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FAULT DIAGNOSIS OF AN AIR HANDLING UNIT

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ABSTRACT

Fault detection is an integral part of any modern building system. If faults are not detected and resolved in a timely manner, health and safety issues may arise in addition to wasted energy from ineffective usage. In this study, various unsupervised, supervised and Artificial Neural Network (ANN) Learning Techniques for fault detection are deployed to perform fault detection for an air handling unit (AHU) within a small commercial building in Iowa. Analysis was performed on both an experimental dataset and a simulated dataset with synthetic data for the given AHU to test algorithm robustness under different fault conditions. Data preparation and exploratory data analysis was performed before application of AI techniques to detect trends and enhance the quality of the dataset. Model goodness was investigated using R-squared, Root Mean Squared Error (RMSE), and Mean Absolute Deviation (MAD) measures. Although all classification and regression methods used displayed satisfactory results, decision-tree based methods (decision trees classification and decision trees regression) displayed the highest accuracy for both experimental and simulated data while being less computationally expensive than ANN techniques with similar accuracy.

Keywords: artificial intelligence, artificial neural network, multi-layer perceptron, long short-term network, fault diagnosis

NOMENCLATURE

AHU	Air Handling Unit
BACnet	Building Automation and Controls Network
BMS	Building Management System
PCA	Principal Component Analysis
SOM	Self-Organizing Maps
EDA	Exploratory Data Analysis
kNN	K-Nearest Neighbor
ANN	Artificial Neural Network
LSTM	Long Short Term Memory
RMSE	Root Mean Squared Error
MAD	Mean Absolute Deviation
MLP	Multi-Layer Perceptron

1. INTRODUCTION

An air handling unit (AHU) connects primary heating and cooling plants with building zones, controls building ventilation air intake, and greatly affects the energy consumed for heating, cooling, and ventilating, as well as supply air temperature and humidity levels. In effect, AHUs manage energy exchange and ventilation in building spaces. Therefore, an AHU's operation significantly impacts building energy use, health, and comfort aspects. For example, faulty AHU ventilation may lead to a higher level of recirculation for unwanted particulates such as the COVID-19 virus. Furthermore, other faults such as leakage from heating or cooling coils results in increased energy consumption, increased costs to building owners, and indoor thermal discomfort. The successful detection of AHU faults in a timely manner can result in improved comfort, energy savings, air quality improvement, increased equipment lifetime, and improved service scheduling.

There are currently several key issues in AHU fault detection. Firstly, even though the fundamental architecture of an AHU is unchanged between individual units, every AHU is a custom system that is made for the specific building and spaces it serves, meaning that there is no standard AHU system for model calibration. For instance, different building owners may implement different energy efficiency measures based on their needs such as an economizer or heat recovery wheel. Furthermore, multiple operational modes are possible in AHUs such as 'occupied mode' and 'unoccupied mode' and AHUs may constantly switch modes or turn off, resulting in frequent transient operation. Finally, due to the aforementioned challenges, there is no generalized analytical model for the complete deterministic analysis of an arbitrary AHU, making fault detection using conventional methods a significant challenge and a key motivator for utilizing AI methods in fault detection.

In this study, fault detection is done for an AHU designated AHU-A in a small size commercial building in Iowa during summer, winter, and the transition season. As this is a benchmark dataset, faults were manually imposed onto the control system. Each fault was tested for one day. The main variables for both the experimental and simulated datasets were temperature (outdoor air, supply air, mixed air, return air, status signals (supply air fan, return air fan), control signals (supply air fan speed, return air fan speed, exhaust air damper, outdoor air damper, return air damper, cooling coil valve, heating coil valve), and occupancy mode indicator. The objective was to determine the fault detection ground truth parameter, which was a binary output with '1' for 'fault' and '0' for 'no fault'.

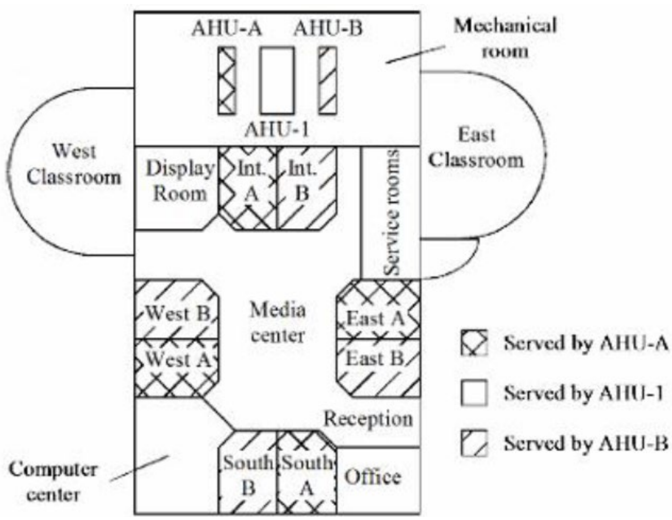

FIGURE 1: SPACES SERVED BY AHU-A

AHU-A features an economizer duct configuration, along with a heating coil and cooling coil for both heating and cooling capabilities.

