



Predictive Maintenance of HVAC Systems using Deep Learning for Optimized Building Energy Efficiency

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Abstract:

Buildings consume approximately one-third of the world's energy, with the commercial and housing sectors' Heating, Ventilation, and Air Conditioning (HVAC) systems being the largest contributors to energy. Energy wastage is significant as a result of system faults, which indicates the importance of efficient control of energy in HVAC in saving energy as well as providing comfort to the occupants. Techniques in Artificial Intelligence (AI), such as Machine Learning (ML) and Deep Learning (DL), are now used to optimize HVAC energy efficiency as well as facilitate predictive maintenance, which reduces downtime as well as costs. Past research has underestimated qualitative faults analysis in HVAC systems or suffered from inaccurate identification using AI. This paper proposes an innovative AI-based framework to manage energy in buildings. The framework uses Fault Tree Analysis (FTA) initially to perform qualitative analysis regarding the effect of HVAC system faults in energy consumption. Next, it applies AI models, namely Long Short-Term Memory (LSTM) networks as well as Gated Recurrent Unit (GRU) networks, trained using experimental data from real-building environments. The models are designed to detect faults accurately as well as in time. The main goal is to save energy from wastage as well as ensure occupant comfort through timely maintenance as well as replacement of faulty equipment. Most notably, the GRU approach showed higher accuracy in the identification of faults compared to LSTM. The framework's accurate identification of the occurrence as well as the nature of the faults is an improvement in the efficiency of the building.

1. Introduction

Global energy dynamics is under huge pressures due to the accelerating population growth as well as the economic development it has triggered, resulting in wasteful energy consumption and environmental deterioration [1]. Buildings, domestic as well as commercial, consume a lot of energy, contributing about one-fifth to global energy use as reported in the U.S. Energy Information Administration reports [2]. To the non-renewable energy consumption in developed countries, the commercial building sector accounts for about 40%, greenhouse gas emissions account for about 40%, as well as consuming about 70% of the electricity in such countries [3].

Of all the systems in the commercial structures, the Heating, Ventilation, and Air Conditioning (HVAC) systems consume the highest energy, about 40% of the energy

in commercial spaces [4]. In spite of the integration of sophisticated building automation equipment and controllers to optimize efficiency, operational faults or failures can arise at the time of installation, during normal usage, or during planned maintenance. The faults waste huge amounts of energy, with UK building surveys showing an energy wastage ranging from 25% to 50% resulting from HVAC system faults [5]. Not only do these inefficiencies have higher operating costs, but also indoor air quality and comfort levels decrease, leading to occupant dissatisfaction [6]. The intrinsic characteristic of modern HVAC systems with several thousand sensors, actuators, and controllers complicates the process of manual FDD, rendering it less effective [5].

To solve these challenges, automatic fault detection and diagnosis (AFDD) has proven to be an important strategy [7], with the promise to minimize energy wastage considerably provided defects are caught early. Artificial Intelligence (AI), including Machine Learning (ML) and

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Deep Learning (DL), has proven to be highly viable in addressing sophisticated challenges in building energy management [8]. FDD methods using AI can accurately determine optimum points in the relationship between energy use and comfort temperatures, forecast energy demand, as well as provide predictive maintenance, minimizing downtime as well as costs [8, 9]. Nonetheless, although data-based FDD methods have proven to be highly effective, previous research has seldom incorporated in-depth qualitative analysis of faults as well as had constrained accuracy in detecting particular fault modes [10].

This paper presents a novel AI-driven framework for comprehensive energy management in buildings, focusing on HVAC systems. The framework first employs Fault Tree Analysis (FTA) to qualitatively assess the root causes and impacts of various faults on energy consumption. Subsequently, it leverages advanced deep learning algorithms to accurately and rapidly detect and diagnose specific fault types using real-world experimental data. This dual-pronged approach aims to facilitate timely interventions, mitigate energy losses, and ensure sustained occupant thermal comfort. The remainder of this paper is structured as follows: Section 2 reviews relevant literature on energy management and AI applications in buildings. Section 3 details the proposed framework, including FTA and the AI implementation methodology. Section 4 presents and interprets the results, and Section 5 concludes the study with a summary of findings, innovations, and future research directions.

2. Literature Review

2.1 Building Energy Management Systems (BEMS) and Strategies

Contemporary buildings are transforming into smart systems that seek to optimize energy usage, comfort, and environmental efficiency. The principles involve green buildings with environmental awareness throughout their entire life cycle; net-zero energy buildings with the goal to achieve energy self-sufficiency from renewable sources; and smart buildings with technology integration to manage automation, resources, and comfort. The central issue in smart buildings is optimally balancing energy needs with comfort [11].

