, 2008, Lee et al., 2019]. Specifically, it uses multiple layers of restricted Boltzmann machines (RBMs) stacked together, with each layer trained sequentially in an unsupervised manner. This approach learns to capture intricate patterns in the data by optimizing the weights between the visible and hidden units. Once the pre-training is completed, the entire network can be fine-tuned using supervised learning to improve fault detection accuracy. Despite the strength of its layer-wise training for learning complex patterns, the method may struggle to effectively capture the spatial and temporal relationships inherent in HVAC data. Additionally, the research focus on only five faults might not comprehensively represent the reality, where more diverse faults can arise from human errors, unexpected device malfunctions, and sensor drift. This highlights the need for further exploration of a broader range of AHU faults to ensure the accuracy and robustness of the diagnostic model

Furthermore, a novel method for encoding time series data into images is introduced in Wang and Oates [2015], using Gramian Angular Fields (GAFs) in a polar coordinate system. In this method, time-series data are transformed into a matrix where each element represents the trigonometric relationship between different time points. Specifically, the data are encoded using angular values derived from the original time-series data, converting them into polar coordinates. This means that each element in the GAF matrix captures the cosine or sine sum of angles between pairs of time points, highlighting temporal dependencies and patterns. The tiled convolutional neural networks (tiled CNNs) are employed to extract high-level features from these GAFs representations. However, the study uses publicly available UCR Time Series datasets which differ significantly from HVAC operational data. In contrast to the diverse and intricate sensor readings associated with HVAC operational faults, learning ECG signals is more straightforward due to their simple continuous waveforms that reflect heart activity.

With this motivation, for advancing HVAC fault detection, a novel unified approach, leveraging both Gramian Angular Fields (GAF) and two-dimensional Convolutional Neural Networks (2D-CNNs) is introduced in this Chapter. Unlike the method outlined in Gao et al. [2023], this approach considers "NORMAL" operating conditions alongside nine significant HVAC faults. This inclusion helps to reduce false alarms and improve accuracy, thereby enhancing overall system performance. Additionally, strategic training during occupied hours, specifically from 6:00 AM to 6:00 PM, increases the robustness of model in dynamic operational environments by capturing specific usage patterns and anomalies. Moreover, utilizing a finer time resolution of one minute allows the system to capture detailed variations, improving the precision and sensitivity of fault detection. The implementation of "occupancy-aware modeling" is further validated using benchmark ASHRAE data, enhancing the generalizability and reliability of the proposed model, thus providing a robust fault detection system that aligns with real-world scenarios.

In the upcoming Section 6.2, the theoretical foundation of transforming time series into images using GAF and the structure of the 2D-CNNs are discussed. Furthermore, the proposed unified framework, GAF-2DCNNs for fault detection, is presented in Section 6.3, along with its training process in Section 6.4. The simulation dataset from Section 3.5.1 and the benchmark ASHRAE data from Section 3.5.2 of Chapter 3 are used for the model training and evaluation. Comparison analysis using both simulated data and the benchmark ASHRAE dataset highlights the robust performance and adaptability of the proposed methods across diverse operational conditions, as detailed in Section 6.5. Finally, limitations, conclusions, and potential future research directions are outlined in Section 6.6.

6.2 Methodological Background

This section examines the theoretical foundations of transforming time series data into images using Gramian Angular Field (GAF) and the architecture of the two-dimensional Convolutional Neural Network (2DCNNs). The GAF, discussed in Section 6.2.1, provides a reliable method for converting temporal patterns into visual representations, capturing detailed temporal dependencies within the data. In contrast, 2DCNNs, covered in Section 6.2.2, are well-known for their ability to extract features from images, making them ideal for pattern recognition tasks. Together, these methods offer a combined approach to fault detection, using the strengths of both GAF and 2DCNNs to improve feature extraction and classification accuracy within HVAC systems

6.2.1 Gramian Angular Field (GAF)

This section presents an exploration of the Gramian Angular Field (GAF), a distinctive method utilized in time series analysis. It transforms time series data into images by encoding temporal relationships and correlations onto a two-dimensional polar coordinate system [Zhou et al., 2022]. By converting data points into angles and distances, where cosine values represent the angular differences, GAF produces images that encapsulate intricate temporal patterns. This technique proves particularly valuable for tasks like fault detection and signal processing. For a given time series $X = \{x_1, x_2, ..., x_n\}$, the initial step in GAF involves normalizing it to a value interval of $[0, 1]$ by:

$$\widetilde{x}_i = \frac{(x_i - \max(X) + x_i - \min(X))}{\max(X) - \min(X)} \tag{6.1}$$

$$\widetilde{x}_i = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{6.2}$$

Following normalization, the normalized time series data are depicted in the polar coordinate system, where the value is encoded as the angular cosine and the time stamp as the radius, given by the equation:

$$\phi_i = \arccos(\widetilde{x}_i), -1 \leq \widetilde{x}_i \leq 1, \widetilde{x}_i \in \widetilde{X} \tag{6.3}$$

$$r_i = \frac{t_i}{N}, t_i \in N \tag{6.4}$$

where $\phi \in [0, \pi]$, t_i is the time stamp, and N is a constant factor to regularize the span of the polar coordinate. The GAF has essential properties of rescaling time series data into different intervals with different angular bounds, where $[0, 1]$ corresponds to the cosine function in $[0, \frac{\pi}{2}]$, while cosine values in the interval $[-1, 1]$ fall into the angular bounds $[0, \pi]$.

After transforming the re-scaled time series to a polar coordinate system, temporal correlations within different time intervals can be identified by considering the trigonometric sum or difference between each point. The Gramian Summation Angular Field ($GASF$) is defined in (6.5) and 6.6, and the Gramian Difference Angular Field ($GADF$) is defined in equations (6.7) and (6.8), which allow easy calculation of the angular viewpoint, where ($GASF$) is based on cosine functions and ($GADF$) is based on sine functions:

$$\text{GASF} = \begin{bmatrix} \cos(\phi_1 + \phi_1) & \cdots & \cos(\phi_1 + \phi_n) \\ \cos(\phi_2 + \phi_1) & \cdots & \cos(\phi_2 + \phi_n) \\ \vdots & \ddots & \vdots \\ \cos(\phi_n + \phi_1) & \cdots & \cos(\phi_n + \phi_n) \end{bmatrix} \tag{6.5}$$

$$GASF = \tilde{X}' \cdot \tilde{X} - \sqrt{I - \tilde{X}^2}' \cdot \sqrt{I - \tilde{X}^2} \tag{6.6}$$

$$\text{GADF} = \begin{bmatrix} \sin(\phi_1 + \phi_1) & \cdots & \sin(\phi_1 + \phi_n) \\ \sin(\phi_2 + \phi_1) & \cdots & \sin(\phi_2 + \phi_n) \\ \vdots & \ddots & \vdots \\ \sin(\phi_n + \phi_1) & \cdots & \sin(\phi_n + \phi_n) \end{bmatrix} \tag{6.7}$$

$$GADF = \sqrt{I - \tilde{X}^2}' \cdot \tilde{X} - \tilde{X}' \cdot \sqrt{I - \tilde{X}^2} \tag{6.8}$$

where I represents the unit row vector, the GAF algorithm offers several advantages. It ensures the preservation of temporal dependencies by encoding per-position movement over the time period. This feature enables the swift conversion of a one-dimensional time series into a two-dimensional image, which can be efficiently utilized by 2D-CNNs, as elaborated in Section 6.2.2.

6.2.2 2D-Convolutional Neural Networks (2D-CNNs)

In this section, the fundamental algorithms and structures of Convolutional Neural Networks (CNNs) are described, as they are essential for classifying time series images transformed through Gramian Angular Fields (GAF). The architecture of CNNs comprises two primary components, the initial segment, which employs convolution and pooling operations to produce a feature map from the raw input signal using a carefully chosen kernel size, and the subsequent segment, which focuses on classifying intricate features using a multi-layer perceptron (MLP) approach. This architecture enables CNNs to effectively extract hierarchical features from input images, facilitating accurate classification and analysis of complex data patterns [Krizhevsky et al., 2012].