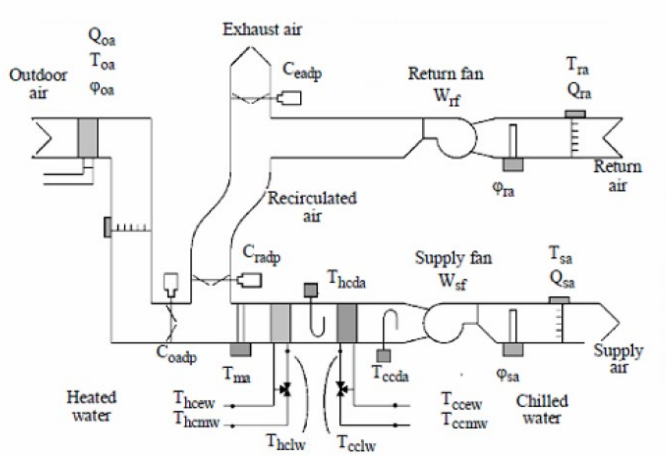

FIGURE 2: SCHEMATIC DIAGRAM OF AHU-A.

2. MATERIALS AND METHODS

For this study, the workflow was divided into five main stages in sequential order. Firstly, the raw data was pre-processed and prepared for further analysis. Afterwards, exploratory data analysis (EDA) was performed to gain deeper understanding of the input variables and detect any possible hidden trends via unsupervised learning methods. Supervised learning and artificial neural network (ANN) methods were then implemented, and results were compared via different measures of goodness and model accuracy to determine the best AI model for fault detection.

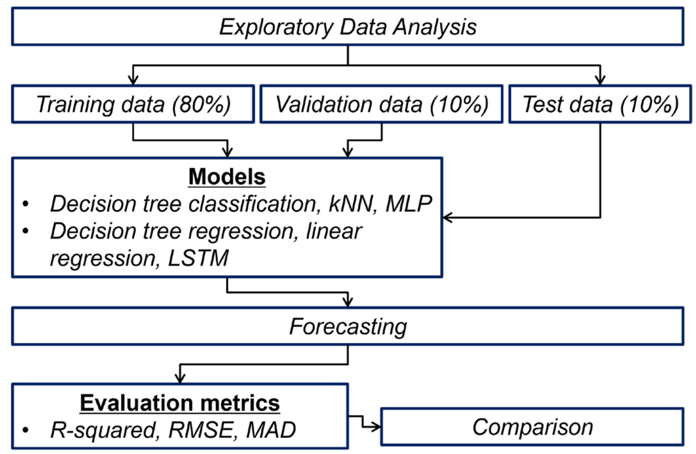

FIGURE 3: PROJECT WORKFLOW

2.1 Pre-processing

Although the raw input data did not have missing values, there were several outliers present. Outliers were removed using the elliptic covariance method.

FIGURE 4: TIME SERIES PLOT OF TEMPERATURE VARIABLES AFTER OUTLIER REMOVAL

Afterwards, methods such as 3-component Principal Components Analysis (PCA) was performed with a focus on the temperature variables to find covariance relations. Cross plots of temperature variables were also performed to check for natural fault clusters. However, these methods did not yield significant insight into the dataset, which necessitated the use of unsupervised learning to attempt finding any hidden relationships.

