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Superheat Prediction & Fault Diagnostics of HVAC from Simple Temperature Measurements Using Big Data Approach

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ABSTRACT

New advancements in data & algorithms have pushed new techniques and methods to the forefront in optimizing energy efficiency as well as keeping the thermal comfort of residents in intelligent buildings research. HVAC elements, being ubiquitous and fundamental elements in buildings today, their diagnostics maintenance, operational functionalities, and control are essential aspects in this regard. The tremendous amount of data generated from buildings every day and recent developments with data science tools have changed the control and monitoring of these units from exhausting physical modeling and operation to data-driven techniques that are more reliable and efficient. The massive streaming data generated by smart building sensors have inspired new ways of controlling and diagnosing faults in comfort systems using machine learning and big data analytics. In this work, we present a big-data driven approach to model the dynamic of two similar HVAC (but, healthy and faulty) systems from simple temperature measurements collected over an extended period. The model showed good accuracy in predicting the system superheat for both systems. This demonstrates the potential of big data approach to substitute the need for having the expensive pressure sensor to measure superheat.

1. INTRODUCTION

It has been reported that HVACs currently consume more than 40% of total electricity use in the U.S [1]–[6]. Due to their significant impact on system efficiency, energy consumption and occupant comfort, faults in building HVAC systems need to be detected appropriately and hence diagnostic measures are taken to restore it to ideal working states. Being responsible for consuming a significant portion of global energy, HVACs require a reliable Fault Detection and Diagnosis (FDD) method to ensure an efficient equipment operation in order to achieve optimal energy usage and deliver a good performance. The figure below shows the classification of FDD methods[7]

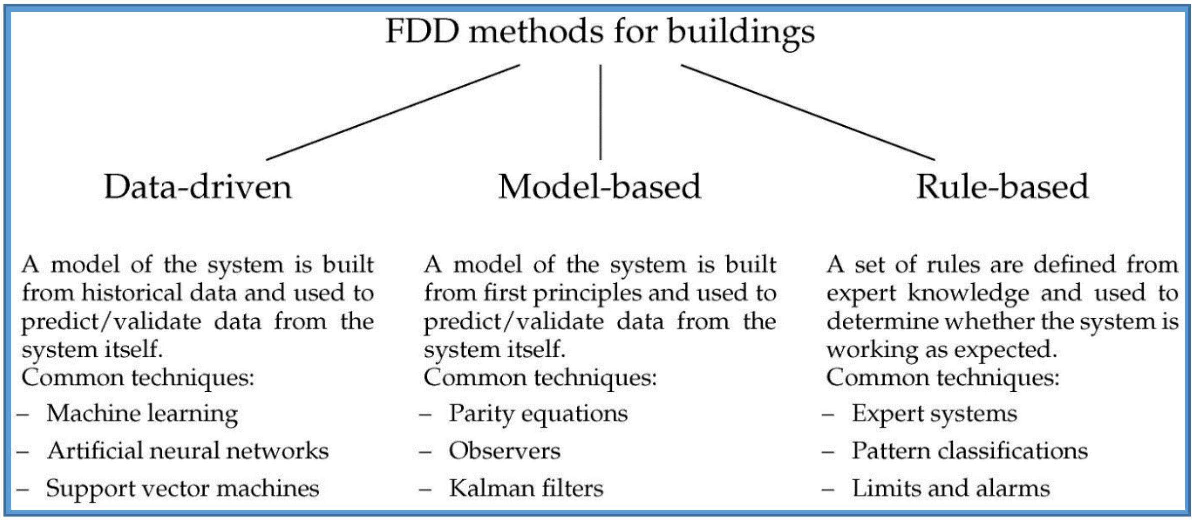


Figure 1: Different classifications of Automated Fault Detection and Diagnostics methods

This study categorizes AFDD methods in HVAC areas into three main categories— namely process history-based, qualitative model-based, and quantitative model-based methods.