Figure 5.1 of Chapter 5 illustrates a typical CNNs configuration featuring convolutional and pooling layers through the use of GAF-encoded images. The initial input layer comprises $N \times k$ neurons, where k signifies the variable count of input time series, and N represents the length of each univariate series. The subsequent layer involves the convolutional layer, executing convolution operations using m filters, convolution stride s, and a $y \times y$ filter size. Additionally, this layer necessitates the consideration of a non-linear transformation function f.

As a next step, the pooling operation is performed in which a feature map is divided into N equal-length segments, and then every segment is represented by its average or maximum value. After several convolution and pooling operations, the original time series is represented by a series of feature maps that connects to final output layers with n classes. The training of CNN is performed by a sequence of training examples: $(x_1, y_1), (x_2, y_2), .., (x_{Nsample}, y_{Nsample})$, with $(x_t \in R^{N\times k}, y_t \in R^n for 1 \leq t \leq N_{sample}$. The multivariate or uni-variate time series x_t is given as input to the network, while the vector y_t denotes the target output. The training procedure consists of a sequence of stages outlined in equations (5.1) through (5.6), in accordance with the configuration depicted in Figure 5.1, resulting in the creation of a robust CNN model.

In practice, understanding the methodological foundations of CNNs is important for advancing fault detection methodologies in HVAC systems. This understanding provides valuable insights into the structure, functionality, and learning mechanisms of these neural networks. In Section 6.3, a detailed presentation of a novel fault detection system design and architecture based on Gramian Angular Field (GAF) and CNNs will be provided, demonstrating its potential to enhance fault detection accuracy and reliability in HVAC systems.

6.3 Unifying GAF and 2D-CNNs for Advancing Fault Detection

This section presents an innovative approach for HVAC fault detection, integrating Gramian Angular Fields (GAF) with two-dimensional convolutional neural networks (CNNs). As shown in Figure 6.1, the GAF technique converts HVAC sensor time series data into images, which are then processed by 2D-CNNs to classify HVAC operational faults and normal conditions. This transformation allows temporal changes to be represented as spatial patterns, enabling the CNNs to capture crucial spatial relationships and patterns related to operational faults. Additionally, the encoded GAF images bridge temporal dynamics and spatial patterns, enhancing the ability of model to detect underlying fault signatures.

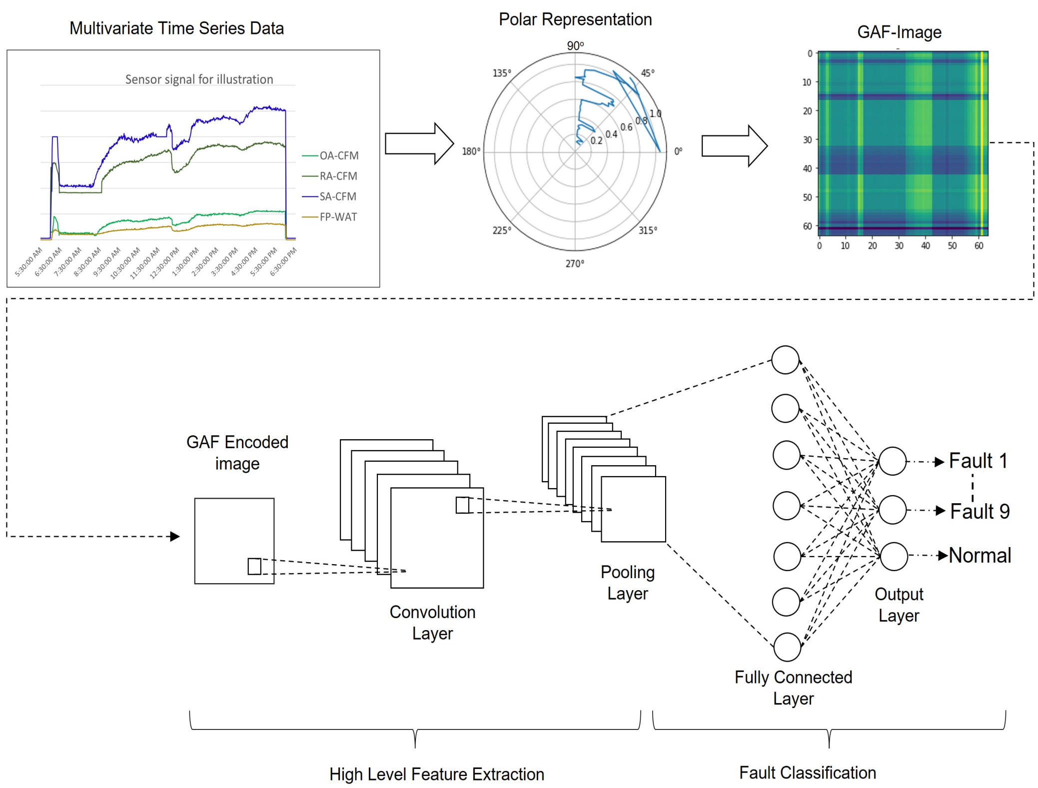


Figure 6.1: The HVAC fault detection system using GAF-2DCNNs.

The proposed unified framework is validated using the simulated data from Table 3.6 of Chapter 3, which represents various HVAC system conditions, both “Normal” and faulty along with benchmark ASHRAE data from Section 3.5.2. During the 2D-CNNs training, the network iteratively learns from these images, following the steps in equations (5.1) through (5.6). It adjusts and optimizes its parameters to detect subtle changes in patterns related to different HVAC system states. Comparison studies highlight the superior accuracy of the proposed GAF-2DCNNs approach, which is further elaborated in Chapter 7. Notably, comparison methods require feature extraction and selection, whereas the proposed fault detection system, as illustrated in Figure 6.1, stands out for its superior accuracy.

6.4 Training Unified Framework GAF and 2D-CNNs FDD System

This section outlines the process of training the proposed unified framework that integrates Gramian Angular Fields (GAF) with two-dimensional convolutional neural networks (2D-CNNs) for HVAC fault detection and diagnosis (FDD). Ensuring the model accurately detects faults in HVAC systems by capturing intricate temporal and spatial patterns within the data is crucial. The first Subsection 6.4.1 addresses dataset preparation, as briefly discussed in Section 3.5 from Chapter 3, encompassing both simulated data and benchmark ASHRAE data used for validation. The second Subsection 6.4.2 focuses on designing parameters crucial for optimizing 2D-CNN performance, including hyperparameter selection, network architecture, and training configurations.

6.4 TRAINING UNIFIED FRAMEWORK GAF AND 2D-CNNS FDD SYSTEM

6.4.1 Dataset Preparation

The dataset used in this Section originates from the dynamic HVAC simulation model discussed in Chapter 3, in which simulated data (Section 3.5.1) considers diverse operating conditions, encompassing both "Normal" and faulty scenarios, following the HVAC control algorithm outlined in Section 3.2.1 and adhering to specified operational parameters detailed in Section 3.2.2. The dataset has been meticulously generated and validated using ASHRAE benchmark data (Section 3.5.2), making it suitable for training and evaluating the HVAC fault detection model due to its inclusion of a broad spectrum of HVAC system conditions.

During the dataset preparation phase, data were extracted from the designated occupancy timeframe, detailed in Table 3.4. This extraction resulted in 720 data points spanning a 12-hour period (from 6 AM to 6 PM). The dataset encompasses a wide array of significant HVAC faults, such as "Control Coil Valve fully opened (CCV100%OP)", "Control Coil Valve fully closed (CCV100%CL)", "Cooling Coil Valve Reverse Action (CCVREV)", "Duct Leak After Supply Fan (DLAFTSF)", "Exhaust Air Damper opened (EADAMPOP)", "Exhaust Air Damper closed", "Outside Air Damper closed (OADAMPCL)", "Outside Air Damper 45% opened", and "Heating Coil Valve Leak—Stage 2 (HCVLSTG2)", alongside samples representing the "Normal (NORMAL) condition". Each fault category is well-represented with 720 samples, while the "Normal" Condition category comprises 2160 samples. This comprehensive dataset provides training and testing for the fault detection model, ensuring robust performance across a spectrum of HVAC system conditions and fault scenarios.