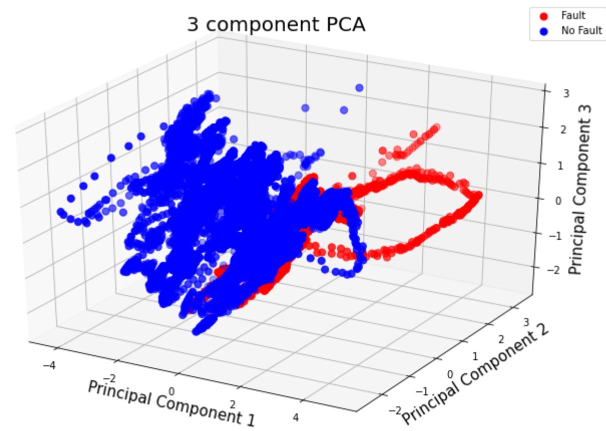

FIGURE 5: PCA FOR TEMPERATURE VARIABLES

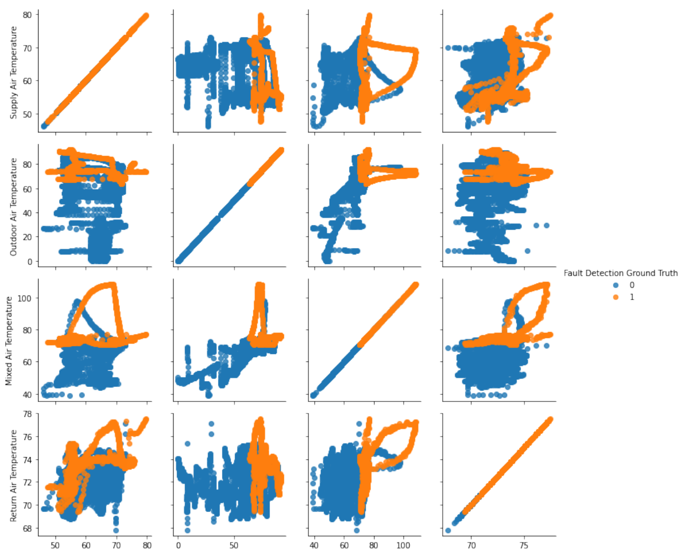

FIGURE 6: CROSS PLOTS OF TEMPERATURE VARIABLES

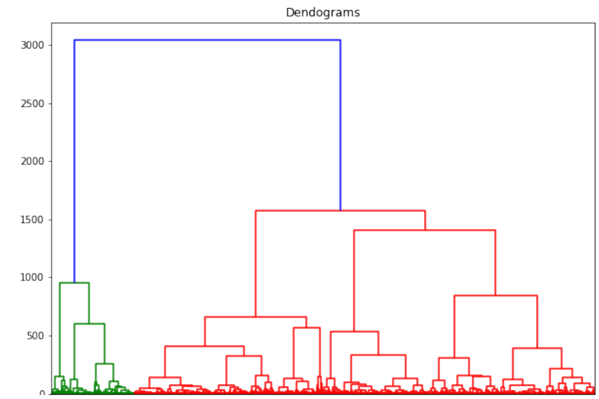

FIGURE 7: HIERARCHICAL CLUSTERING DENDOGRAM

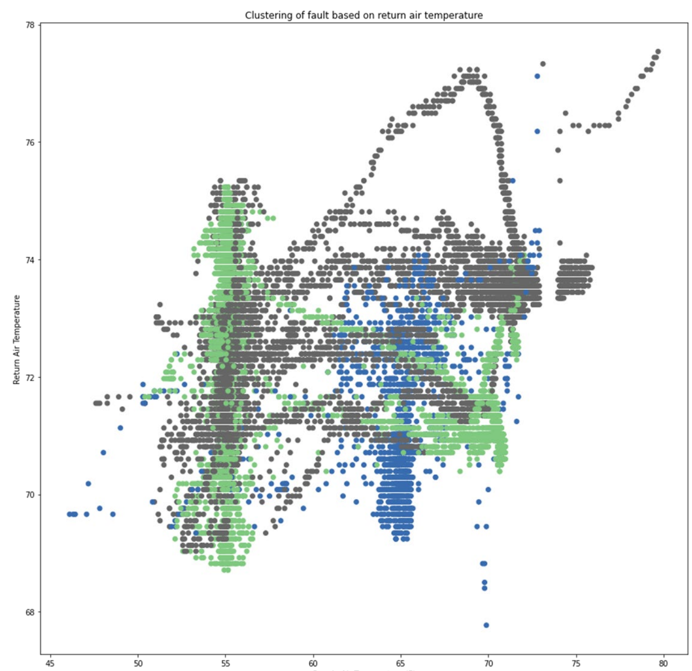

FIGURE 8: K-MEANS CLUSTERING USING 3 CLUSTERS

2.1 Unsupervised learning

Unsupervised learning is a set of machine learning techniques primarily used to detect hidden trends in data via clustering. K-means clustering, hierarchical clustering, Gaussian Mixture Modeling, and Self-Organizing Maps (SOMs) were used in this study to attempt finding meaningful clusters of data. Although the 'elbow method' in k-means clustering suggested 3 clusters as optimal, hierarchical clustering suggested 4 clusters. However, attempts at clustering via these suggestions yielded no results that had physical significance.

As a further measure, SOMs with 2 clusters specified for 'fault' and 'no fault' were attempted. This yielded an accuracy of approximately 57%, which was unstable and varied between each run.

2.2 Supervised learning

Supervised learning methods were the primary methods used to predict faults. To ensure that overfitting was not occurring, the dataset was split into training, validation, and test data with a percentage split of 80, 10, and 10 respectively. Decision trees classification, k-nearest neighbors (kNN), and multi-layer perceptron (MLP) ANN were used for classification, while decision trees regression, linear regression, and long short term memory (LSTM) ANN were used for regression.

