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Fault-Aware Adaptive Temporal–Feature Fusion for Multi-Scale Transformer-Based Early Predictive Maintenance in Smart-Building HVAC Systems

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Abstract

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HVAC fault detection is essential for reliable smart-building operation and predictive maintenance, yet existing data-driven approaches often exhibit limited multi-scale temporal modeling and insufficient adaptation to fault-relevant sensor interactions. This study proposes a Multi-Scale Temporal Transformer with Adaptive Attention to address these limitations by jointly learning short-, medium-, and long-term HVAC operating patterns and dynamically fusing temporal and feature-level representations for early fault identification. The framework is implemented using Python with PyTorch and evaluated using a publicly available HVAC dataset containing 15-minute measurements from a non-residential building in Turin, Italy, including temperature, humidity, setpoint, fan power, and energy variables. The proposed model achieves 97.59% accuracy, 97.72% precision, 97.31% recall, 97.51% F1-score, and 0.987 AUC, outperforming the strongest baseline accuracy of 96.30% by 1.29 percentage points (1.34% relative improvement). The results demonstrate the potential of adaptive multi-scale temporal learning for reliable HVAC fault detection and early-warning predictive maintenance.

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1. Introduction

Heating, ventilation and air conditioning (HVAC) systems are a significant part of the smart building infrastructure as their performance directly affects the indoor environmental conditions, energy consumption and building sustainability level [1]. As increasing building automation systems and sensor technologies are deployed, there has been a proliferation of high-frequency multivariate operational data, providing opportunities for data-driven monitoring and intelligent maintenance. Artificial Intelligence (AI) based Fault Detection and Diagnosis (FDD) has been emerged as an effective method to determine abnormal operation of HVAC systems without relying solely on physics-based models or continuous expert monitoring [2]. Machine learning and deep learning have been proven to be applicable to HVAC fault detection, and data-driven methods have been found to be more scalable and less reliant on detailed system models. But the operating conditions of any HVAC system are dynamic in nature, and faults can occur as sudden deviations, slow degradation, or sustained temporal variations in several interacting variables. Thus, models that are able to learn complex temporal relationships from multivariate sensor sequences, not just a single measurement, are required for reliable early detection of faults [3].

Existing research has investigated conventional machine learning, recurrent neural networks, and more recently Transformer-based architectures for HVAC FDD. Supervised deep learning models have shown good predictive performance, and the use of Transformer-based models to capture long-range dependencies have been investigated, and more recently, to decrease reliance on fault data by employing self-supervised learning. However, current solutions are still limited in their capacity to model the multi-scale temporal behavior and relevance of the different fault types [4]. The abnormalities of the HVAC system may occur over different time scales, and the significance of the temperature, humidity, setpoint, and fan-related variables can change depending on the operating condition. However, challenges such as dynamic environments, time varying environments, generalization, and fault-detection resolution have been identified in existing studies. Hence, an adaptive learning strategy is needed to differentiate informative temporal patterns and sensor characteristics of emerging faults. To address this challenge, this study introduces a novel Fault-Aware Multi-Scale Temporal Transformer with Adaptive Temporal–Feature Fusion network for early HVAC fault detection. The proposed framework is able to jointly capture both the short-, medium- and long-term operational patterns, adaptively weight the temporal and sensor level information and incorporate the two representations into an early-warning indication for predictive maintenance by employing a fault-aware fusion mechanism. The key contributions of this study are as follows,

- • A fault-aware multi-scale temporal learning framework is developed to model short-, medium-, and long-term dependencies in multivariate HVAC operating data for early fault detection.
- • An adaptive temporal–feature attention mechanism is introduced to dynamically identify the most informative time intervals and HVAC variables associated with abnormal operating conditions.
- • A fault-aware adaptive fusion mechanism is proposed to selectively integrate temporal and sensor-level representations, improving the discrimination of emerging HVAC faults.
- • An early-warning fault-risk estimation strategy is incorporated to transform model outputs into calibrated abnormality indicators that support timely predictive-maintenance decisions.

The rest of this paper is organized as follows: Section 2 discusses related works, Section 3 presents the proposed methodology, Section 4 reports and discusses the experimental results, and Section 5 concludes the study and outlines future research directions.