Building Management Systems (BMS) control the mechanical and electrical machinery in the building. Building Energy Management Systems (BEMS) specialize in energy efficiency and performance, with intelligent BEMS (iBEMS) adding smart services and optimizing occupant comfort further. There is either the passive way, in which energy consumption is controlled indirectly, or the active way through the use of inbuilt sensors and actuators to directly control energy use. The active strategies in BEMS

are further divided into Model Predictive Control (MPC), Demand Side Management (DSM), Optimization, and Fault Detection and Diagnosis (FDD) [11].

MPC anticipates building responses to control actions to achieve optimized operations. It uses different models such as physics-based, data-based, or hybrid models to predict energy. DSM uses measures to control energy consumption from the customer side in the form of Demand Response (DR) or Energy Efficiency (EE) methods. Optimization is essential in EMS to choose the optimum solution under existing constraints using methods such as Stochastic Optimization (SO) and Robust Optimization (RO) due to the existence of uncertainties in data. FDD is important in BEMS to detect faults and isolate them to avoid further system failures as well as energy wastages. FDD methods can be generally categorized as knowledge-based or data-based [11].

2.2 Artificial Intelligence: Concepts and Techniques

Artificial Intelligence (AI) has had far-reaching impacts in many areas, such as in architecture and in sustainability, allowing machines to carry out functions originally needing human intelligence. Stemming from initial ideas such as those by Alan Turing in his Bombe machine, AI formally became recognized as an academic field in 1956 with John McCarthy. After initial hope followed by successive "AI winters" as expectations were unmet, the AI has experienced another revival with the development in computational capabilities, bringing to us the contemporary sub-fields such as Machine Learning (ML) and Deep Learning (DL) [12].

AI is categorized into Narrow AI (ANI), Artificial General Intelligence (AGI), and Artificial Superintelligence (ASI) in broad terms. ANI is specialized in performing particular functions, AGI is intended to match human capability, whereas ASI attempts to exceed human capability. AI involves elements like learning, knowledge representation, perception, planning, action, as well as communication. The applicable sub-branches in the construction field are Machine Learning, Computer Vision, Automated Planning and Scheduling, as well as Optimization [13,14].

Machine Learning is the practice of developing programs which learn from data without explicit programmability. Its core forms consist of Supervised Learning (learning from labeled data), Unsupervised Learning (unlabeled data pattern discovery), Reinforcement Learning (learning from interaction with the environment), and Deep Learning. Deep Learning, one form of ML, uses multi-layered artificial neural networks to learn from unstructured, complex data, in many cases with improved accuracy compared to conventional ML approaches. Some important AI techniques, apart from ML/DL, are Fuzzy Logic (dealing with uncertainty), Genetic Algorithms (optimization using principles from natural selection), Neural Networks

(modelling brain-like arrangements to capture complex relationships), and Simulated Annealing (heuristic search strategy to obtain optimal solutions) [15-17].

2.3 AI Applications in Building Energy Management and Fault Detection

Growing computational capabilities and data availability have driven the global uptake in the use of AI in building management to enhance energy efficiency and minimize wastage. AI can be combined with Building Information Modeling (BIM) to perform analysis of large sets of data from existing projects with automatic recommendations for optimizations therein [18].

Artificial intelligence-driven control strategies have the potential to reduce HVAC energy consumption by up to 40% through dynamic adaptation to environmental conditions and occupancy levels, bridging the science–practice gap in optimizing building performance [19]. AI is critical for building energy demand prediction, using historical data from sensors and IoT devices to forecast consumption and optimize supply-demand balance. AI also improves indoor air quality (IAQ) and thermal comfort through the forecast of environmental parameters and pollutant levels to facilitate adaptive controls [11]. AI has particularly transformed Fault Detection and Diagnosis (FDD) in HVAC systems, which is important to eliminate wasteful energy usage and ensure comfort. The conventional methods in FDD were rule-based, but with the advancements in AI, especially data-driven methods, now enable timelier as well as better identification of faults. The advantages of automated FDD are vast, such as lower maintenance costs, lower electricity bills, enhanced commissioning, decreased peak demand, as well as environmental benefits. Cost analysis indicates some faults are recurrent in nature (e.g., control faults), whereas others, such as compressor failures, occur less frequently but cost dearly to repair [6].