3. RESULTS AND DISCUSSION

For the experimental dataset, both classification and regression methods yielded extremely accurate results, with overall accuracy generally exceeding 97% in classification for both faults and no faults with no indication of overfitting.

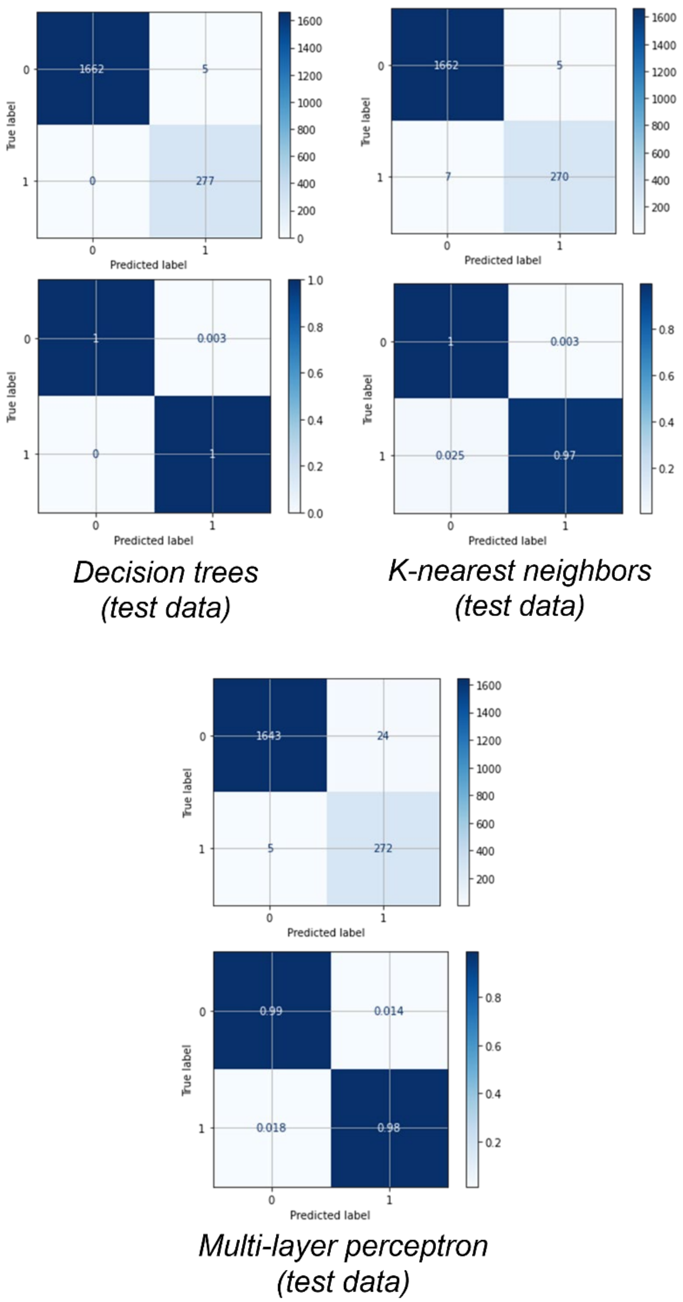

FIGURE 9: CONFUSION MATRIX FOR DIFFERENT AI METHODS WITH TEST DATA (EXPERIMENTAL DATASET)

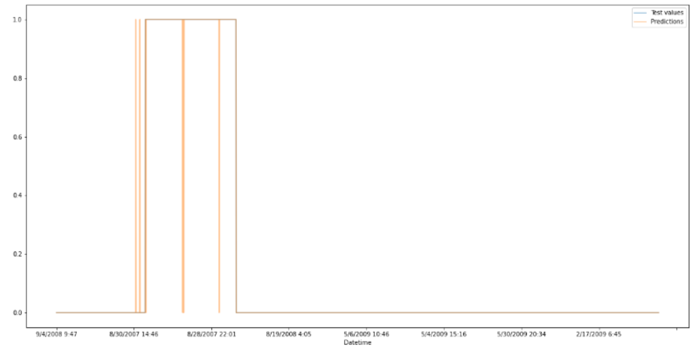

FIGURE 10: PREDICTED VS ACTUAL FAULTS FOR DECISION TREES CLASSIFICATION (EXPERIMENTAL DATASET)