Furthermore, the dataset used in this chapter is consistent with Chapters 4 and 5 to conduct a comparison study of the proposed advanced FDDs. A detailed comparison will be presented in Chapter 7. Similarly, the dataset was divided into an 80% random subset for training and a 20% subset for testing, involving 6912 samples for training and 1728 samples for testing. Starting with 194 raw feature input data points, the GAF-2DCNNs methodology began by applying the Gramian Angular Field (GAF) technique (Section 6.2.1) to transform the initial time series data into image data, enabling the model to capture both temporal and spatial relationships. The transformed image data was subsequently fed into the CNNs (Section 6.2.2) for final fault and normal classification. Further details on the CNN architecture and its design parameters are elaborated in the subsequent Section 6.4.2.

6.4.2 Design Parameters

This section discusses the design parameters of the GAF-2DCNNs fault detection system, focusing on critical parameters such as the number of convolutional layers, kernel size, pooling layers, dropout rates, activation functions as given in equations (5.1) - (5.6). These parameters are essential for shaping the network architecture and governing its learning process. Furthermore, the section elaborates on the rationale behind selecting specific parameter values and the methodology used to fine-tune them for optimal performance in HVAC fault detection.

In this experiment, a sequential model was employed to construct the CNN using Keras, allowing the model to be developed layer by layer. With an input image size of $[6912 \times 64 \times 64 \times 1]$, the CNN model architecture was created, consisting of three convolutional layers, three max pooling layers, and a final fully connected classification layer. The first layer employed 32 filters, while the second and third layers utilized 64 and 128 filters, respectively. The filter size in each layer can be adjusted based on the dataset. The convolution operations employed kernel sizes of $[6 \times 6]$, $[6 \times 6]$, and $[3 \times 3]$ for the first, second, and third filter matrices respectively, generating feature maps.

Layer	**Filters**	**Kernel**	**Output**	**Parameters**
Input Layer	-	-	(64, 64, 1)	-
Conv2D	32	6×6	(59, 59, 32)	1,184
Max Pooling	-	-	(29, 29, 32)	-
Dropout	-	-	(29, 29, 32)	-
Conv2D	64	6×6	(24, 24, 64)	73,791
Max Pooling	-	-	(12, 12, 64)	-
Dropout	-	-	(12, 12, 64)	-
Conv2D	128	3×3	(10, 10, 128)	73,856
Max Pooling	-	-	(5, 5, 128)	-
Dropout	-	-	(5, 5, 128)	-
Flatten	-	-	(3,200)	-
Dense	-	-	(256)	819,456
Dropout	-	-	(256)	-
Classification	-	-	(10)	2,570

Table 6.1: GAF-2DCNNs HVAC fault detection: CNN network architecture and parameters

The “Rectified Linear Activation (ReLU)” was applied in the initial two convolutional layers prior to the max pooling step. The final classification layer utilized the Softmax activation function. For parameter optimization, the Adam (Adaptive Moment Estimation) optimizer was employed, offering an alternative to traditional stochastic gradient descent for iterative network weight updates based on training data [Mehta et al., 2019]. Information regarding the number of optimized parameters in the CNN architecture for the proposed GAF-2DCNNs HVAC fault detection system is outlined in Table 6.1.

Therefore, the CNNs network architecture and parameters detailed in Table 6.1 play a crucial role in the fault detection process. By leveraging convolutional layers with varying filter sizes and kernel shapes, the model effectively captures spatial patterns within the transformed GAF images. Furthermore, the inclusion of dropout layers helps prevent overfitting by randomly deactivating neurons during training. This optimized architecture ensures that the CNNs can efficiently learn and classify HVAC faults with high accuracy and robustness.

6.5 Experimental Result and Discussion

The experimental results on the GAF-2DCNNs approach for HVAC fault detection are presented in this Section. The comparison results in Table 6.2 show the effectiveness of the proposed GAF-2DCNNs method across nine significant faults and "Normal" operating conditions. The generalization ability of the model is validated by comparing it to both the simulation dataset (HVACSIM+) and the ASHRAE benchmark dataset, as briefly discussed in Sections on HVACSIM+ data and ASHRAE data in Chapter 3. Notably, the GAF-2DCNNs method demonstrates superior performance, especially in identifying critical faults that were challenging to detect using the previous approaches discussed in Chapter 4 and Chapter 5.

For instance, "CCVREV" has a Precision, Recall, and F1-score (Section 4.4.3) of 99%, while "HCVSTG2L" records 96% Precision, 100% Recall, and a 98% F1-score. Other faults such as duct leak after the supply fan ("DLAFTSF") and exhaust air damper open ("EADAMPOP") also show strong performance, with DLAFTSF achieving 98% across all metrics and EADAMPOP recording a Precision of 100%, Recall of 93%, and F1-score of 96%. Overall, the model achieves an impressive accuracy of 97% on the HVACSIM+ data, indicating its robustness and reliability in fault detection and classification across various scenarios.

DataSet	Fault Code	Precision (%)	Recall (%)	F1-score (%)
HVACSIM+	NORMAL	99	97	98
	CCV100%CL	95	97	96
	CCV100%OP	92	98	95
	CCVREV	99	99	99
	DLAFTSF	98	98	98
	EADAMPCL	94	94	94
	EADAMPOP	100	93	96
	HCVSTG2L	96	100	98
	OADAMP45%OP	93	96	94
	OADAMPCL	100	98	99
	Overall Model Accuracy	97		
ASHRAE-RP1312	NORMAL	98	93	95
	CCV100%CL	86	91	91
	CCV100%OP	97	97	97
	CCVREV	95	97	97
	DLAFTSF	91	93	93
	EADAMPCL	94	87	87
	EADAMPOP	94	95	95
	HCVSTG2L	97	97	97
	OADAMP45%OP	93	94	94
	OADAMPCL	98	97	97
	Overall Model Accuracy	95		

Table 6.2: Classification Reports for Hybrid GAF-2DCNNs Using HVACSIM+ and ASHRAE-RP1312 Data

Similarly, on the ASHRAE-RP1312 dataset, the GAF-2DCNNs method continues to perform well, particularly for the faults "CCVREV" and "HCVSTG2L", both achieving Precision, Recall, and F1-scores of 95% to 97%, respectively. Other faults such as exhaust air damper open ("EADAMPOP") also maintain high performance with 94% Precision, 95% Recall, and a 95% F1-score. The model shows a consistent and reliable accuracy of 95% on the benchmark ASHARE data, demonstrating its capability to generalize effectively across different datasets and maintain high performance.

The GAF-2DCNNs model shows strong and consistent performance across both the HVACSIM+ and ASHRAE datasets. With an accuracy of 97% on simulated data and 95% on ASHRAE benchmark, the method demonstrates its robustness in accurately detecting and classifying HVAC faults. By prioritizing normal states, the accuracy of fault detection is significantly improved, enabling the method to accurately classify faults even in intricate operational scenarios. This is evident from the recall rates presented in the same table, where recall values consistently exceed 95%, with the exception of one fault category ("EADAMPOP") showing a 93% recall rate. This underscores the reliability of the proposed method in identifying a large proportion of actual faults, further validating its effectiveness in practical settings.

Furthermore, the F1-score, which evaluates the ability of model to handle imbalanced datasets, underscores the robust performance of the GAF-2DCNNs. The F1-scores provided in Table 6.2 illustrate the effectiveness of model in managing an unbalanced input dataset, demonstrating its applicability in scenarios where certain fault types may be less prevalent or inherently challenging to detect. The high precision, recall, and F1-scores for critical faults across both datasets highlights the effectiveness and reliability of the proposed fault detection system. This comprehensive evaluation shows the potential of GAF-2DCNNs as a powerful tool for practical HVAC fault detection applications, capable of maintaining high performance and reliability across varied data sources.