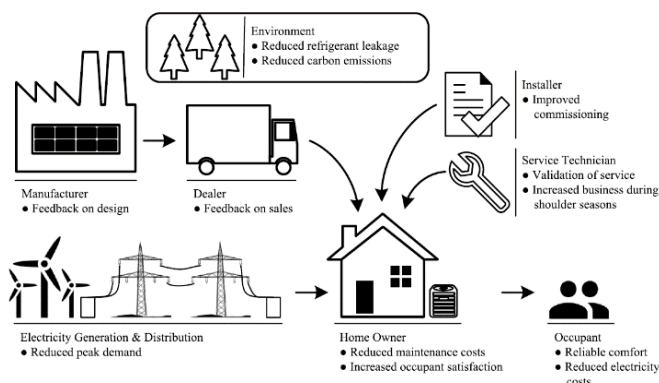


Fig. 1: Examples of the benefits that automated FDD can bring across the HVAC value chain [20]

Figure 1 illustrates the diverse benefits of automated FDD across the HVAC value chain. Deep learning models, including Multi-Layer Perceptrons (MLP), Convolutional

Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), have demonstrated high capabilities in FDD. Each of these algorithms has unique advantages and disadvantages for HVAC FDD applications, collectively enabling rapid and precise identification of fault types, enabling efficient predictive maintenance. Deep learning models such as LSTM and GRU demonstrate high accuracy (over 90%) and computational speed in defect detection, with GRU often outperforming LSTM due to its simpler design, making them suitable for identifying temporal relationships in HVAC time-series data [21].

2.4 Conclusion of Literature Review

This review stresses the high contribution of buildings to global energy consumption as well as the crucial role played by HVAC systems in this consumption. AI, particularly ML and DL, offers encouraging avenues in the optimization of energy management in buildings, ranging from energy forecasting to occupant behavior analysis to thermal comfort, IAQ, as well as, most importantly, FDD. Advances have been tremendous, yet the current literature has frequently pointed to the lack of holistic qualitative faults analysis as well as the accurate determination of the nature of the faults, with the need to have additional real-world datasets to develop robust AI models. The research attempts to fill these voids with the formulation of an innovative framework combining qualitative faults analysis with accurate AI-aided faults identification as well as diagnosis in HVAC systems towards overall energy management.

3. Methodology

Building construction is responsible for the majority of the world's energy consumption, with the largest energy wasters in commercial and household applications being HVAC systems. Faulty HVAC systems contribute to greenhouse emissions, impaired occupant comfort, and excessive energy wastage. The above highlights the imperative need for sophisticated information integration and smart operations to minimize such avoidable energy wastages. The existing solutions tend to incorporate smart HVAC systems with the use of dynamic features in the building modeling, trading rule-based control methods with adaptable alternatives, as well as incorporating data-driven advanced Fault Detection and Diagnosis. Compared to the conventional physical or rule-based models with limitations in empirical rules or mechanical specs in isolating faults, data-driven methods, especially DL, provide an appealing alternative in light of the capability to learn faults' complex patterns in an automated manner. This section describes the suggested framework, where DL methods for FDD are combined with Fault Tree Analysis to perform qualitative analysis with the intent to facilitate improved energy management.

3.1 Proposed Framework for Building Energy Management

Having definite objectives and gathering data to be analyzed is essential in developing an effective energy management strategy. Such a strategy, with continuous monitoring, maintenance, and reporting, generates financial returns in the form of energy savings. With the integration of Artificial Intelligence (AI) algorithms and data analysis, energy efficiency can be greatly enhanced with smart adjustments and knowledge-based decision-making. Then, Fault Tree Analysis (FTA) can also be used to determine the causes of potential system failures and the establishment of strategic measures against them. The framework under consideration to build energy management has an objective to promote efficiency, dependability, and intelligence with the integration of AI and FTA. The integration allows stakeholders in the building to make informed decisions based on data, with real-time optimization of the operations, while the FTA guarantees the robustness as well as the flexibility in the system. Eventually, the combined strategy optimizes energy usage, costs, environmental footprint, as well as overall sustainability.

The proposed framework, as illustrated in Figure 2, consists of two main components. The first component involves a qualitative assessment of HVAC system faults using Fault Tree Analysis (FTA) to identify causal relationships. The second component utilizes an AI algorithm, trained on experimental data from both faulty and fault-free conditions, to detect and diagnose HVAC system faults in real-time. This timely detection allows for prompt repairs and component replacements, preventing energy waste and ensuring occupant thermal comfort, which are key objectives of energy management.