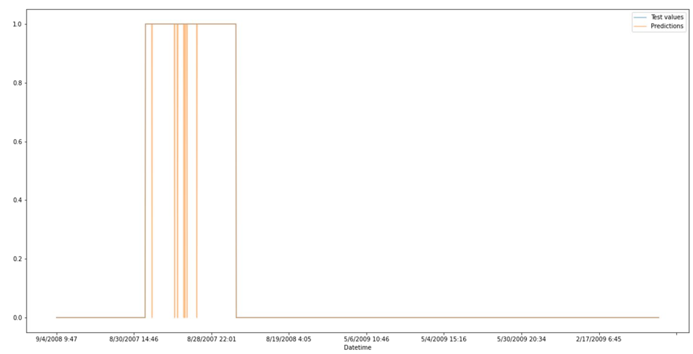

FIGURE 11: PREDICTED VS ACTUAL FAULTS FOR KNN CLASSIFICATION (EXPERIMENTAL DATASET)

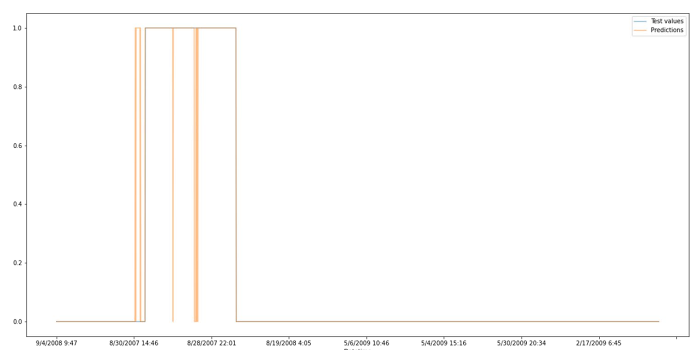

FIGURE 12: PREDICTED VS ACTUAL FAULTS FOR MLP ANN CLASSIFICATION (EXPERIMENTAL DATASET)

Similarly, regression produced highly accurate results with good metrics for the relevant goodness measures of R-squared, Root Mean Squared Error (RMSE), and Mean Absolute Deviation (MAD). Decision trees regression outperformed linear regression and LSTM for the experimental dataset with an accuracy of over 99%.

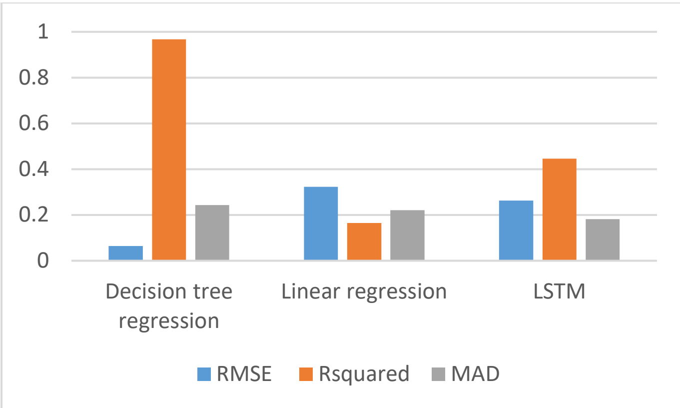

FIGURE 13: GOODNESS MEASURES FOR REGRESSION METHODS UTILIZED (EXPERIMENTAL DATASET)

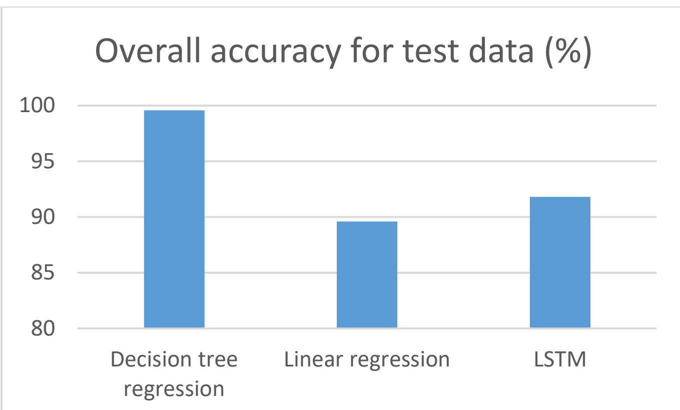

FIGURE 14: OVERALL ACCURACY FOR REGRESSION METHODS UTILIZED (EXPERIMENTAL DATASET)

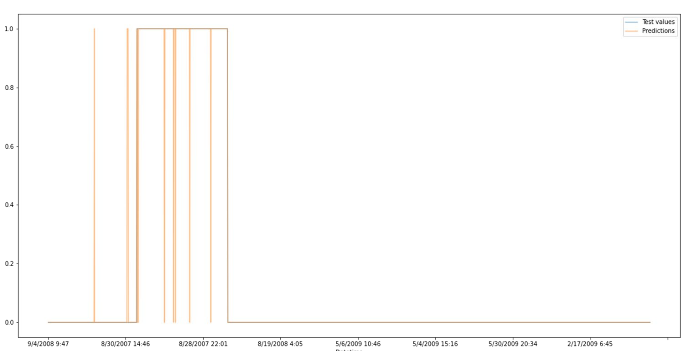

FIGURE 15: PREDICTED VS ACTUAL FAULTS FOR DECISION TREES REGRESSION (EXPERIMENTAL DATASET)