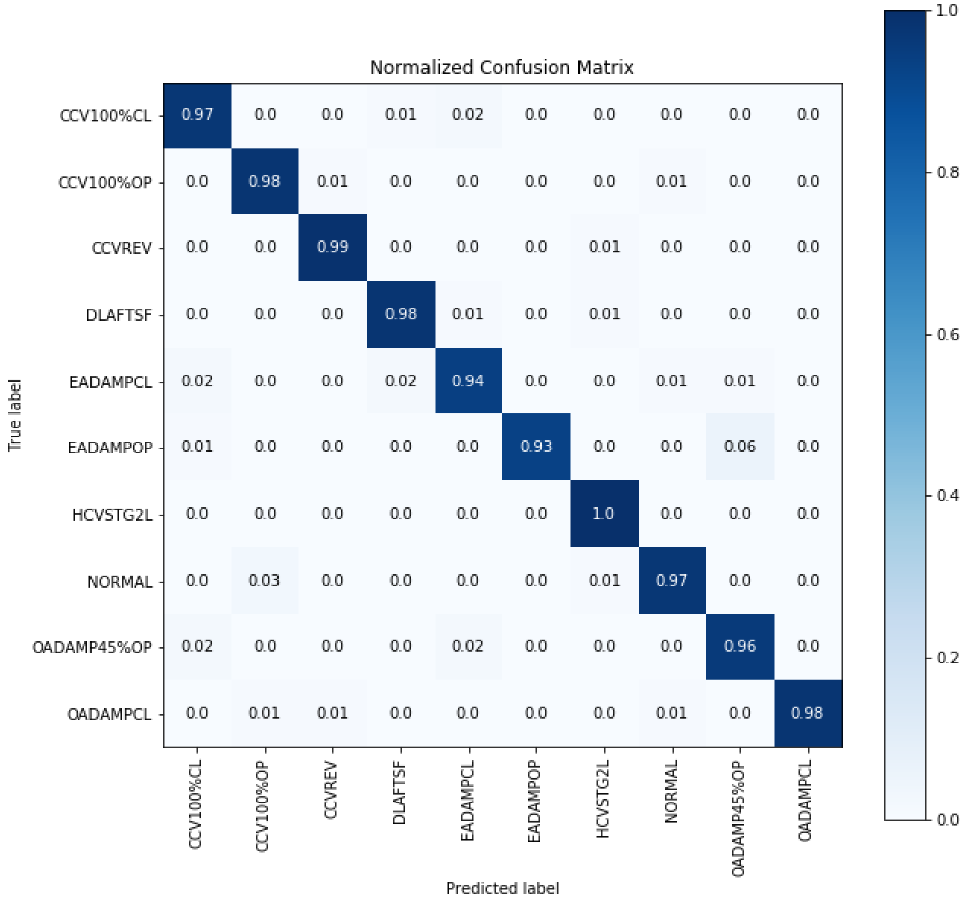


Figure 6.2: GAF-2DCNNs confusion matrix.

In addition, the effectiveness of the proposed unified framework is initially assessed through an examination of the confusion matrix presented in Figure 6.2. The results reveal that the GAF-2DCNNs model achieves an impressive diagnostic accuracy of 95% for most faults and normal conditions, with only slight variations observed for specific fault types. Notably, the system demonstrates 100% accuracy in detecting heating coil valve leakage faults ("HCVSTG2L") and a robust 99% accuracy in identifying cooling coil valve reverse action faults ("CCVREV"). Achieving such high accuracy levels in fault detection, particularly for critical issues like heating coil valve leakage and cooling coil valve reverse action, highlights the exceptional capability of the proposed model. This level of accuracy ensures the prompt identification and diagnosis of these faults, enabling timely interventions to address and mitigate potential issues within HVAC systems.

While the developed “GAF-2DCNNs” fault detection system achieves better performance in the HVAC faults detection, it may introduce moderately higher computational requirements due to its image-based input representation and network depth. Transforming time-series data into two-dimensional GAF images may increase data dimensionality, leading to greater memory usage and longer processing time during model training. In addition, the CNNs architecture developed in this study considers multiple convolutional layers with increasing filter depths and kernel sizes, resulting a network with several trainable parameters (Table 6.1). In this study, the “Adam” optimizer was used as the default optimization algorithm for training the trained 2D-CNNs model. This selection also aligns with standard practice in deep learning, as it provides adaptive learning rates, efficient convergence, and generally reliable performance across a wide range of CNN architectures [Kingma and Ba, 2014].

Although GAF-2DCNNs introduce higher computational requirements due to their image-based input representation and deep network architecture, they have been increasingly adopted in the research community for time-series classification tasks. This growing interest is attributed to their ability to effectively capture both spatial and temporal dependencies in complex multivariate datasets, which is particularly advantageous for applications such as fault detection in dynamic systems [Gao et al., 2023, Yang et al., 2019]. In contrast, although traditional machine learning models are computationally efficient, their classification performance tends to be lower, as discussed in Chapters 4 and 7. These models often lack the inherent capability to learn from raw sensor data, relying instead on manually engineered features and feature importance.

As a consequence, they were less effective in identifying major fault conditions, particularly in cases involving nonlinear interactions or temporal variations, as further elaborated in Chapter 7. This reflects a fundamental trade-off between computational efficiency and diagnostic performance. However, with the continued advancement of high-performance computing infrastructure and the accessibility of GPU-enabled platforms, such as the NVIDIA RTX 3090 and Tesla V100, the computational demands during training for deep learning models can be significantly reduced [Xu et al., 2021]. These platforms offer notable improvements in training speed and scalability, making GAF-2DCNNs a practical and promising solution for large-scale or real-time HVAC fault detection applications.

6.6 Summary

In conclusion, the unified framework introduced in this study marks a significant advancement in HVAC fault detection, leveraging the integration of HVACSIM+ simulated data with GAF-2DCNN. This approach not only enhances the classification accuracy of major HVAC faults and normal conditions to 97%, but also ensures robustness in distinguishing between normal and faulty states without additional interpretability techniques. By conducting a comprehensive comparison with HVACSIM+ and ASHRAE datasets, the framework achieves an overall accuracy of 97%, with precision, recall, and F1 scores consistently exceeding 90% for each fault category. This highlight its efficacy in capturing both temporal and spatial data nuances, aided by considerations of occupancy patterns and finer data intervals. Nonetheless, the effectiveness of framework could be further optimized by addressing challenges related to data availability and quality. Future research directions may thus focus on enhancing model robustness through techniques like data augmentation and transfer learning, thereby advancing its applicability in real-world HVAC systems.

Chapter 7

Evaluation of the Proposed Fault Detection Approaches

This chapter presents a comparative analysis of three fault detection and diagnosis (FDD) approaches developed for HVAC systems: a hybrid Random Forest–Support Vector Machine (RF-SVM) model, a one-dimensional convolutional neural network (1D-CNN), and a method that combines Gramian Angular Fields (GAF) with two-dimensional convolutional neural networks (2D-CNNs). Each method adopts a distinct learning strategy, including ensemble-based classification, temporal feature extraction, and image-based spatio-temporal representation, to address the challenges of identifying operational faults in HVAC systems. The comparison focuses on classification performance, generalisation capability, and model robustness across a range of typical fault types and normal operating conditions. By evaluating their respective strengths and limitations, this chapter provides insights into the effectiveness and applicability of these approaches for reliable, data-driven fault detection in HVAC applications.

7.1 Overview of Developed Fault Detection Methods

Recent advancements have provided a comprehensive approach to HVAC system dynamic modeling, fault simulation, validation, and detection using three innovative methods. With the use of cost-effective simulated dataset as given detail in Chapter 3, the first hybrid approach, Random Forest with Support Vector Machine (RF-SVM) has developed by leveraging the strengths of both algorithms. As presented in Chapter 4, the RF-SVM hybrid is highly proficient in managing high-dimensional data and accurately capturing complex relationships between features and classes. It makes particularly effective in detecting and diagnosing faults in HVAC systems. However, it is important to recognize that this hybrid method may require significant computational costs, especially with large datasets as well as challenges in parameter fine-tuning. Despite these challenges, it offers improved accuracy and reliability in classifying HVAC faults from normal conditions and enhances robustness and classification capabilities.

The second technique, one-dimensional convolutional neural networks (1D-CNNs), presented in Chapter 5, is one of the deep learning models mainly built for sequential input data. Due to its automatic learning process, 1D-CNNs are known for detecting specific features by applying convolutional filters to input data and generating feature maps. These maps are further processed to capture complex patterns and temporal dependencies, making 1D-CNNs effective for analyzing sequential data. While 1D-CNNs are effective at HVAC faults detection, its limited capacity to capture spatial correlations between multiple sensors can decrease the overall accuracy of faults detection system.