Rule-based & qualitative physics-based modeling techniques use a priori knowledge to set up thresholds and rules to identify fault symptoms and make a final decision about the state of a system. On the other hand, quantitative model-based methods rely on established & explicit mathematical models to represent each component of the plant and simulate the steady and transient behaviors of the system to reach an analytical outcome to detect and diagnose the cause of faults[8]. This analytical result is followed by experimental data for validation. Process history-based methods, such as black-box models, rely on the relationship between inputs and outputs of a process without any consideration for physical significance. Those models include Bayesian networks [7]–[12] and artificial neural networks (ANNs) [13]–[19]

Another work in [20] relies on experimental data-driven approaches and algorithms for modeling, optimizing, and controlling HVAC systems. In this work, supply air duct static pressure and supply air temperature are used as control variables to improve energy efficiency and maintain thermal comfort. Data-driven approaches are used in [21] to estimate HVAC specific energy consumption in buildings using an improved Fourier series decomposition. Having no prior knowledge about abnormal phenomena that occurred in the system, researchers in [22] designed a semi-supervised data-driven approach, namely Principal Component Analysis (PCA). The PCA was employed for fault detection and isolation by distinguishing anomalies from normal operation variability as well as isolating variables related to faults.

2. METHODOLOGY

In this field experiment, we have a healthy and faulty unit. For the healthy unit, a baseline approach was used to monitor the deviation of the system from normal working conditions. Here, a reliable model has been designed to learn and predict superheat values of an HVAC unit from temperature measurements only, namely suction, outdoor and liquid line temperatures, excluding pressure variables. In this approach, a prediction with high accuracy has been obtained. Having reliably designed baseline model & predicted the superheat of a healthy unit, it was applied to new data collected from another unit with fault for successive months to establish & study a machine learning-based diagnostics nature of the HVAC units. Accordingly, the fault in the system has been identified. Based on this approach, control algorithms could be applied to bring superheat values to acceptable ranges or a decision could be made to replace the elements depending on the degree of severity and malfunction, to maintain the comfort of occupants.