2. Related Works

More recently, deep learning has been used to advance the intelligent monitoring, energy management and predictive maintenance of HVAC systems. Almatared et al. [5]designed an LSTM ensemble with mode-aware segmentation, calibration, and RUL-based maintenance triggers to achieve a reduction in unplanned outages, downtime, and energy consumption, but the single building evaluation in Riyadh limits the cross-climatic generalization. Likewise, Arun et al. [6]incorporated CNN, RNN, sensor networks and reinforcement learning in multifaceted smart building management which was mainly simulation based and had a high computational complexity. Although Alijoyo [7] used a CNN-IoT framework for energy prediction and anomaly detection, the anomaly modeling and real-world validation was limited and the accuracy was 88%. However, Boutahri and Tilioua [8] emphasized the prediction of thermal comfort based on traditional machine learning methods, which led to a comfortable analysis but not a comprehensive temporal fault detection. Together, these studies illustrate the potential of data-driven HVAC intelligence, but fail to adequately incorporate multi-scale temporal dependencies and adaptive representations of fault-relevant data.

Wang et al. [9] proposed a HVAC fault diagnosis system based on the modified Transformer with adapter-based transfer learning, with an accuracy of 91.38% for various fault types and severity levels. Transformer-based modeling [9] has demonstrated superiority in modeling complex temporal dependencies compared to recurrent and conventional machine-learning methods [5] and [8] and CNN-IoT and integrated smart-building frameworks [6] and [7] focus on broader operational goals. However, the existing methods typically focus on temporal modelling, energy management, comfort prediction, or on adapting to multiple systems, but they do not learn multi-scale temporal behaviour and dynamically adapt between temporal and sensor-level information. This limitation inspires the proposed Multi-Scale Temporal Transformer with Adaptive Attention that specifically aims at capturing temporal patterns and feature interactions related to faults and provide early fault detection and predictive maintenance support for HVAC systems.

3. Proposed Multi-Scale Temporal-Fusion Framework for HVAC Predictive Maintenance

Framework for HVAC Predictive Maintenance

The proposed system introduces an AI-based framework for early HVAC fault detection based on multivariate operational time-series data. The methodology combines data preprocessing, multi-scale temporal sequence construction, temporal representation learning using a Transformer, and temporal–feature fusion based on an adaptive mechanism for fault awareness. The resulting representation is used to estimate fault probability and to calculate an early-warning risk score, which allows for early detection of abnormal operating conditions of the HVAC which can then be used for predictive-maintenance applications. The Workflow of the Proposed Fault-Aware Multi-Scale Temporal Transformer for Early HVAC Fault Detection and Predictive Maintenance is illustrated as in Fig.1.

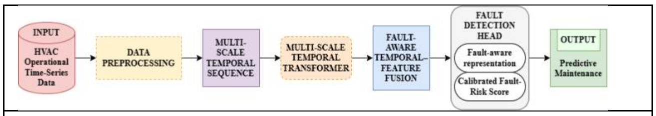

Figure 1. Workflow of the Proposed Framework

3.1 Dataset Collection:

The dataset used in the study is the publicly available "Development of Anomaly Detectors for HVAC Systems using Machine Learning" dataset which can be obtained from the Mendeley Data repository [10]. The data set consists of time-series measurements of HVAC collected from a non-residential building in Turin, Italy, every 15 minutes between 2019 and 2020, and 2020 and 2021 during the winter season. It contains supply, return, and outdoor temperatures, supply, return, and outdoor relative humidity, return-air temperature setpoint, humidifier saturation temperature, fan power, and fan energy, and offers comprehensive multivariate operational information for intelligent HVAC fault detection.

3.2 Data Preprocessing and Temporal Sequence Construction:

Data from the HVAC are compiled in chronological order, screened for missing and duplicate observations, and standardized with the statistics in the training set. These variables are all transformed as follows in (1).

$$x_i' = \frac{x_i - \mu_i}{\sigma_i} \tag{1}$$

Where x_i denotes the original value of feature i, μ_i represents its training-set mean, and σ_i denotes its training-set standard deviation. Then, the normalized observations are grouped into sliding windows and span multiple scales for multi-scale learning.

3.3 Multi-Scale Temporal Transformer:

The preprocessed HVAC sequences are shown in three temporal scales to capture different rate of abnormality development: short-term (4 samples; 1 h), medium-term (12 samples; 3 h), long-term (24 samples; 6 h) with 15-min sampling interval. For each scale s, the input sequence X_s∈R^(L_s×d), where L_s is the window length and d is the number of HVAC variables, is projected into a d_m=128-dimensional embedding. Temporal self-attention is then used to detect the temporal relationships between the observations in each window as in (2).

$$_s = \text{softmax}\left(\frac{Q_s K_s^T}{\sqrt{d_k}}\right) V_s \tag{2}$$

Where Q_s, K_s, and V_s are query, key, and value representations, respectively, and d_k is the key dimension. The resulting scale dependent representations are then added together to preserve both short-term temperature or humidity changes and long-term changes in fan power and energy. The added value of this stage is the explicit multi-scale representation of the operating behaviour of the HVAC system, which enables the model to differentiate transient variations from abnormal patterns.