The third method involves integrating Gramian Angular Field (GAF) with Convolutional Neural Networks (CNNs) for fault detection. As presented in Chapter 6, this approach starts by transforming time series data into GAF representations, which convert pairwise angular distances between data points into images. By feeding these GAF-transformed data into CNNs, the method leverages the powerful feature extraction capabilities of CNNs while retaining the sequential nature of the data. This integration allows for the exploration of spatial relationships within the time series data, thereby enhancing HVAC operational fault detection accuracy. However, a potential limitation of the GAF-2DCNNs approach lies in the complexity introduced by the GAF transformation, which may make the model less interpretable compared to more direct approaches.

This Chapter provides a comparison analysis of the three proposed fault detection algorithms introduced in Chapters 4, 5, and 6, focusing on their unique features, underlying principles, network complexity, and learning capabilities. The aim is to evaluate the efficiency in detecting faults in complex HVAC systems, considering their ability to identify nine major HVAC faults, the "Normal" operating condition, and their adaptability to varying operational contexts. The summary of these comparative studies is presented in Section 7.2, highlighting the key findings and their implications for future research. Furthermore, Section 7.3 provides a statistical comparison of the GAF-2DCNNs with other approaches, including 1D-CNNs, RF-SVM, RF, OvR-SVM and SVM, for various fault types.

7.2 Comparison Studies on Experimental Results

In this section, a comprehensive comparison analysis evaluates the performance of the proposed GAF-2DCNNs [Tun et al., 2023a] model alongside recently developed machine learning techniques for fault detection and diagnosis (FDD) systems. The evaluation includes 1D-CNNs [Tun et al., 2023b], hybrid RF-SVM [Tun et al., 2021], conventional Random Forest (RF) [Jin et al., 2017], Support Vector Machine (SVM) [Pan et al., 2011], and one-vs-rest SVM [Mohammadi and Yazdanian, 2014]. The comparison studies presented in Table 7.1 and Figure 7.1 demonstrate that the GAF-2DCNNs model achieves an overall accuracy of 97%, highlighting its effectiveness in fault detection across various scenarios. Notably, it excels in accurately classifying faults such as "CCVREV" and "HCVSTG2L", with accuracy of 99% and 100% respectively. However, it faces challenges with faults like "EADAMPOP" and "EADAMPCL", where their accuracies are slightly lower at 93% and 94% respectively.

Furthermore, in comparison with GAF-2DCNNs, 1D-CNNs also shows its competitive performance across various fault categories with slightly lower overall accuracy rates at 94%. The highest accuracy of 99% for the "CCV100%CL" fault shows its proficiency, even exceeding "GAF-2DCNNs" by a small margin about 2%. However, 1D-CNNs tends to exhibit lower accuracy rates for certain faults, such as "EADAMPCL" and "HCVSTG2L", suggesting potential limitations in effectively capturing the complex features of these fault types. Despite these deviations, 1D-CNNs still demonstrates notable strengths, including its ability to process sequential data efficiently and extract relevant features automatically, making it a feasible option for fault detection in HVAC systems.

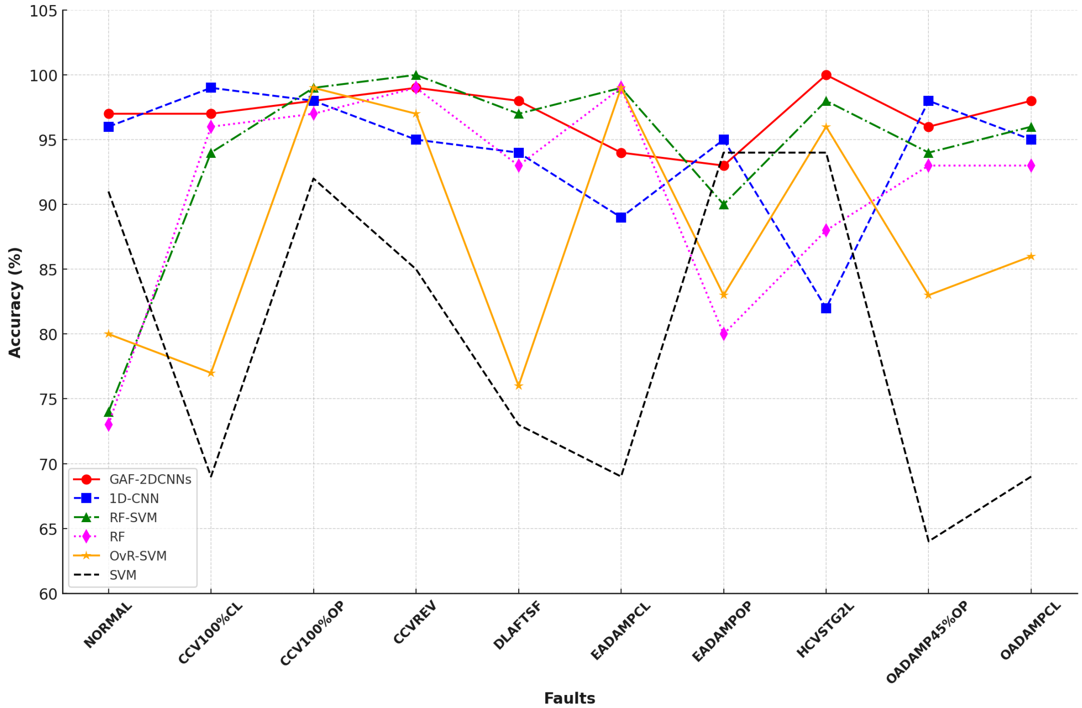


Figure 7.1: Performance Comparison of Different Methods

In addition, the hybrid RF-SVM method demonstrates creditable performance, especially in its high accuracies of 100% and 99% for the “CCVREV”, “CCV100%OP” and “EADAMPCL”. However, despite these strengths, the overall accuracy of the hybrid RF-SVM falls slightly behind that of GAF-2DCNNs and 1D-CNNs, standing at 91%. It particularly struggles with classifying the “Normal” condition, achieving only 74% accuracy. This inconsistency could potentially arise from the complexity of distinguishing normal operating conditions from fault scenarios, highlighting the challenges in accurately detecting deviations from expected behavior in HVAC systems.

FAULT	GAF-2DCNNs (%)	1D-CNNs (%)	RF-SVM (%)	RF (%)	OvR-SVM (%)	SVM (%)
NORMAL	97	96	74	73	80	91
CCV100%CL	97	99	94	96	77	69
CCV100%OP	98	98	99	97	99	92
CCVREV	99	95	100	99	97	85
DLAFTSF	98	94	97	93	76	73
EADAMPCL	94	89	99	99	99	69
EADAMPOP	93	95	90	80	83	94
HCVSTG2L	100	82	98	88	96	94
OADAMP45%OP	96	98	94	93	83	64
OADAMPCL	98	95	96	93	86	69
Model Accuracy	97	94	91	88	86	82

Table 7.1: Performance Comparison of GAF-2DCNNs with 1D-CNNs, RF-SVM, and OvR-SVM

In contrast, traditional RF, OvR-SVM, SVM methods demonstrate lower overall accuracies of 88%, 86% and 82% respectively, with varying accuracies across different fault categories. While RF performs well for certain faults like "CCVREV" and "EADAMPCL", it struggles with others such as "HCVSTG2L" and "EADAMPOP". Similarly, SVM shows strong performance for "EADAMPOP" but comparatively weaker performance for faults like "OADAMP45%OP" and "CCV100%CL", achieving accuracy about 60%. Therefore, Table 7.1 highlights the effectiveness of the proposed GAF-2DCNNs in achieving robust fault detection across various faults. Its superior performance, highlights its potential as a leading fault detection algorithm. Nonetheless, further research could explore hybrid approaches and algorithmic refinements to address specific challenges encountered by each method.