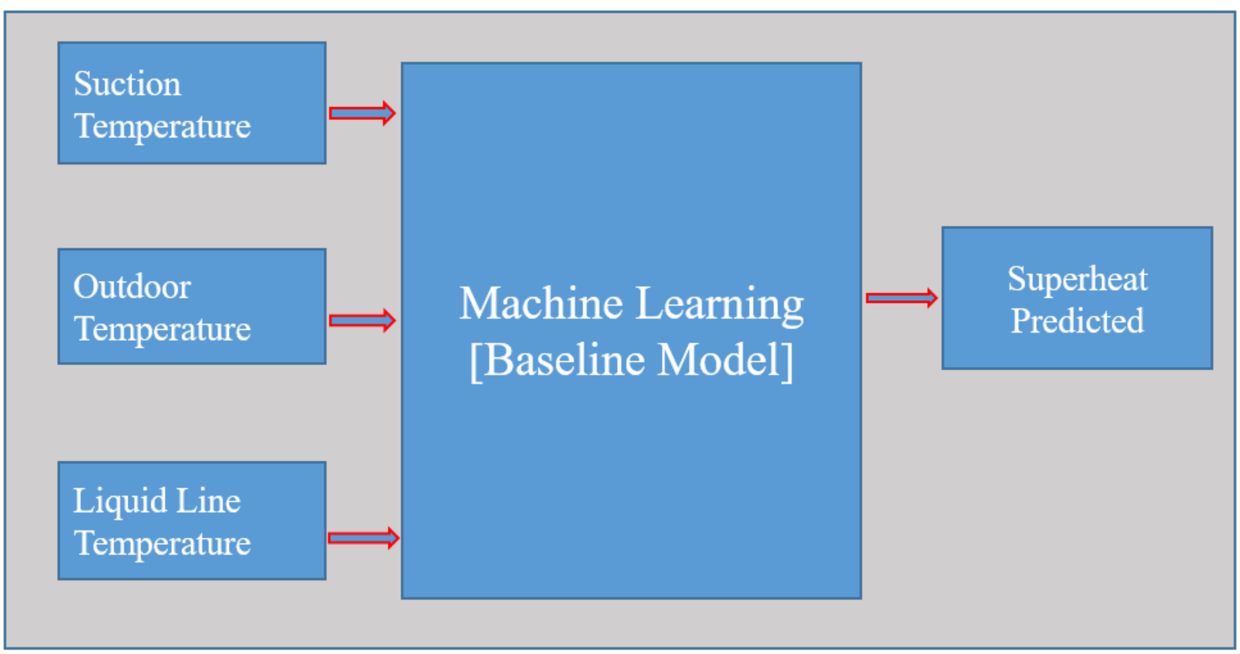


Figure 2: Baseline model design and predictors

3. THE PROPOSED DESIGN APPROACH

After massive data has been collected from our remote site, a local database has been set up to clean and process it. Since separating the ON and OFF data is necessary to analyze the performance of the HVAC, cleaning the data was the primary task to do before starting an in-depth study on the acquired sensory data. The dynamics of superheat throughout the operation time of the HVAC units has been chosen as a good variable to investigate the behavior and health of the element. To this end, leveraging the power of the huge data collected and many machine learning techniques, a model has been trained to learn the superheat from all temperature inputs. Superheat values have been predicted from these models and compared with actual measurements to verify their validity.

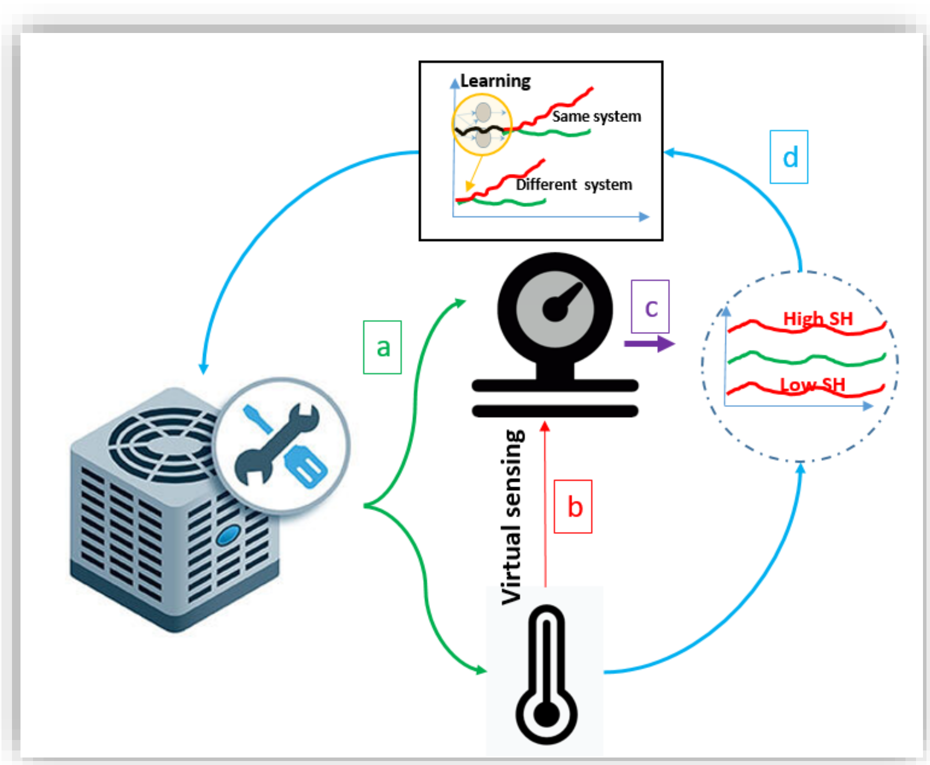


Figure 3: A comprehensive proposed design approach

Once a reliable model has been designed & the healthy pattern has been identified, it has been established as a baseline model against which past and future measurements of the same unit or other units are compared. As a continuation of this work, once the optimal superheat values of a sufficiently healthy system are identified, this range of values can be fed as set point to a control system that functions to maintain the comfort level of dwellers. The feedback from the resident, in the form of continuous data captured via wearable devices or intermittent reports on their comfort states, completes the cycle.