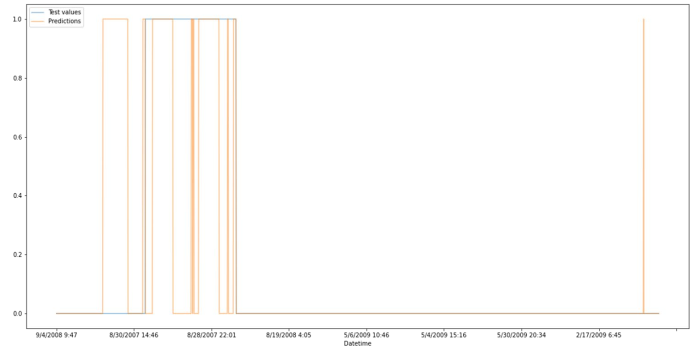

FIGURE 16: PREDICTED VS ACTUAL FAULTS FOR LINEAR REGRESSION (EXPERIMENTAL DATASET)

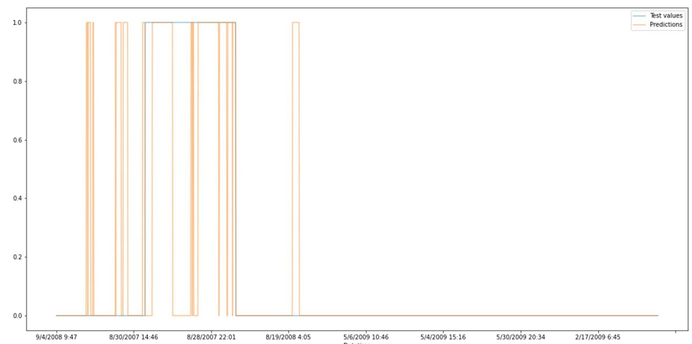

FIGURE 17: PREDICTED VS ACTUAL FAULTS FOR LSTM ANN REGRESSION (EXPERIMENTAL DATASET)

Given these accurate results, further testing was performed by applying the AI techniques used for the experimental dataset onto the simulated dataset to examine robustness with more failure modes (such as a stuck outdoor air damper and stuck cooling coil valve) and more stochastic variation (noise).

FIGURE 18: TIME SERIES PLOT OF TEMPERATURE VARIABLES FOR SIMULATED DATASET AFTER OUTLIER REMOVAL

For the simulated dataset, both classification and regression methods still yielded accurate results with a minimal drop in performance. Overall accuracy generally exceeded 90% in classification for both faults and no faults with no indication of overfitting.