The selection of this framework is driven by the significant impact of operational faults on HVAC system energy performance. A survey in California revealed that 65% of residential and 71% of commercial HVAC units had faults. These common HVAC faults are generally categorized into control, sensor, and equipment faults (e.g., fouling, seizing, performance degradation). The occurrence of numerous operational faults in HVAC systems can lead to 20% or more of HVAC energy consumption being wasted. Faulty HVAC equipment also negatively affects indoor thermal comfort and occupant productivity. Consequently, there is a growing demand for robust FDD methods for HVAC systems, as FDD has been shown to reduce HVAC energy consumption by 10% to 40%.

Evaluation of fault impacts is essential to FDD method development, particularly to data-driven methods. Firstly, since dozens of faults may occur with different impacts on energy consumption, analysis of fault impacts allows FDD developers to determine priorities in which faults to address,

maximizing detection accuracy for high-impact faults at the costs of potentially lower accuracy for less impacting ones. Secondly, it is applicable in the case of concurrent faults in HVAC equipment, where several faults happen simultaneously. Studies, like in [22], have simulated the impacts of faults in energy consumption as well as in thermal comfort in hypothetical buildings. For example, the stuck inlet air damper (OD0) can elevate fan electric energy consumption by 0.03%, cooling coil electric energy by 51.37%, decrease reheating coil electric energy by 0.01%, decrease heating coil gas energy by 23.61%, as well as raise the total HVAC system electric energy by 18.72%. Implementing FDD can prevent energy waste and ensure thermal comfort, which is the goal of energy management in buildings. Furthermore, incorporating repair/replacement costs into the energy management framework via FTA can provide guidelines for addressing or even foregoing fault rectification based on a cost-benefit analysis.

3.2 Fault Tree Analysis (FTA)

Fault Tree Analysis (FTA) is a widely used graphical method for analyzing the failure logic of a system and calculating its overall reliability. A Fault Tree (FT) is a directed acyclic graph (DAG) that models how failures propagate through a system, from component failures to system failures. An FT consists of two types of nodes: events and gates. Events represent occurrences in the system, ranging from subsystem failures to single component failures. Events are categorized into basic events (BEs), which occur spontaneously, and intermediate events (IEs), caused by one or more other events. The top event (TE) is the event at the apex of the tree, representing the system failure under analysis. Some events, though not true BEs, may be treated as such due to insufficient information or perceived insignificance for further development. Gates represent how failures propagate and combine in the system, leading to system failures. Each gate has one output and one or more inputs. Common gates in fault trees include:

AND gate: Output O occurs if and only if all input events A and B occur.

OR gate: Output O occurs if any of the input events A or B occur.

FTA models interactions between events using logic gates, explaining how the system faces failure. Qualitatively, FTA provides useful information about the causes of undesired events; quantitatively, it offers insights into the probability of the top event and the importance of basic events. When the failures or failure probabilities of the components are known, the overall system reliability can be determined.

Using FTA, the causes of the identified HVAC faults—more especially, those related to the heating coil valve, cooling coil valve, and inlet air damper—have been qualitatively examined in the current literature.