The existing approach in HVAC performance characteristics is mainly virtual sensing where pressures values at the inlet and outlets of compressors are estimated from temperatures. In another case, expensive equipment and sensors are deployed in the field to acquire real-time data to analyze HVAC behavior and performance. This is economically demanding and complicates the work of personnel. Though it is neither easy to calculate nor cheap to measure, superheat of a system, and sometimes Subcooling, is known as a very important indicator whether a system is healthy or faulty.

In this work, leveraging the availably of big data and many machine learning methods, we have come up with a novel way of estimating the superheat from simple temperature measurements. Utilizing this superheat and other predictor variables, a comprehensive baseline model has been designed for one of our healthy units, against which future and previous measurements on the state of the system are compared & hence detect whether faulty or not. Moreover, this same model can be used to identify & diagnose faults in other units where their data is unreliable to build models, *cross-unit detection*.

4. MACHINE LEARNING ALGORITHMS USED

Decision tree

The decision tree algorithm, specifically ***rpart*** function, is a non-parametric supervised learning method and is one of the simplest and yet most successful forms of machine learning for classification and regression. It has a tree-like graph representation that can be trained as a classifier to decide from multiple possible choices. The depth of the tree is one of the main parameters that can be tuned to enhance learning performance.

Gradient Boosting Regressor

The Gradient Boosting Regressor, XGBoost, is another ensemble learning technique used for classification and regression. This algorithm is known as a robust method to avoid overfitting[23].

Random Forest Regressor

Random Forest is based on utilizing the aggregation of decision trees built from various sub-samples of the datasets and their averages to improve the predictive accuracy Similar to the previous classifiers, it was employed while varying the estimator count to achieve better accuracy

5. RESULTS AND DISCUSSION

On a complete departure from previous trends, in this approach we devised a mechanism to depend on a system that we know is healthy from other previous studies and build a model based on which current and future data gathered from that system are measured against to detect fault.

Figure 4: Predicting superheat of the healthy unit using the baseline model[℃]

In this model, the accepted ranges of variables of a properly functioning HVAC are learnt and in a later use the model takes field measured values of important predictors and predicts the superheat values. These values are then compared to the actual measured values of superheat to determine the drift in performance of the system and hence its health. In this study, the model exhibited excellent prediction accuracy and the mean error values are very small. Fig4 below shows, the actual prediction residual levels.

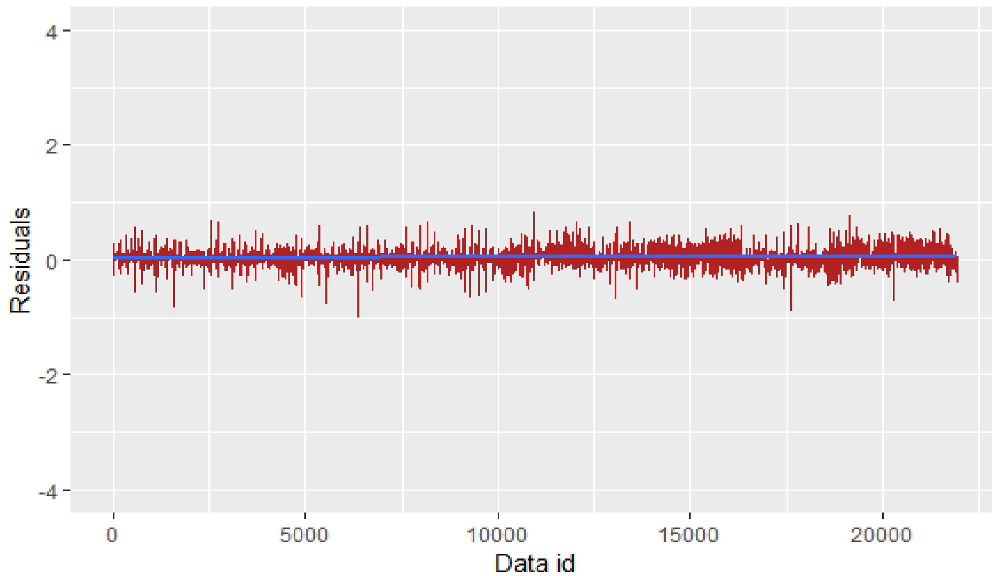


Figure 6: The superheat prediction errors are very small for healthy unit [°C]