3.4 Fault -Aware Adaptive Temporal-Feature Fusion:

The multi-scale representation is enriched by feature-level attention to highlight the most relevant variables for an emerging HVAC fault. Temporal and feature representations, H_T and H_F, are integrated using a learnable gate expressed as in (3) and (4).

$$G = \sigma\left(W_g[H_T; H_F] + b_g\right) \tag{3}$$

$$H_{\mathrm{FAF}} = G \odot H_T + (1 - G) \odot H_F \tag{4}$$

Where G is the adaptive fusion weight, W_g and b_g are learnable parameters, σ is the sigmoid function, [;] denotes concatenation, and ⊙ denotes element-wise multiplication. The main methodological novelty is this fault-aware fusion, as it is not static and depends on the temporal evolution of the system and the information from the sensors, rather than being fixed.

3.5 HVAC Fault Detection and Early-Warning Prediction:

A classification head is used to estimate the probability of abnormality for the fused representation. It is computed as in (5).
computed as in (5).

$$p_t = \sigma(W_o H_{\mathrm{FAF}} + b_o) \tag{5}$$

Where p_t is the predicted fault probability at time t, W_o and b_o are learnable output parameters, and H_"FAF" is the fused representation. A calibrated p_t is used as the early-warning risk score, enabling the system to distinguish normal operation from developing abnormal conditions and generate a maintenance alert before persistent HVAC faults become critical.

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In contrast to previous fault detection methods focusing on temporal modelling, single-scale feature extraction or transformer-based prediction, the proposed framework is able to simultaneously model short-, medium- and long-term operational dependencies, and automatically fuse temporal and sensor level information through a fault-aware adaptive algorithm. This allows the creation of the patterns relevant to the fault, emphasizing based on their temporal evolution and variable importance, thereby allowing them to serve as a more application-oriented basis for early maintenance warnings.

4. Results and Discussion

The proposed framework successfully detects the abnormal HVAC operating conditions by learning short-, medium-, and long-term temporal dependencies in the multivariate sensor data. The Multi-Scale Temporal Transformer reflects temporal evolution in operation, and adaptive temporal–feature fusion dynamically highlights time segments relevant to faults and HVAC variables. This fault-risk representation allows detecting a growing abnormality earlier than instantaneous monitoring. The attention analysis also provides insights in the temporal and sensor characteristics associated with detected faults.

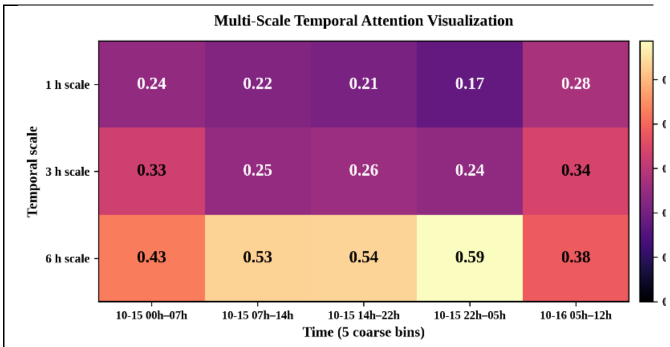

Figure 2 Multi-Scale Temporal Attention Visualization

Fig. 2 shows the results of the attention score calculation for the 1-hour, 3-hour, and 6-hour time scales, highlighting the distinct temporal dependency of HVAC abnormalities and the need for multiple time horizons to effectively identify faults.

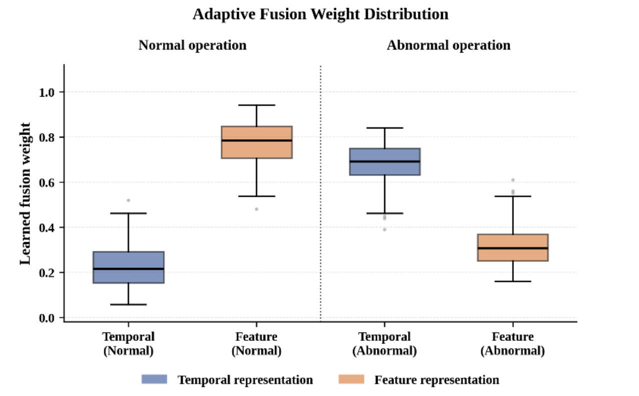

Figure 3. Adaptive Fusion Weight Distribution

Temporal and feature representation weights are shown under normal and abnormal conditions in Fig. 3, indicating that the proposed adaptive fusion mechanism dynamically prioritizes fault-relevant information based on operating conditions.

