Feature Sensitivity Analysis for Enhanced HVAC Fault Detection and Diagnosis

Arash Hosseini Gourabpasi [1], Farzad Jalaei [1], Mazdak Nik-Bakht [2]

[1]National Research Council of Canada, Ottawa, Canada
[2]Concordia University, Montreal, Canada
Arash.HosseiniGourabpasi@nrc-cnrc.gc.ca, Farzad.Jalaei@nrc-cnrc.gc.ca, mazdak.nikbakht@concordia.ca

Abstract – Automated Fault Detection and Diagnostics (AFDD) is a data-driven approach that enables the timely detection of faults, their types, and severity in Heating, Ventilation, and Air Conditioning (HVAC) systems. Machine learning models can be used to develop and implement AFDD models for HVAC at the system, sub-system, and equipment levels. However, there is a discrepancy between experimental facilities and actual buildings in practice.

This study implements sensitivity analysis to determine how variations in the features used in the case study under investigation affect the performance of the AFDD models. The analysis includes techniques such as correlation analysis and machine learning models (Support Vector Machine (SVM) and Artificial Neural Network (ANN)) to assess the sensitivity of the models to changes in input features. The results depict how sensitive the AFDD models are to different features and the extent to which variations in these features can impact the models' performance. These findings can facilitate the selection of robust features for machine learning-based Fault Detection and Diagnostics (FDD) models of HVAC in buildings by building operators, including facility managers, asset managers, and owners.

Keywords –

Sensitivity analysis, Feature impact analysis, Data Mining, Fault detection and diagnostics, Machine Learning, Artificial Neural Network, Support Vector Machine, HVAC

1 Introduction

Automated Fault Detection and Diagnostics (AFDD) is crucial for maintaining the efficiency and reliability of HVAC systems [1], [2]. AFDD models are constructed using data that reflects the behavior and performance of facilities and HVAC systems, enabling the prediction of fault occurrences and types. In this regard, machine learning models offer a promising approach to FDD, but there is a significant gap between the controlled environments of experimental facilities and the real-world conditions of actual buildings. This study aims to bridge this gap by performing a sensitivity analysis to understand how variations in features affect the performance of AFDD models [3] .

Presently testing facilities used for AFDD development are often using controlled environments to reduce uncertainty. They are heavily instrumented, which means that test facilities contain many sensors installed in different building spaces and HVAC equipment to detect subtle changes in the system and building space environment. However, in practice, the existing stock of commissioned buildings does not possess the same sensor variety and is limited in numbers compared to experimental labs. The current differences in real case scenarios and research facilities do not make the machine learning-based AFDD models feasible for utilization in actual buildings [4].

This study implements sensitivity analysis to determine how variations in the features used in the case study under investigation affect the performance of the AFDD models. The analysis includes techniques such as correlation analysis and data mining techniques to assess the sensitivity of the models to changes in input features. The study investigates how sensitive the AFDD models are to different features and the extent to which variations in these features can impact the model's performance. In addition, the results of feature importance can be used to facilitate the selection of robust features for machine learning-based FDD models of HVAC in buildings.

2 Methodology

This study utilizes data from a Building Information Model (BIM), which contains building spatial data, and Building Management System (BMS), which includes time-series data representing HVAC, to create a comprehensive dataset for fault detection and diagnostics of an HVAC system. The BIM model includes static features such as room area, window area, door area, opening area, distance to HVAC from VAV (Variable

Air Volume), room adjacency to shafts, and whether rooms are exterior or interior. These features collectively form 80 static features representing the facility's contextual information. The BMS dataset includes 68 dynamic features such as VAV temperature, room temperature, humidity, status, supply and return temperature, metered data, set points, and flow rates.

A key aspect of our methodology is feature engineering, where we generate new features from existing data to enhance the accuracy and effectiveness of machine learning models. For instance, we created a calculated feature called "space air conditioning," which combines contextual information from BIM and air conditioning conditions from BMS for each room. This feature is crucial for identifying faults related to occupancy patterns and other contextual factors.

Feature engineering in AFDD involves generating new features from existing data to improve the accuracy and effectiveness of machine learning models. This is particularly important when dealing with limited sensor data, a common problem in real-world building environments. For example, one can combine time-series data from BMS (e.g., supply air temperature) with spatial data from BIM (e.g., room occupancy) to create a new feature that represents the air conditioning state of a space. This type of feature can help to identify faults that are related to occupancy patterns or other contextual factors.