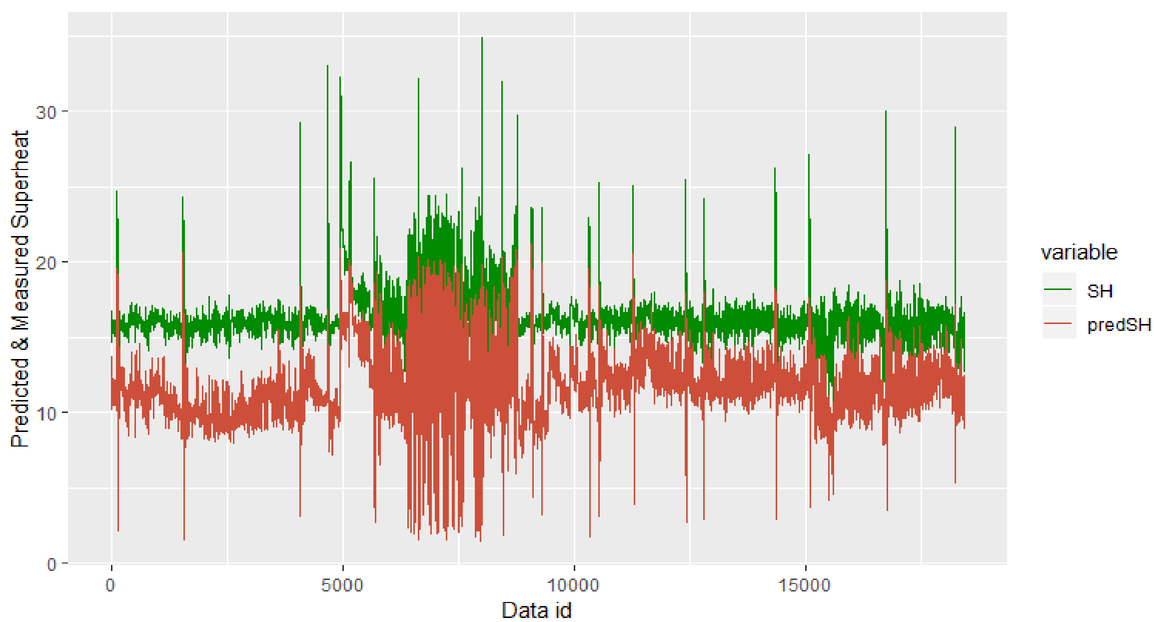


Figure 5: Predict SH of Unit-2 from Baseline Model trained by Unit-1 Data

However, the biggest contribution of this work is in its comprehensive capability in analyzing, diagnosing and monitoring malfunctions on other HVAC units, hence cross-unit detection. In instances where there is no enough data to learn the behavior of systems or when the data acquired from these units is deemed unreliable for various reasons, the general model built from a healthy & reliable unit can be employed to make comparative studies.