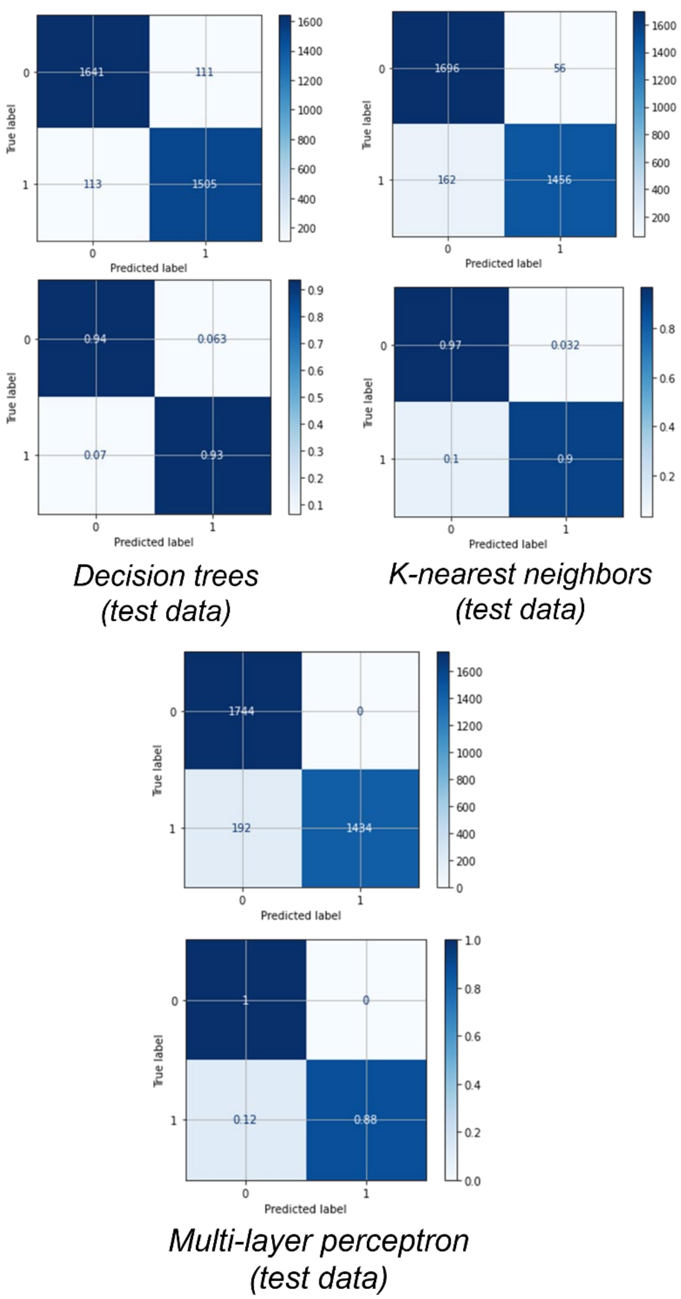

FIGURE 19: CONFUSION MATRIX FOR DIFFERENT AI METHODS WITH TEST DATA (SIMULATED DATASET)

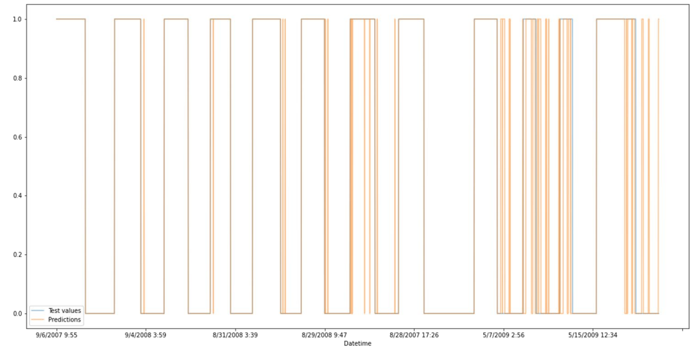

FIGURE 20: PREDICTED VS ACTUAL FAULTS FOR DECISION TREES CLASSIFICATION (SIMULATED DATASET)

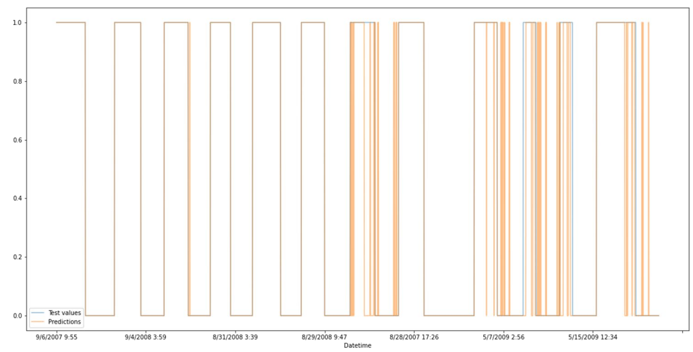

FIGURE 21: PREDICTED VS ACTUAL FAULTS FOR KNN CLASSIFICATION (SIMULATED DATASET)

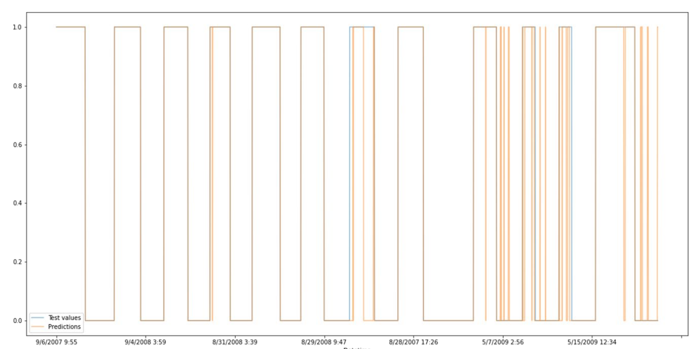

FIGURE 22: PREDICTED VS ACTUAL FAULTS FOR MLP ANN CLASSIFICATION (SIMULATED DATASET)

Similarly, regression still produced highly accurate results with good metrics for the relevant goodness measures. Decision trees regression outperformed linear regression and LSTM for the experimental dataset with an accuracy of over 91%.