To make the features workable, two grouping systems were formed: one based on system-related features or zone/space features, and the second based on the feature source.

Table 1: Grouping based on System related features or Zone/Space related features

Grouping based on level	No of groups	Feature groups formed based on simillarity names
Zone/Space level	4	VAV temp, Room temp, humidity, set point
System level	3	Circuit 1 and 2, supply and return, Flow rate
Mix	1	Status
Building	1	Meter

Table 2: Grouping based on feature source and type (Static/Live)

Grouping based on source and type	No of Features	Full form
BMS	68	BMS dataset
BIM	80	BMS + Live BIM dataset
Dy+St	160	BMS + Live BIM dataset + Static
BIM		BIM dataset
St BIM	148	BMS + Static BIM dataset

Two approaches were used the first being feature impact analysis and second sensitivity analysis. Feature impact analysis evaluates the importance of groups of features, while sensitivity analysis assesses the impact of individual features on model performance. Sensitivity analysis helps to identify the most important features for fault detection and diagnosis, as well as to understand how the model's performance is affected by missing or incomplete data. One way to perform sensitivity analysis is to train multiple models with different combinations of features and compare their accuracy. For example, one might train a model with all available features, then train another model with a subset of features, and compare their performance.

Feature impact analysis is useful when the set of features is large, as in the case of the facility, which will enable the modelers to identify which features are suitable for the machine learning algorithm to identify the faults of the HVAC systems.

3 Model Development

This study utilizes data from the LBNL (Lawrence Berkeley National Laboratory) Automated Fault Detection for Buildings Data [5], [6], [7], [8], [9], [10], [11]. A Building Information Model (BIM) is developed based on the specifications, and further, the Building Management System (BMS) is used to create a comprehensive dataset for fault detection and diagnostics of an HVAC system [12], [13], [14], [15]. The BIM model of the facility is created using the documentation of the test facility. The dataset generated for fault detection and diagnostics of the HVAC system includes a rooftop unit (RTU) connected to variable air volume (VAV) systems.

The BIM and BMS data were combined to form a comprehensive dataset [4]. The BIM features were grouped into categories such as distance to HVAC from VAV, room area, window area, door area, opening area, room adjacency to shafts, and whether rooms are exterior or interior. The BMS features were grouped into categories such as VAV temperature, room temperature, humidity, status, supply and return temperature, metered data, set points, and flow rates.

In this research, various machine learning algorithms are modeled to identify the most impactful features for fault detection and diagnostics. For feature importance analysis, classifiers like XGBoost, Random Forest, and Decision Tree were used. The machine learning algorithms specifically employed for fault detection and diagnostics (FDD) were Support Vector Machine (SVM) and Artificial Neural Network (ANN). They were selected based on the findings of earlier research, which highlighted their adoption for system-level and subsystem-level faults [16]. The performance of each algorithm was evaluated based on its ability to identify impactful features and detect faults. The faults considered in this study included condenser fouling, HVAC setback errors (delayed onset, early termination), excessive infiltration, lighting setback errors (delayed onset, early termination), no overnight HVAC setback, and thermostat measurement bias.

For feature importance evaluation, several models were developed. In the case of the Random Forest classifier, feature importance was computed as the mean and standard deviation of the impurity decrease within each tree, also known as Gini importance. For the Decision Tree classifier, feature importance was determined by the normalized total reduction of the criterion brought by that feature. XGBoost classification was based on gain, which measures the improvement in accuracy brought by a feature to the branches it is on.

Table 3: Machine Learning algorithms used as classifier for feature importance analysis

XGBoost Classification	Random Forest Classification	Decision tree classification
Condenser Outlet Pressure (Circ 1)	Condenser Outlet Pressure (Circ 1)	Condenser Outlet Pressure (Circ 1)
VAV Reheat Status	Room 205 Air Humidity	Discharge Temperature (Circ 2)
Discharge Temperature (Circ 2)	Room 206 Air Humidity	Room 204 Air Humidity
Room 203 Air Humidity	Room 204 Air Humidity	Room 205 Air Humidity
Room 203 Air Temperature	Room 106 Air Humidity	Room 206 Air Humidity
Discharge Pressure (Circ 1)	Suction Temperature (Circ 2)	Room 202 Air Humidity
X Air Humidity	Room 203 Air Humidity	Room 102 Air temperature
X Air Humidity	Room 102 Air Temperature	Room 106 Air Humidity
Suction Temperature (Circ 2)	Room 103 Air Humidity	Lighting system
X Air Humidity	Discharge temperature (Circ 2)	Room 205 Air Temperature

The calculated air conditioning feature shows a negative correlation and is the only feature that is found to have an impact when brought in from BIM, as shown below.