Furthermore, the comparison studies continues by examining precision, recall, and

F1-score metrics (equations (4.4)-(4.6) from Chapter 4) for each fault category across the three fault detection methods, GAF-2DCNN [Tun et al., 2023a], 1D-CNN [Tun et al., 2023b], and hybrid RF-SVM [Tun et al., 2021]. As given in Table 7.2, the GAF-2DCNNs consistently achieves high precision, recall, and F1-score values across most fault categories, reflecting its robustness in accurately detecting and classifying faults in HVAC systems. For instance, GAF-2DCNNs demonstrates precision values ranging from 92% to 100% and recall values ranging from 93% to 100%, highlighting its effectiveness in both minimizing false positives and capturing actual fault instances. Similarly, the F1-score, which is the average of precision and recall, highlights the superior performance of GAF-2DCNNs, with values exceeding 90% across most fault categories.

In contrast, while 1D-CNNs shows its competitive performance, it shows slightly lower precision, recall, and F1-score values compared to GAF-2DCNNs across several fault categories. For example, 1D-CNNs achieves precision values ranging from 82% to 100%, recall values ranging from 82% to 99%, and F1-scores ranging from 88% to 98%. While still maintaining relatively high accuracy rates, these metrics suggest potential areas for improvement in accurately classifying certain fault types, particularly those with lower recall values.

In addition, RF-SVM presents varying performance outcomes, with precision, recall, and F1-score metrics differing across fault categories. Although RF-SVM achieves high precision values for some fault types, its performance is less consistent compared to GAF-2DCNNs and 1D-CNNs. For instance, precision values range from 65% to 100%, recall values range from 77% to 100%, and F1-scores range from 77% to 100%. This variability underscores the sensitivity to different fault characteristics and highlights potential challenges in achieving robust fault detection across diverse

HVAC system faults.

Method	Fault Code	Precision (%)	Recall (%)	F1-score (%)
GAF-2DCNNs	NORMAL	99	97	98
	CCV100%CL	95	97	96
	CCV100%OP	92	98	95
	CCVREV	99	99	99
	DLAFTSF	98	98	98
	EADAMPCL	94	94	94
	EADAMPOP	100	93	96
	HCVSTG2L	96	100	98
	OADAMP45%OP	93	96	94
	OADAMPCL	100	98	99
	Overall Model Accuracy	97		
1D-CNNs	NORMAL	96	96	96
	CCV100%CL	95	99	97
	CCV100%OP	92	98	95
	CCVREV	98	95	96
	DLAFTSF	82	94	88
	EADAMPCL	91	89	90
	EADAMPOP	100	96	98
	HCVSTG2L	99	82	90
	OADAMP45%OP	91	98	95
	OADAMPCL	98	95	97
	Overall Model Accuracy	94		
RF-SVM	NORMAL	97	74	84
	CCV100%CL	65	94	77
	CCV100%OP	93	99	96
	CCVREV	97	100	98
	DLAFTSF	97	97	97
	EADAMPCL	100	99	100
	EADAMPOP	99	90	94
	HCVSTG2L	96	98	97
	OADAMP45%OP	73	94	82
	OADAMPCL	98	96	97
	Overall Model Accuracy	91		

Table 7.2: Comparative Analysis: Classification Reports on HVACSIM+ Simulated Data

Overall, the comparision analysis reveals that GAF-2DCNNs consistently outperforms both 1D-CNNs and hybrid RF-SVM in terms of precision, recall, and F1-score metrics across various fault categories in HVAC systems. Therefore, based on the overall performance metrics, GAF-2DCNNs emerges as the most effective and reliable method for fault detection and diagnosis in HVAC systems, offering promising implications for enhancing system reliability and operational efficiency in real-world applications.

7.3 Statistical Analysis of FDD Methods

In this Section, the proposed methods from Table 7.1 are compared and analyzed using a box plot. As shown in Figure 7.2, the box plot provides a visual representation of the accuracy distributions for each method, allowing for a clear comparison of their performance. For the GAF-2DCNNs method, the box plot indicates a consistently high accuracy with minimal variation, demonstrating its robustness and reliability. This method consistently achieves accuracy values close to the upper quartile, suggesting that it outperforms other methods in most scenarios.

For 1D-CNNs, it also shows high accuracy but with greater variability compared to GAF-2DCNNs, as evidenced by a wider interquartile range. While the median accuracy of 1D-CNNs is similar to that of GAF-2DCNNs, the broader spread indicates that its performance can fluctuate more significantly across fault scenarios, suggesting it may be slightly less reliable. The RF-SVM method, on the other hand, demonstrates a broad range of accuracy values, with several instances of near-optimal performance. However, the presence of outliers and a wider spread in the data highlights its inconsistency, indicating that while RF-SVM can achieve exceptional results in specific cases, it lacks the consistent reliability observed in GAF-2DCNNs. These findings confirm the superior robustness and reliability of GAF-2DCNNs across diverse fault detection scenarios.

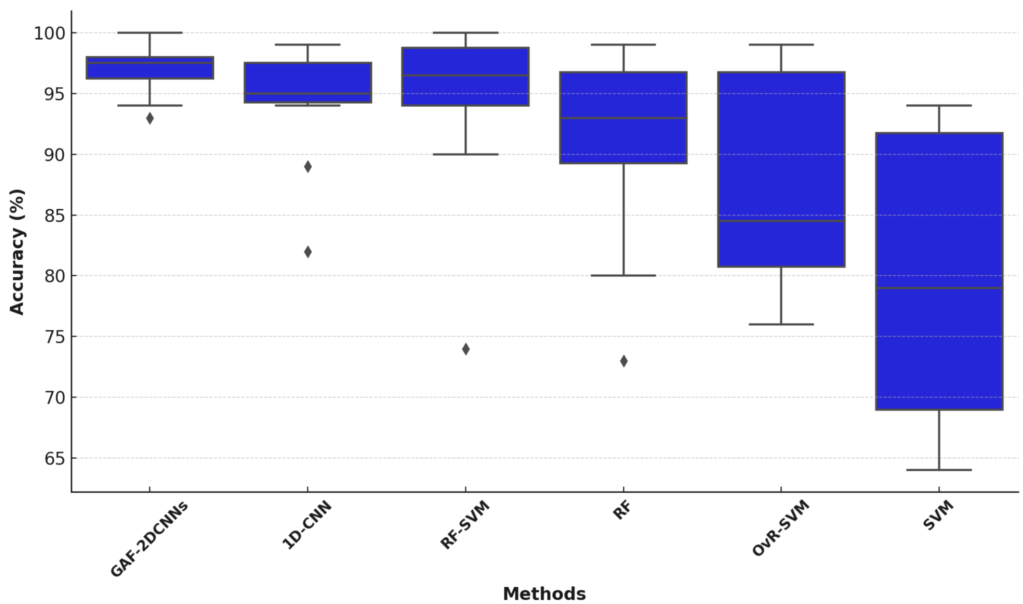


Figure 7.2: Distribution of Accuracy Across Proposed Fault Detection Methods

In addition, the RF method demonstrates moderate performance, with a noticeable spread in its accuracy values as shown in the box plot. While RF can achieve high accuracy in certain instances, the broader interquartile range and presence of lower-performing cases highlight its variability, making it less favorable compared to GAF-2DCNNs and 1D-CNNs. The OvR-SVM method also exhibits a relatively wide range of accuracy values, with a few outliers indicating occasional strong performance. However, its overall variability and median accuracy position it below RF-SVM and the top-performing methods.

Among the methods compared, the SVM has the lowest median accuracy and the greatest variation as evidenced by the presence of outliers and a wide interquartile range. The results indicate that SVM is generally less reliable, with several instances of accuracy falling significantly below the median, highlighting its inconsistency in handling diverse fault scenarios. Overall, the box plot analysis confirms that GAF-2DCNNs is the most robust and reliable method, with consistently high accuracy and minimal variation, followed by 1D-CNNs, RF-SVM, RF, OvR-SVM, and finally SVM, which shows the least consistent performance.

Statistic	GAF-2DCNNs (%)	1D-CNNs (%)	RF-SVM (%)	RF (%)	OvR-SVM (%)
Mean Accuracy	97.0	94.1	94.1	91.1	87.6
Standard Deviation	2.05	4.83	7.29	8.09	8.77
Coefficient of Variation	2.11	5.13	7.74	8.88	10.01
Accuracy Range	7	17	26	26	23

Table 7.3: Statistical Measures for Fault Detection Methods

Additionally, Table 7.3 presents a comparative analysis of fault detection methods based on four statistical measures such as mean accuracy, standard deviation, coefficient of variation (CV), and accuracy range. These metrics provide insights into the overall performance, variability, and reliability of each method in detecting faults across diverse scenarios.