FIGURE 23: GOODNESS MEASURES FOR REGRESSION METHODS UTILIZED (SIMULATED DATASET)

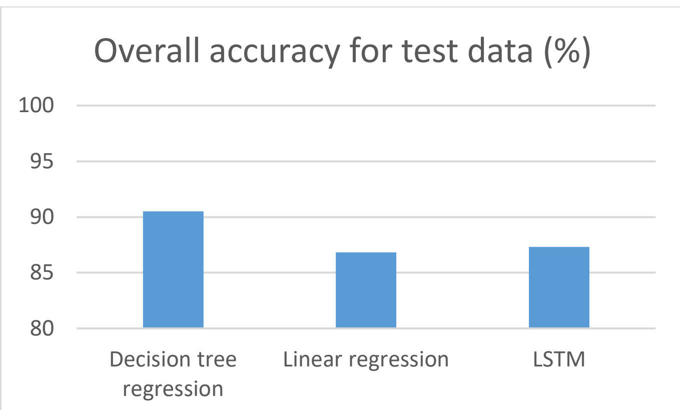

FIGURE 24: OVERALL ACCURACY FOR REGRESSION METHODS UTILIZED (SIMULATED DATASET)

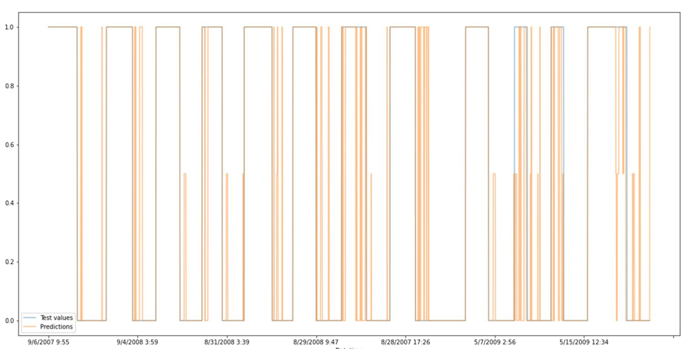

FIGURE 25: PREDICTED VS ACTUAL FAULTS FOR DECISION TREES REGRESSION (SIMULATED DATASET)

For both experimental and simulated datasets, results from regression were truncated to standardize the predictions and eliminate trailing decimals. For example, a result of 1×10^{-14} is automatically truncated to 0. Therefore, in some cases where the algorithm failed to predict the outcome, the prediction would show as 0.5 instead of a number close to 0 or 1 as in Figure 25.

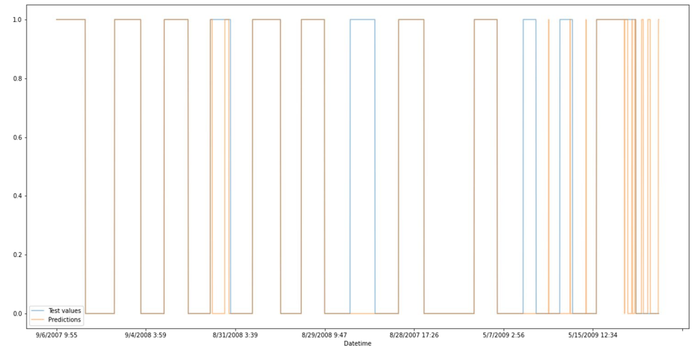

FIGURE 26: PREDICTED VS ACTUAL FAULTS FOR LINEAR REGRESSION (SIMULATED DATASET)

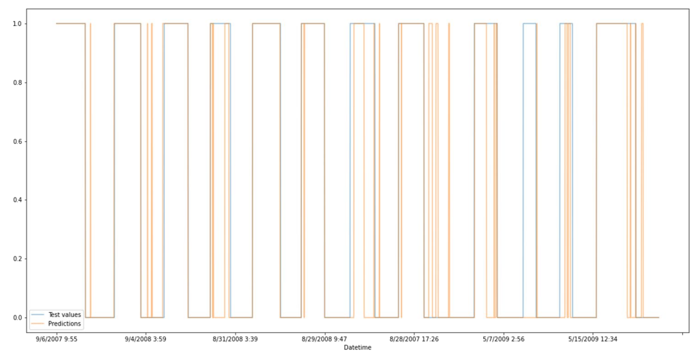

FIGURE 27: PREDICTED VS ACTUAL FAULTS FOR LSTM ANN REGRESSION (SIMULATED DATASET)

4. CONCLUSION

In this study, various AI methods were used to perform fault detection for a specified AHU. Although unsupervised learning methods did not yield significant insight into the dataset, supervised learning techniques yielded accurate outputs. In both classification and regression, decision-tree based methods performed excellently, likely due to similarities with conditional programming. In practice, an AI model would be fed data from AHU operations from the building management system (BMS) via BACnet, and a prediction would be made for each timestamp. Further work may focus on AI improvements such as ensemble learning and functionality improvements such as the ability to discriminate between specific types of faults along with fault intensity.

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