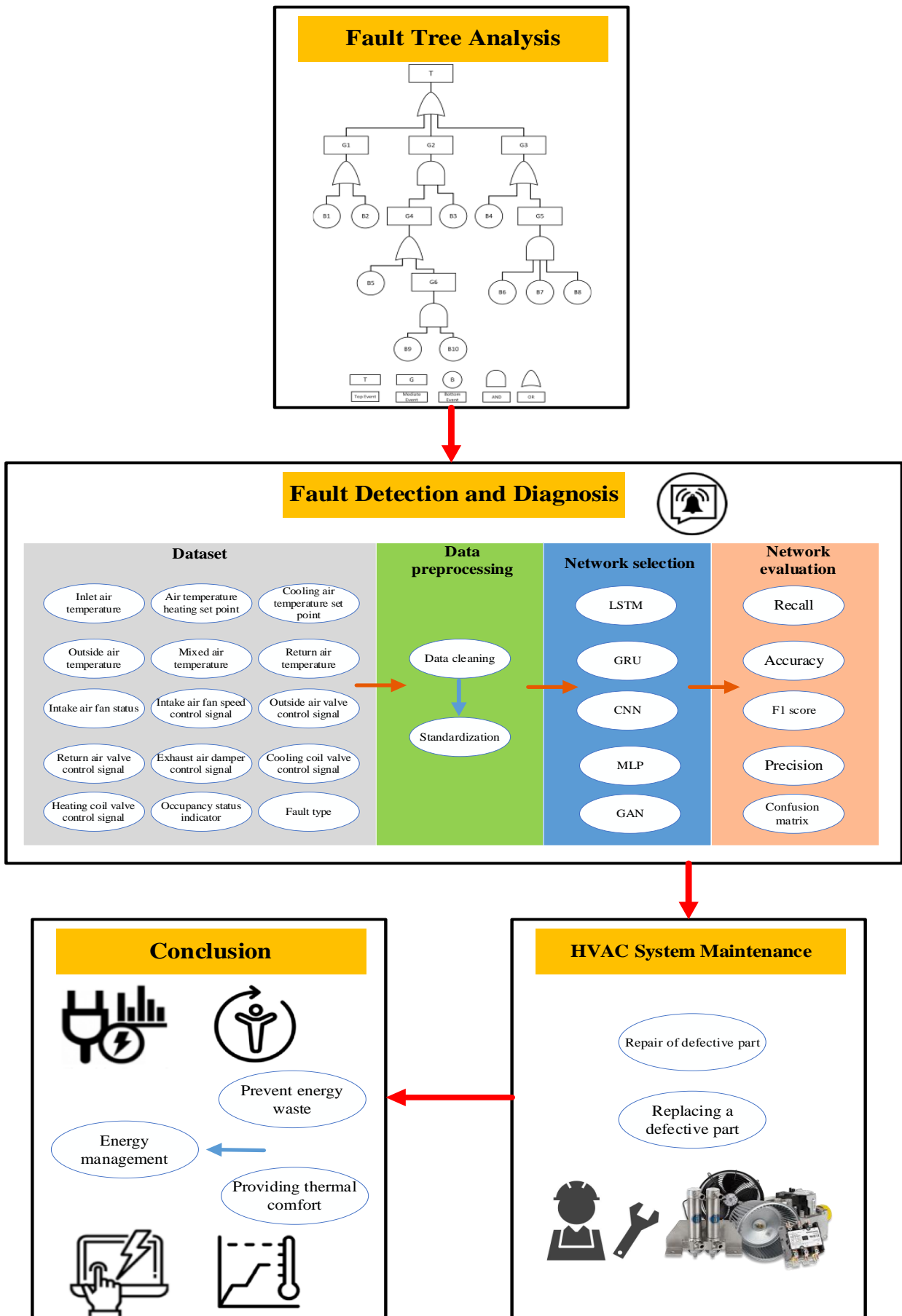


Fig. 2: Proposed framework for energy management in buildings

Using an individual fault tree, one may also investigate the part the faults contribute to the energy usage. With the provision of fault trees, qualitative analysis of faults can be carried out, facilitating the rectification of the identified faults through repair or replacement of faulty equipment, in accordance with the possible causal factors. This section highlighted the relevance of FTA in energy management.

3.3 Dataset

A long-standing difficulty in creating and benchmarking FDD techniques has been the lack of standard data sets and test procedures. Public-access operational data sets for applications related to building energy efficiency (e.g., smart-meter data, HVAC control data, lighting system data) tend to be few in number and subject to restrictions under Non-Disclosure Agreements (NDAs) or similar data-sharing limitations. Datasets with validated information on fault existence or absence are especially rare for FDD applications since most buildings lack FDD technology and problems often go undetectable. Even where FDD tools are implemented, researchers may not verify identified faults, and false positives/negatives can distort historical records. Although Building Automation Systems (BAS) in larger buildings may include historical trend data, these data are typically not labeled as faulty, fault-free, or simply anomalous. Reliable experimental datasets are crucial for FDD developers, users, and research investors to compare performance, identify performance gaps for future development, and understand the overall improvement of FDD technology over time.

FlexLab at Lawrence Berkeley National Lab (LBNL) in Berkeley, California, USA produced the experimental dataset used in this work. FlexLab is designed to evaluate the efficiency of core building systems under real-world conditions, monitoring and assessing heating, ventilation, air conditioning, lighting, windows, building envelopes, control systems, and electrical loads in various combinations. The facility consists of identical paired test cells and is managed via a National Instruments control and data acquisition platform. The specific test cell, FlexLab X3A, used for data generation, is a 20 by 25-foot (6.1 by 7.6 meters) zone, served by a 10-ton direct expansion chiller shared with an adjacent cell. The test cell includes a dedicated Air Handling Unit (AHU) with water-source heating and cooling coils and a Variable Frequency Drive (VFD)-controlled supply fan. Heating water is supplied by a natural gas boiler. The test cell features a south-facing wall and window, an insulated concrete slab, and otherwise near-adiabatic walls and ceiling.

3.4 Artificial Intelligence Algorithm Implementation

The implementation of the AI algorithm for fault detection and diagnosis is a critical component of the proposed energy

management framework. This process involves several key steps.