As can be seen in Table 7.3, the GAF-2DCNNs method achieves the highest mean accuracy at 97.0%, accompanied by the lowest standard deviation (2.05%) and coefficient of variation (2.11%). This indicates exceptional consistency and reliability, as evidenced by its minimal accuracy range of 7%. In contrast, the 1D-CNNs method also demonstrates high mean accuracy (94.1%), but its higher standard deviation (4.83%) and coefficient of variation (5.13%) suggest slightly greater variability in performance. The wider accuracy range of 17% further highlights the moderate variation in 1D-CNNs fault detection capability compared to GAF-2DCNNs.

For RF-SVM and RF, the performance give similar mean accuracies of 94.1% and 91.1%, respectively, but their higher standard deviations (7.29% and 8.09%) and coefficients of variation (7.74% and 8.88%) reflect more variability. Both methods also have the largest accuracy ranges (26%), highlighting their inconsistency in maintaining reliable performance across all fault scenarios. The OvR-SVM method, while achieving a mean accuracy of 87.6%, shows the highest coefficient of variation (10.01%) and an accuracy range of 23%, indicating significant variability and reduced reliability compared to other methods.

Overall, the statistical analysis in Table 7.3 highlights GAF-2DCNNs as the most robust and reliable fault detection method, with 1D-CNNs following closely. While RF-SVM, RF, and OvR-SVM demonstrate competitive performance in certain faults detection scenarios, their higher variability suggests they may be better suited for applications where occasional fluctuations in accuracy are acceptable.

7.4 Summary

This chapter has provided a comprehensive evaluation of three advanced fault detection and diagnosis (FDD) methods such as RF-SVM, 1D-CNN, and GAF-2DCNNs, developed using simulated HVAC system data, and validated using benchmark dataset. Each method demonstrates unique capabilities in capturing and classifying HVAC faults, with varying degrees of accuracy, robustness, and generalisation. The comparative analysis, supported by both performance metrics and statistical measures, shows that the GAF-2DCNNs model consistently outperforms the others, achieving the highest accuracy and lowest variability across multiple fault types. While 1D-CNNs also offers strong performance with relatively efficient processing of sequential data, RF-SVM provides a reliable baseline but is more susceptible to inconsistencies in certain faults scenarios. Overall, the findings highlight the potential of GAF-2DCNNs as a robust and scalable solution for HVAC fault detection, offering valuable insights for future research and practical implementation.

Chapter 8

Key Findings, Contributions, Limitations, and Future Research Directions

The background studies, key findings, and main contributions of this thesis are comprehensively outlined in Chapters 1 to 7, providing an in-depth exploration of HVAC system dynamics modeling, fault simulation, and detection through the application of advanced machine learning and deep learning techniques. This Chapter provides a summary of these findings in Section 8.1, discusses the key contributions in Section 8.2, and highlights the limitations encountered along with recommendations for future research in Section 8.4. Addressing the identified gaps and challenges in future work can further improve the robustness, accuracy, and applicability of the proposed methods.

8.1 Summary of Findings

To understand the dynamics and operational faults of HVAC systems, the HVAC Simulation Plus (HVACSIM+) is employed for its superior performance in demonstrating system dynamics. The complex interactions of components such as fans, pumps, valves, and controllers are effectively considered. In this study, nine major faults along with normal conditions are simulated, utilizing 194 sensor signals from each HVAC component in a single-story, four-room building. The simulation lasts for 24 hours, covering scheduled occupancy from 6:00 AM to 6:00 PM and unoccupied periods from 6:00 PM to 6:00 AM. The analysis includes three days of normal operation and nine days of faulty operation, with data sampled at one-minute intervals, resulting in 1440 samples per sensor per day. Comparison studies with ASHARE benchmark data reveal minimal mean absolute error and high correlation coefficients, thereby confirming the accuracy and reliability of the simulation data for training and validating fault detection systems.

To address operational HVAC faults, a hybrid method combining random forest (RF) and support vector machine (SVM) classifiers has been developed. This RF-SVM system leverages the strengths of both techniques, starting with RF for fault identification and followed by SVM to enhance accuracy. The RF classifier effectively selects significant features, improving generalization and computational efficiency, and achieves an overall accuracy of 91%, as well 90% as validated by the ASHRAE benchmark.

Besides, the hybrid system is particularly successful in identifying faults related to cooling coil valves ("CCV100%CL" with 94%, CCV100%OP with 99%, and "CCVREV" with 100%), outdoor air dampers ("OADAMP45%OP" with 94% and "OADAMPCL" with 96%), exhaust air dampers ("EADAMPCL" with 99% and "EADAMPOP" with 90%), and duct leakage after the supply air fan ("DLAFTSF" with 97%). Notably, the hybrid RF-SVM classifier also demonstrated strong performance in identifying cooling coil valve faults ("CCV100%CL") with an accuracy of 94%, an area where other fault detection methods struggled. This highlights the superior performance of the proposed hybrid RF-SVM approach in accurately classifying a wide range of fault types while maintaining high overall accuracy.

In addition, a convolutional neural networks (CNNs)-based fault detection system has been developed to directly learn patterns and relationships from raw sensor data, thereby eliminating the need for manual feature extraction and selection inherent in traditional methods. By reducing the complexity associated with manual feature engineering, this method significantly improves classification performance. Utilizing extensive simulated data from dynamic simulation model, the 1D-CNNs fault detection system effectively classifies nine major HVAC faults and normal conditions with better accuracy rate of 94%. Furthermore, the generalization of model ability is validated through the use of ASHRE benchmark data, confirming its accuracy and reliability in diverse scenarios.

Furthermore, the 1D-CNNs based fault detection system shows strong performance in detecting "EADAMPOP" , achieving perfect precision, recall, and F1-score of 100%, 95%. and 98%. Similarly, the fault type "CCV100%CL" demonstrated high precision (95%), recall (99%), and F1-score (97%), indicating effective detection with minimal false positives and negatives. However, the "DLAFTSF" fault type showed lower precision at 82%, despite a relatively high recall (94%) and F1-score (88%). This suggests some misclassifications of other faults as "DLAFTSF," highlighting an area for potential improvement in the fault detection accuracy.

Additionally, an advanced fault detection framework utilizing Gramian Angular Field (GAF) and two-dimensional convolutional neural networks (2D-CNNs) has been developed, offering a robust and proactive solution. This method transforms time series sensor data into visual representations through GAF, which encodes pairwise angles between data points. These visual representations are then processed by 2D-CNNs for fault detection, leveraging their spatial processing capabilities to improve accuracy and effectiveness. This approach addresses the limitations of 1D-CNNs in capturing complex temporal patterns and spatial dependencies in time series data. The proposed GAF-2DCNNs framework was evaluated through comparative studies, and its generalization ability was confirmed using a benchmark dataset, achieving 97% accuracy. In addition, the model achieves a Precision, Recall, and F1-score of 99% for "CCVREV", while HCVSTG2L has a Precision of 96%, Recall of 100%, and an F1-score of 98%. Other faults, such as duct leak after the supply fan ("DLAFTSF") and exhaust air damper open ("EADAMPOP"), also demonstrate strong performance. This demonstrates consistent performance and accuracy across various fault scenarios, validating its robustness and reliability in real-world applications.

Along with the development of fault detection, Chapter 7 conducts a detailed comparison of three proposed methods, focusing on their unique characteristics, underlying principles, network complexity, and learning capabilities. Specifically, the algorithms are assessed based on their effectiveness in identifying nine different types of faults and their generalization ability to various operating conditions. The results of the comparison analyses are summarized and presented, offering a clear overview of the findings and their implications for future research. The statistical comparison of GAF-2DCNNs with other methods (1D-CNNs, RF-SVM, RF, SVM) for different types of faults is also discussed, highlighting the significance of the findings. The proposed fault detection systems demonstrate impressive accuracy, precision, recall, and F1 scores. Future research could explore methods to improve model robustness, such as data augmentation, transfer learning, or integrating with other fault detection techniques.

8.2 Contributions

The thesis presents notable advancements in dynamic HVAC modeling, fault simulation, validation, and fault detection, with significant theoretical, methodological, and practical contributions. These are discussed in the following subsections.