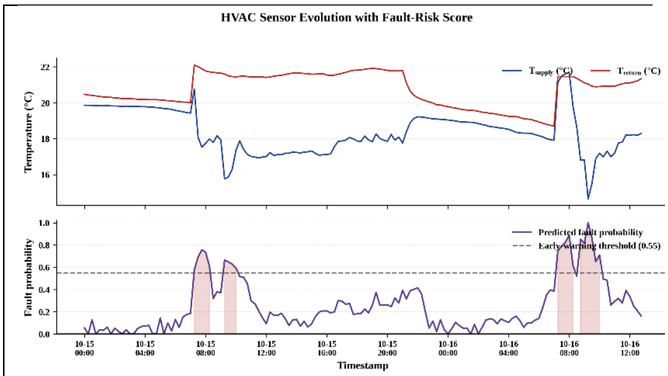

Figure 4. HVAC Sensor Evolution with Fault-Risk Score

Changes in representative HVAC variables are shown along with the predicted fault probability and the warning threshold in Fig. 4, where an increase in operational deviations leads to early identification of fault risk.

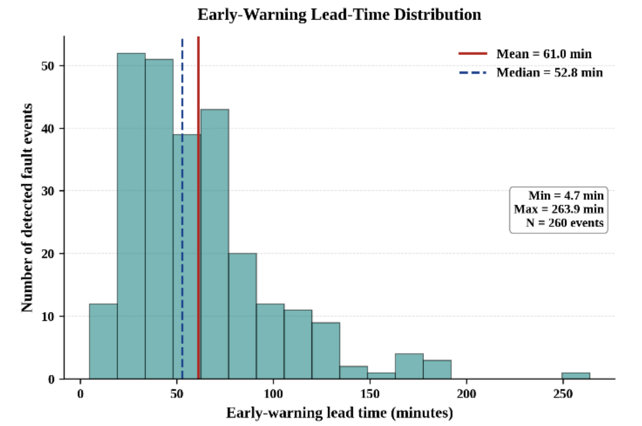

Figure 5. Early-Warning Lead-Time Distribution

Fig. 5 shows the HVAC fault warning lead time distribution generated prior to the HVAC fault detection, where early warnings are consistently provided with the mean, median, minimum and maximum warning lead times.

Table 1. Performance Comparison

Model	Accuracy (%)
CNN-IoT-based framework [7]	88.00
Transformer [9]	91.38
CNN + LSTM + SVM [11]	96.30
KNN + SVM [12]	95.00
Proposed Multi-Scale Temporal Transformer + Adaptive Attention	97.59

As shown in Table 1, the proposed framework outperforms the compared methods in terms of accuracy, and it shows that multi-scale temporal modeling and adaptive attention are more effective in HVAC fault discrimination.

4.1 Discussion:

The proposed Multi-Scale Temporal Transformer with Adaptive Attention achieved 97.59% accuracy, 97.72% precision, 97.31% recall, 97.51% F1-score, and 0.987 AUC, which shows reliable HVAC fault discrimination. The performance shows that the integration of the short, medium and long-term temporal dependencies offers richer representations than traditional single-scale methods. The adaptive temporal–feature fusion further enhances detection by focusing on fault-relevant sensor variables and temporal patterns. The proposed model outperformed the CNN-IoT, Transformer, CNN+LSTM+SVM and KNN+SVM baselines, demonstrating the power of the proposed temporal modeling and adaptive attention mechanism. The attention analysis also discovers influential HVAC variables and abnormal temporal areas, contributing to the interpretability and early risk assessment. Evaluation of a single-building dataset, however, restricts generalizability to different HVAC systems and weather conditions.

5.Conclusion and Future Work

This study proposes a Multi-Scale Temporal Transformer with Adaptive Attention for AI-based HVAC fault detection and early-warning predictive maintenance. The framework handles multivariate HVAC time-series data and models the dependencies among HVAC operations, both in the short-, medium-, and long-term, via multi-scale temporal representation learning. The suggested adaptive temporal–feature fusion mechanism dynamically focuses on informative temporal patterns and HVAC variables during abnormal operating conditions. This framework offers a data-based approach to detecting emerging HVAC anomalies and issuing forecasts for maintenance. It is mainly based on multi-scale temporal modeling and adaptive fault-relevant feature fusion, which allow the HVAC condition assessment to be more context-aware than traditional temporal prediction methods. The attention mechanism is also used to interpret the temporal and sensor-based factors that affect the identification of the fault. However, the generalizability to a wide range of HVAC configurations, building characteristics and climatic conditions is limited when using a single non-residential building dataset for evaluation.

The framework will be tested at different buildings, HVAC configurations and climatic conditions in the future to enhance the generalizability. Additional fault categories, longer multi-season datasets, and streaming of real data will allow for more extensive validation. In future, lightweight model compression for deployment at the edge, uncertainty-aware risk estimation, and integration with building-management systems for automated maintenance prioritisation and adaptive HVAC control will be explored.

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