3.4.1 Preprocessing

The initial step in implementing the AI algorithm is data preprocessing, applied to the collected dataset. Preprocessing stages include:

- **Missing Value Imputation using Median:** Missing values can hinder data analysis. Using the median of existing data to fill these gaps helps preserve the central tendency of the distribution, especially when data is not normally distributed or contains outliers that could skew the mean.
- **One-Hot Encoding:** Categorical variables (e.g., colors, types) pose a challenge for algorithms preferring numerical inputs. One-hot encoding converts each category into a new binary column, where a '1' indicates membership in that category and '0' otherwise. This bridges the gap between categorical and numerical data, allowing the model to understand distinctions without arbitrary numerical assignments. This method is particularly useful for distinct classification classes.
- **Standardization:** Data often comes in varying scales, which can be incompatible with machine learning algorithm requirements. Standardization transforms data values to have a mean of zero and a standard deviation of one, ensuring homogeneity across scales and enabling algorithms to better interpret features. This is vital for distance-based algorithms. Standardization focuses on aligning scales without altering the distribution's shape, ensuring that data magnitude does not overshadow its patterns, providing a level playing field for different features.

3.4.2 Neural Network Models

Neural network models, a subset of deep learning, have shown high capabilities in fault detection and diagnosis in previous studies, as summarized in Table 1. This section provides details on the algorithms used in this study's modeling. This chapter presented a framework that integrates qualitative fault analysis and Artificial Intelligence for fault detection and diagnosis, addressing the gaps identified in previous studies. The qualitative analysis of fault occurrences, specifically for inlet air dampers, heating coil valves, and cooling coil valves, along with their impact on energy consumption, was performed using Fault Tree Analysis. The experimental dataset, its characteristics, and the process of AI algorithm implementation, including preprocessing and the chosen neural network models (LSTM and GRU), were detailed. The aim is to achieve high-accuracy fault detection and diagnosis, enabling prompt rectification of faults to reduce energy consumption and ensure occupant thermal comfort, which are the primary objectives of energy management in buildings.

Table 1: Advantages and disadvantages of each algorithm in the field of fault identification and diagnosis in HVAC systems

Deep Learning Algorithms	Advantages	Disadvantages
MLP	Simple design	State is not preserved across time steps, limited ability to model system temporal dependencies for an HVAC system
1D CNN	High efficiency, suitable for online FDD or real-time condition monitoring of an HVAC system	Local temporal feature extractor, limited ability to model long-term temporal dependencies compared to LSTM-based methods
2D CNN	Natural choice for image data, feasibility for transfer learning, effective for processing multi-dimensional metrics which makes it possible to use sensor fusion techniques to improve FDD performance	Data transformation steps for non-image data which potentially causes information loss and extra computational cost, collected data quality heavily responds to the type of cameras, weather conditions, etc., large amount of training parameters
LSTM	Effective for modeling the thermodynamic changing characteristics and long-term temporal patterns of the system	Complex mechanisms, potential risk of slow convergence speed and overfitting
GRU	More simplified structure than LSTM, less computational cost, favored for an online HVAC health condition monitoring system	Simplified structure could potentially limit a GRU's ability when modeling a complex HVAC system
BDLSTM/BD GRU	Able to model temporal dependencies from both forward and backward directions, effective for detecting subtle drift faults	Complex structures and more parameters
GAN	Generates samples that match the true distribution without explicitly assuming a particular form of probability distribution, useful for generating faults and alleviating the problem of FDD data scarcity	Difficult to train due to mode collapse, non-convergence, and instability
VAE	Fast and easy to train compared to GAN	Data generated by VAEs have less diversity
DBN	Works for a small amount of fault data	Difficult due to its complex data models
DL-based Hybrid Models	More robust and complement the advantages of individual models involved	Increased complexity in design, structure, more computational cost, not ideal for real-time FDD

4. Results

This section presents the findings from the qualitative fault analysis using Fault Tree Analysis and the results obtained from the AI model developed for identifying and diagnosing HVAC system faults.

4.1 Fault Tree Analysis & Fault Data Analysis

The Fault Tree Analysis (FTA) provided a qualitative investigation into the root causes of various HVAC system faults, such as those in the inlet air damper, heating coil valve, and cooling coil valve. It also illustrated how these individual faults can lead to increased energy consumption, which was identified as the top event. The dataset utilized in this study, derived from the FlexLab X3A test cell, contained data points with 14 features and exhibited an imbalanced distribution across the different fault classes.

Figure 3 shows fault tree related to the vertex fault event of increased energy consumption.