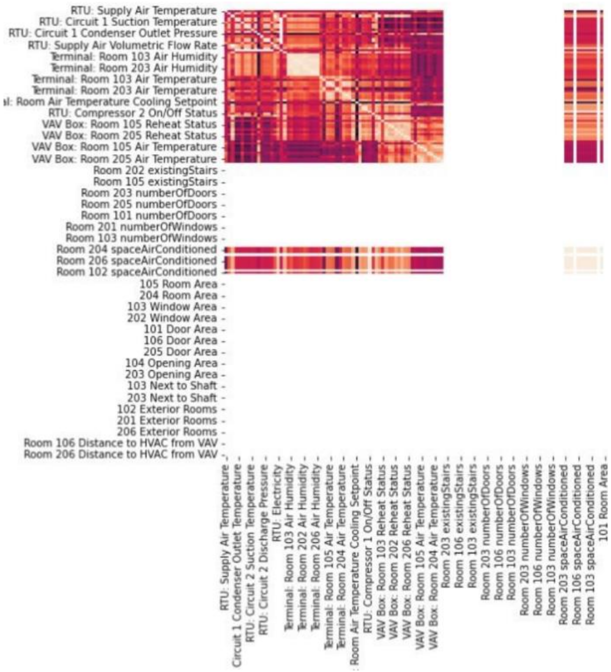

Figure 1: Excerpt of correlation analysis and of important features for AFDD in the curated dataset including BIM features

4 Results and Discussion

The result of this research indicated that the Random Forest classifier was most suitable for the dataset, particularly when it came to calculated features. For sensory data features, the classification algorithms showed similar feature types, with humidity being the most impactful feature.

The comparison of SVM and ANN indicates that the ANN is more sensitive to selected features, showing higher levels of sensitivity. The maximum impact that a feature can have on fault detection is 67% for both the suction temperature feature and the air-cooling temperature. Additionally, the diagnostics models show that the air temperature cooling setpoint can have a 62% impact, followed by the discharge temperature with a 37% impact.

The top 5 groups of features identified are then checked to see what percentage of accuracy impact these features have on the dataset for each of the algorithms for both fault detection and diagnostics.

Table 4: Impact of top 5 features on Fault detection and diagnosis using SVM Machine Learning Algorithms

Top 5 features	SVM Accuracy for Fault Detection	SVM Accuracy for Fault Diagnostics
Air Humidity	80%	71%

Discharge temperature (Circuit 2)	67%	38%
Suction Temperature (Circuit 2)	67%	38%
Room Temperature	79%	71%
Cooling setpoint	67%	33%

Table 5: Impact of top 5 features on Fault detection and diagnosis using ANN Machine Learning Algorithms

Top 5 features	ANN Accuracy for Fault Detection	ANN Accuracy for Fault Diagnostics
Air Humidity	87	55
Discharge temperature (Circuit 2)	71	37
Suction Temperature (Circuit 2)	67	39
Room Temperature	85	41
Cooling setpoint	65	33

The analysis illustrate that the random forest classifier is most suitable for the dataset when it comes to calculated features. For sensory data features, classification algorithms show similar feature types, with humidity being the most impactful feature. The top features identified include air humidity, discharge temperature, suction temperature, room temperature, and cooling setpoint.

The calculated feature, "space air conditioning," is the only feature in the BIM dataset that shows a negative correlation and is present in the important feature list when analysis is performed using a random forest classifier, which has a weak correlation of an average of 25%.

The results highlight the importance of certain features in the performance of AFDD models. For instance, air humidity and room temperature consistently show high impact across different models. The findings suggest that incorporating dynamic BIM features can enhance the sensitivity of AFDD models, especially when certain BMS features are unavailable. This has practical implications for facility managers and asset owners in selecting robust features for fault detection and diagnostics.

This study demonstrates the significance of feature impact analysis in developing effective AFDD models for HVAC systems. By identifying the most impactful features, facility managers can improve the accuracy and reliability of fault detection and diagnostics. Future work should explore the integration of additional contextual features and the application of these findings to a broader range of building types.

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