8.2.1 Theoretical Contributions

- **Hybrid Conceptual Framework Linking Simulation and AI**: This research advances theoretical frameworks by integrating dynamic HVAC system modeling using HVACSIM+ with AI-driven fault detection. It conceptualizes a hybrid paradigm that bridges physical system simulation and data-driven diagnostics, offering a new lens for understanding and analyzing HVAC system behavior.

- **Reframing Fault Detection to Include Normal Conditions**: The study challenges existing theoretical assumptions by demonstrating the critical role of normal operating data in simulation-based fault detection. By incorporating normal conditions explicitly into the training process, it contributes to a richer theoretical understanding of class definition, boundary behavior, and model generalization in fault diagnosis research.

8.2.2 Methodological Contributions

- **HVACSIM+ Dynamic Modeling for Dataset Generation**: A dynamic simulation approach using HVACSIM+ was designed to replicate real-world HVAC conditions. This includes detailed modeling of 194 sensors across a four-room building, simulating nine major fault types and normal states under realistic operational schedules. The simulation ensures fine-grained (1-minute resolution) data collection, offering high temporal fidelity for machine learning applications.

- **Hybrid RF-SVM Framework for Fault Detection**: The study proposes a novel hybrid framework that combines Random Forest (RF) for feature selection and Support Vector Machine (SVM) for classification. This method balances model interpretability, computational efficiency, and classification performance, particularly under imbalanced fault scenarios.

- **Development of Deep Learning Models (1D-CNN and GAF-2DCNNs)**: Two advanced deep learning frameworks were designed. 1D-CNNs handle sequential HVAC sensor data effectively without manual feature extraction. The GAF-2DCNNs approach converts time-series data into image representations using Gramian Angular Fields (GAF), enabling 2D CNNs to learn spatial-temporal correlations. This is a novel application in HVAC diagnostics.

- **Comprehensive Model Evaluation and Comparison**: A detailed comparative study of RF-SVM, 1D-CNNs, and GAF-2DCNNs models was conducted, using multiple performance metrics including accuracy, precision, recall, F1-score, standard deviation, coefficient of variation, and accuracy range. Benchmarking with ASHRAE-RP1312 data strengthens the generalizability.

8.2.3 Practical Contributions

- **Cost-Effective Data Generation for Training**: Collecting fault data from real HVAC systems is often expensive, time-consuming, and operationally disruptive. This research addresses this challenge by employing HVACSIM+ to simulate diverse fault scenarios, enabling low-cost, safe, and repeatable generation of high-quality datasets for training AI-based fault detection systems. This approach supports scalable development of data-driven models, even in the absence of real-world fault data.

- **Fault Detection in Operational Hours**: The models developed in this study are trained and tested on data collected during typical building occupancy hours (6:00 AM to 6:00 PM), aligning closely with real-world HVAC usage patterns. This focus enhances the practical applicability of the models, ensuring that they are tuned to detect faults under conditions that most affect occupant comfort and energy efficiency.

- **Reduction in Sensor Dependency**: Through the use of feature selection via the Random Forest (RF) algorithm, the proposed hybrid RF-SVM model effectively reduces the number of sensors required for accurate fault diagnosis. This contribution is particularly significant for implementation in resource-constrained or retrofit environments, where the deployment of extensive sensor networks may be impractical or cost-prohibitive.

- **Benchmarking Against Industry Standards**: All proposed models are rigorously validated using benchmark datasets from ASHRAE, a recognized industry standard. This validation enhances the credibility, robustness, and generalizability of the proposed methods, ensuring alignment with established norms and facilitating broader adoption in commercial building automation systems. Although the validation was conducted using the ASHRAE RP-1312 dataset, a well-established and publicly available benchmark, it is acknowledged that relying solely on secondary data introduces certain limitations, particularly in capturing real-world variability. However, benchmarking against an industry-recognized standard such as ASHRAE enhances the credibility, consistency, and generalisability of the results. To further strengthen the applicability of the proposed models, future work should incorporate primary, empirical data from operational HVAC systems.

These contributions collectively strengthen the theoretical foundation, methodological rigor, and practical relevance of data-driven fault detection in HVAC systems.

8.3 Conclusion

This thesis presents a unified framework for simulating, detecting, and diagnosing HVAC operational faults using a combination of dynamic modeling and advanced machine learning techniques. Leveraging HVACSIM+ for high-fidelity dynamic simulation, the study generated a large-scale, labeled dataset encompassing nine major fault types and normal operational conditions. These data were used to develop and evaluate three fault detection approaches: a hybrid Random Forest–Support Vector Machine (RF-SVM), a one-dimensional Convolutional Neural Network (1D-CNN), and a Gramian Angular Field-based two-dimensional CNN (GAF-2DCNN). Among these, the GAF-2DCNN method exhibited the highest overall accuracy, demonstrating superior robustness and generalizability.

Theoretically, the research advances the integration of physics-based simulation with data-driven machine learning for fault diagnostics, contributing a novel perspective to the HVAC domain. The use of occupancy-aware time-frames and high-resolution temporal sampling reflects realistic system behavior and enhances data granularity. Methodologically, the proposed RF-SVM pipeline reduces sensor dependency while maintaining classification performance, and the CNN-based frameworks eliminate the need for manual feature engineering. Practically, the study demonstrates the feasibility of using simulation-generated data for training diagnostic models, significantly lowering the cost and complexity associated with real-world data acquisition. Validation using the ASHRAE RP-1312 dataset confirms the reliability and industry relevance of the proposed methods.

Overall, the objectives outlined in section 1.3 of Chapter 1 have been fully addressed and successfully accomplished through the course of this study. The research developed a dynamic simulation-based framework using HVACSIM+ for fault data generation, addressing the challenges associated with limited availability of labelled fault datasets in real-world HVAC systems. Multiple fault detection models—including a hybrid RF-SVM, a 1D-CNNs, and a GAF-2DCNNs—were implemented and comprehensively evaluated. Each model demonstrated strong classification performance across a wide range of operational faults. The effectiveness and generalisability of the proposed methods were further validated using the ASHRAE RP-1312 benchmark dataset, reinforcing their practical applicability. Collectively, these outcomes confirm that the goals outlined in the introductory chapter have been met, contributing meaningful theoretical, methodological, and practical advancements to the field of data-driven HVAC fault detection.

8.4 Limitations and Future Research Directions

Studying HVAC system performance across multiple seasons, rather than limiting analysis to summer conditions, provides a broader understanding of system behaviour under varying environmental influences. Enhancing HVACSIM+ configurations by incorporating different building types, along with attention to both design parameters and operational and maintenance characteristics, can significantly improve the accuracy of simulation outputs. Design considerations include building geometry and equipment capacity, while operational and maintenance aspects relate to control logic, usage schedules, component degradation, and service quality. Validating simulation results against benchmark datasets from actual building operations is also essential for ensuring the credibility of the models. Refining simulation models in this way enables more accurate representation of real-world HVAC dynamics and supports the development of fault detection methods that are both reliable and widely applicable.

Despite the promising outcomes, this study is subject to several limitations. The simulation scenarios were limited to cooling-mode operations during the summer season, which may not capture the full spectrum of fault behaviors seen under heating or mixed-mode operations. Additionally, the study focused on a single-story, four-zone building configuration. As such, generalization to more complex or larger-scale buildings has not been empirically tested. Real-time performance evaluation and resilience to practical issues—such as sensor drift, data loss, and noisy environments—were not addressed in this study.

Future research should aim to extend the framework by simulating seasonal variability, different climate zones, and a broader array of HVAC configurations and building types. Real-time model deployment and validation under real-world operational constraints will also be important to evaluate robustness and practical usability. Exploring transfer learning and domain adaptation techniques could further improve model adaptability to new environments with minimal re-training. The integration of interpretable machine learning techniques is also recommended to enhance transparency and support human decision-making in building management systems.

Moreover, although this study employed a specific layout and climate scenario, the modular design of the proposed framework allows for adaptation across different building geometries, operational schedules, and sensor configurations. Future studies will explore its application to diverse building typologies and geographic contexts to validate its scalability, transferability, and practical utility in varied real-world environments.

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