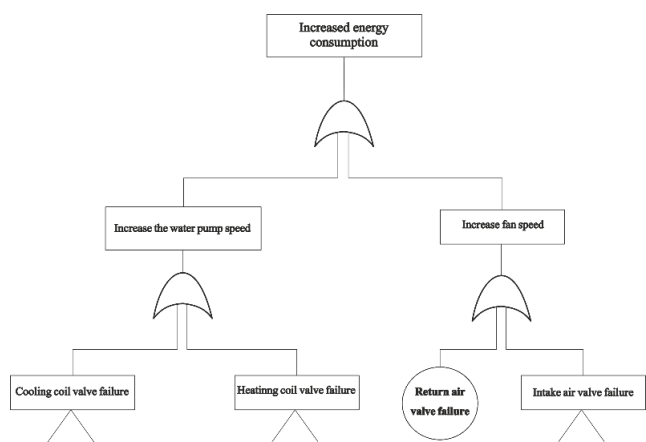


Fig. 3: Fault tree related to the vertex fault event of increased energy consumption

4.2 Model Evaluation

Initial comparison between baseline LSTM and GRU models revealed that the GRU model consistently demonstrated superior performance across all evaluation metrics, leading to its selection for further optimization. Through hyperparameter tuning, the optimal configuration for the GRU network was identified as 3 layers with 64 neurons, a batch size of 64, utilizing the Adam optimizer, and a learning rate of 0.001. The model's performance was then assessed on unseen test data, where its accuracy remained consistent with validation results, confirming its strong generalization capability. The F1-score and loss function trends over epochs, shown in figure 4, also indicated robust training performance without significant overfitting or underfitting. Furthermore, the confusion matrix analysis confirmed the model's effective balance between precision and recall across all fault classes, demonstrating its reliability in distinguishing between various operational states.

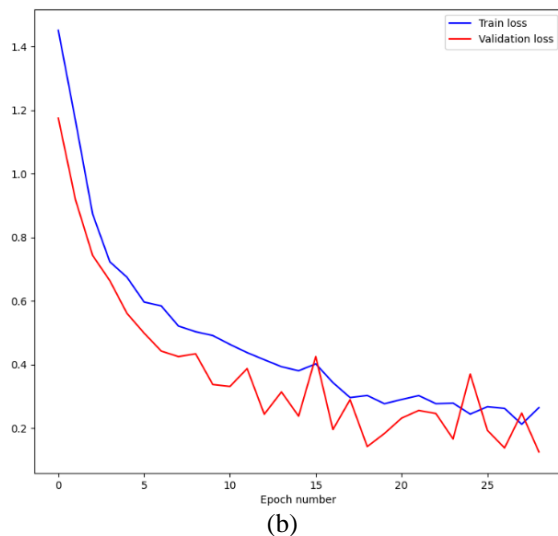
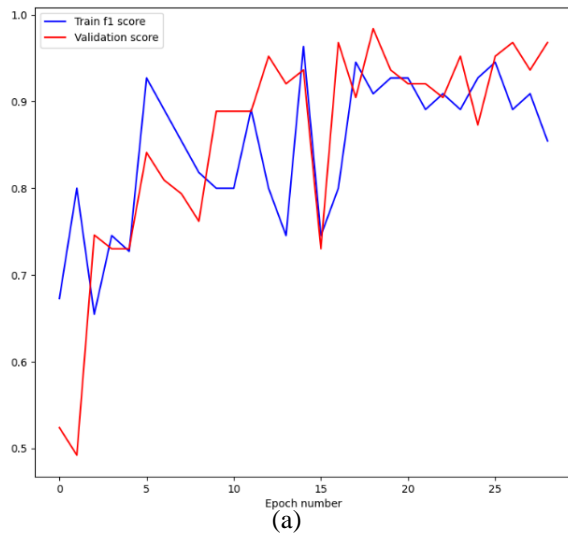


Fig. 4: (a) The F1 score, and (b) the loss function of the model on the training (blue) and validation (red) data.

Table 2 shows the performance of the two base models. The results show that GRU performs better in all criteria. Also, Table 3 shows that Adam's method provides better performance.

Table 2. Performance of Two Baseline Models

Model	Accuracy	F1-score	Precision	Recall
LSTM	0.9365	0.9206	0.9365	0.9365
GRU	0.944	0.9683	0.98	0.9444

Table 3. Results of Optimization Algorithms Review.