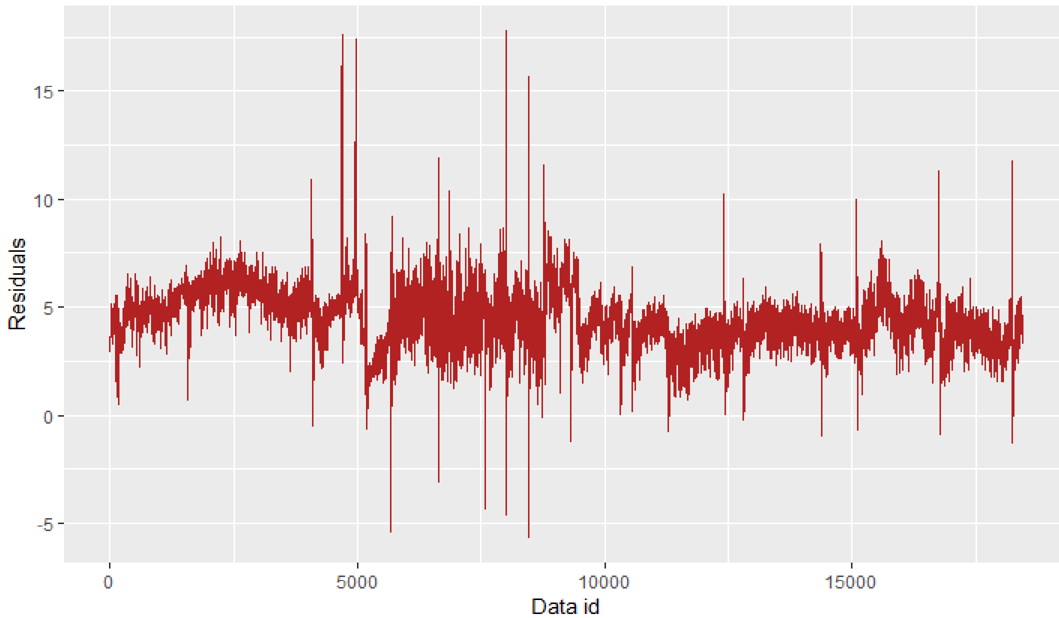
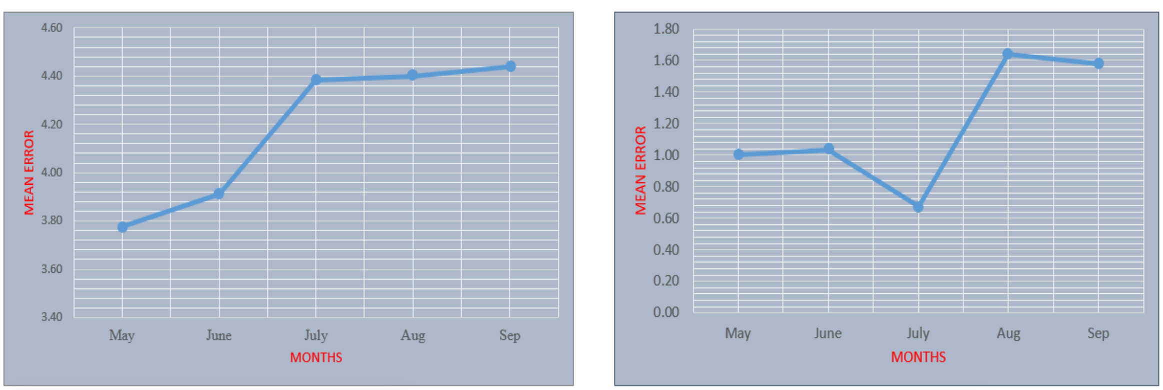


Figure 7: Actual Computed mean Residuals[°C]

This is exactly what we have implemented in this work. Figures 6 and 7 demonstrates the superheat values predicted for a faulty system using the baseline model. The predicted values are 5-10 degrees lower than those predicted, indicating that the HVAC unit had operational malfunction.



Using Model from Unit-1/ON Cycle

# May	June	July	Aug	Sep
# 3.775985	3.912517	4.400075	4.381936	4.437900

Unit-2 performance

UNIT-1 Mean-Error using Model from Unit-1 data

# May	June	July	Aug	Sep
# 1.0014	1.03477	0.67263	1.63780	1.581187

Unit-1 performance

Figure 8: Mean prediction errors of unhealthy and healthy units

The two figures above show the comparative performance of the models for both the healthy and faulty systems. The mean superheat prediction error for the unit based on which the model was designed is approximately in the range of [1 to 1.6]. On the other hand, the error for the defective unit upon which the base-model was applied is within the ranges of [3.5 to 4.5]

6. CONCLUSION

In this work, by using a simple temperature sensor, we were able to build reliable machine learning models that successfully detect and diagnose faults in HVAC systems. Moreover, the accuracy of predictions of these models was investigated for both the defective and healthy units. These results confirmed the preliminary assessment that was conducted based on few superheat and subcooling values. Among the machine learning algorithms applied, Gradient Boosting Regressor showed better performance.

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