Optimization Algorithm	Accuracy	F1-score	Precision	Recall
Adam	0.9891	0.9875	0.9841	0.9891
SGD	0.5	0.3112	0.4921	0.5
NAdam	0.9737	0.98	0.9683	0.9737
Adagrad	0.8844	0.8673	0.8413	0.8844
AdaDelta	0.5	0.299	0.4921	0.5
RMSProp	0.8844	0.8673	0.8413	0.8844

4.3 Interpretation of Results

The integration of qualitative fault analysis and the AI algorithm successfully enabled the precise identification and classification of HVAC system faults. This capability allows for prompt intervention, significantly contributing to the prevention of energy waste. The model's high accuracy in detecting faults, including those not previously well-identified by other algorithms, underscores its effectiveness. Overall, the proposed framework demonstrates substantial benefits for optimizing energy management in buildings for both owners and occupants.

The confusion matrix of the proposed model depicted in Figure 5. It visually evaluates model's classification performance for each of the four distinct fault types, No Fault (F1), Inlet Air Damper Fault (F2), Heating Coil Valve Fault (F3), Cooling Coil Valve Fault (F4), by showing the counts of actual versus predicted classifications for each class.

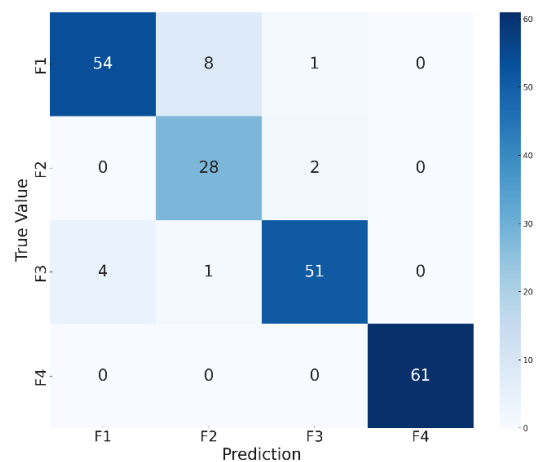


Fig. 5: Confusion matrix of the proposed model

5. Conclusion

The building sector represents a substantial portion of global energy consumption, with HVAC systems being primary contributors. Consequently, there is immense potential for energy savings by enhancing HVAC system efficiency, a goal effectively supported by various Fault Detection and Diagnosis (FDD) methods. Data-driven FDD approaches, especially Deep Learning (DL) techniques, have shown promising results in this regard.

This study successfully developed and implemented a framework for building energy management. This framework integrates qualitative fault analysis using Fault Tree Analysis (FTA) to understand the impact of faults, and AI-driven methods for accurate fault identification and diagnosis. Specifically, experimental laboratory data, which carefully documented fault impacts on various parameters, was utilized. Given the time-series nature of the data, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) algorithms were employed. The GRU algorithm demonstrated superior accuracy compared to LSTM in fault detection.

The AI tool proved effective in identifying and diagnosing HVAC system faults with high accuracy and speed. Real-time fault detection enables prompt repairs, leading to significant energy savings and improved occupant thermal comfort. Overall, AI offers considerable benefits for energy management in buildings. A limitation of this AI approach, however, is the difficulty in acquiring sufficient diverse fault data, restricting the number of identifiable fault types.

Previous studies primarily focused on fault detection using AI, often without specifying the fault type or providing a framework for subsequent fault management. This led to difficulties in building maintenance post-detection. This research introduces several key innovations:

- **Precise Fault Type Identification:** Beyond merely detecting a fault, this study identifies the specific type of fault, enabling easier localization and rectification.
- **Integrated Qualitative Fault Analysis:** Fault Tree Analysis is employed for root-cause investigation and qualitative management of faults, providing a systematic approach to understanding and addressing issues.
- **Comprehensive Energy Management Framework:** A novel framework is proposed that integrates qualitative fault analysis (via FTA) with AI-driven fault detection and diagnosis. This holistic approach aims to prevent energy waste and ensure thermal comfort, representing a significant step towards comprehensive energy management in buildings.

For future research, incorporating a quantitative analysis of each fault's impact could significantly enhance decision-making in energy and cost management, by comparing increased energy consumption due to a fault against its repair costs. Such analysis could also pinpoint frequent fault locations, guiding improvement efforts and facilitating better future decisions through fault tracking over time.

Further studies could expand the number of identifiable fault types within HVAC systems using AI algorithms. A major challenge in this field is the scarcity of publicly available, real-world benchmark datasets for actual building systems. Existing datasets often come from laboratory experiments or simulations, which may not fully capture real-world complexities, including simultaneous, unknown, or novel fault scenarios. Therefore, creating a comprehensive public dataset that encompasses these real-world complexities would be highly beneficial for future researchers, enabling the development of robust AI approaches for practical building FDD systems.

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