Automated Fault Detection and Diagnosis for Energy Recovery Units using Statistical Machine Learning Method

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V National Conference on Refrigeration and Air Conditioning

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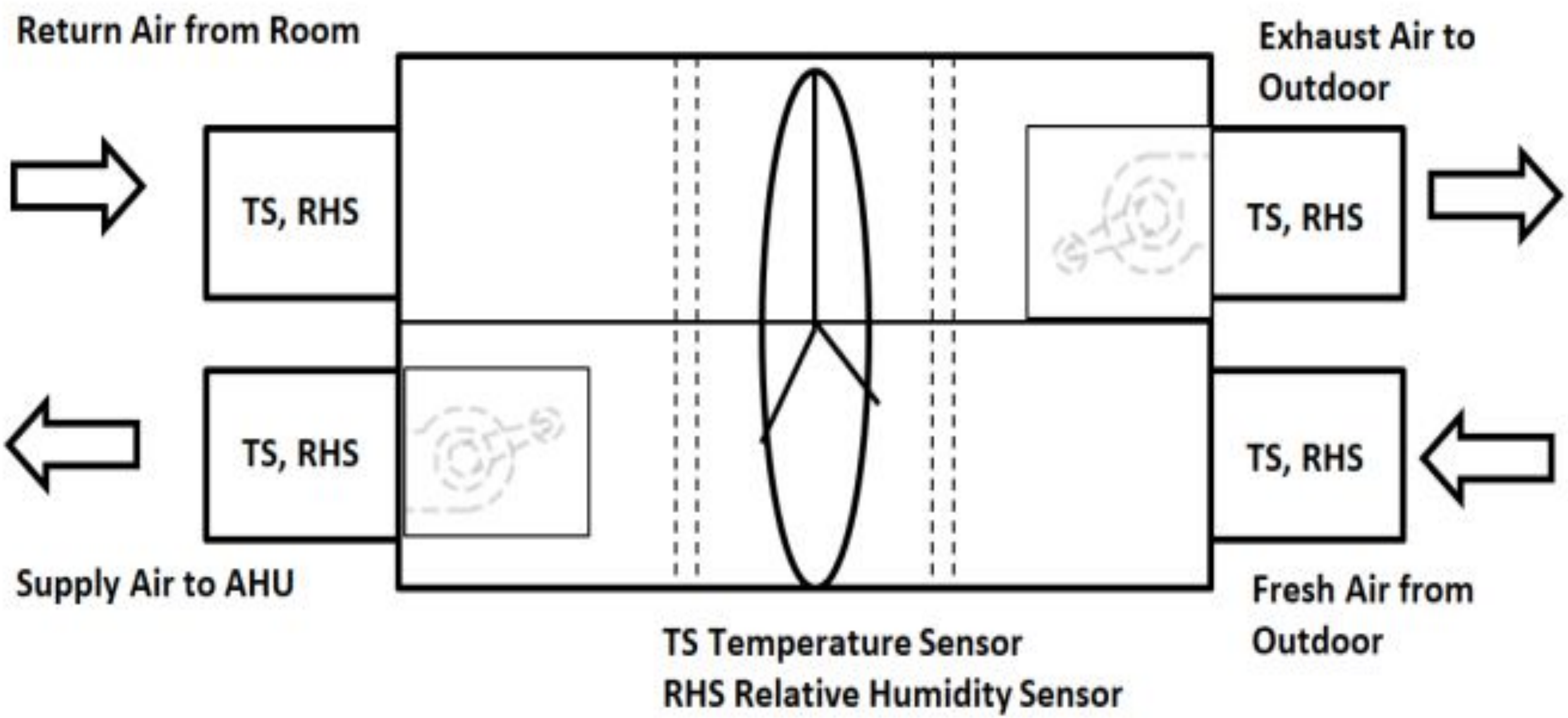
Abstract

To maintain indoor air quality, there is a need to provide fresh air supply to mechanically conditioned spaces. In tropical climates, supply of fresh air at high temperature increases cooling energy consumption. To reduce the wastage of energy, energy recovery from exhaust air is useful. Energy Recovery Wheel (ERW) can be used to recover both sensible and latent heat from exhaust air at room temperature. If there is a fault in ERW system, it may cause a significant increase in energy consumption compared to the recovered energy. In large commercial buildings with various HVAC equipment installed, faults can remain undetected for hours to months depending on the nature of the fault, results in poor indoor air quality and wastage of energy. In this paper, a method is developed for automating Fault Detection and Diagnosis (FDD) of ERW units. The paper describes the implementation of SVM algorithm on the measured data.

Energy Recovery Wheel Units

- In tropical climates like in India, supply of fresh air (for maintaining indoor air quality) at high temperature increases cooling energy consumption.
- To reduce the wastage of energy, energy recovery from exhaust air is useful.
- Recovers both sensible and latent heat from exhaust air at room temperature.

Schematic of ERW Unit



Why there is a need to detect faults in ERW units?

If there is a fault in ERW system, it may cause a significant increase in energy consumption compared to recovered energy.

In large commercial buildings, with various HVAC equipment installed, faults can remain undetected for hours to months depending on the nature of the fault results in poor indoor air quality and wastage of energy.

What are we doing?

- A method is developed for automating fault detection and diagnosis (FDD) of ERW units.
- This paper describes the implementation of statistical machine learning algorithm for finding faults in ERW units.
- Support Vector Machine (SVM) algorithm is used.

Research Gaps

- Researchers mainly focused on the FDD of Air Handling Units (AHUs) and chillers.
- Not many experimental datasets available for developing FDD techniques for ERW units.
- Fills the gap by creating ERW faults dataset.
- Developed a FDD technique.

Types of Faults

- Fault type 1, an improper working of supply air fan.
- Fault type 2, caused by the improper working of exhaust air fan.
- Fault type 3, caused because of improper functioning of rotary wheel.
- Fault type 4, caused because of improper functioning of both supply and exhaust air fans.

Data Collection

- Fresh air temperature
- Supply air temperature
- Return air temperature
- Exhaust air temperature
- Fresh air relative humidity
- Supply air relative humidity
- Return air relative humidity
- Exhaust air relative humidity

Preprocessing of data

- It is done to convert raw data which is generally incomplete, noisy and inconsistent to an understandable format.
- Raw data has some missing, out of range and inconsistent values which affect the results, so they are removed.
- Data is also normalized so that one feature doesn’t dominate other.

Support Vector Machine Algorithm

- It is a supervised machine learning algorithm.
- We used it for classifying the features obtained through pre-processing.
- One-against-all classification is used for classifying the features. The resultant class of the feature helps in identifying if there is a fault present in the system and if present, then what type of the fault, which in turn helps in diagnosing the fault.
- For SVM classifier, three hyper-parameters c, γ and kernel are optimized to avoid underfitting and overfitting of the model.

Results and Discussion

- SVM has given high classification accuracy in many existing works done in FDD.

- Gives flexibility of selecting a large number of sensors.

Table

S.No.	SVM Kernal Function	Accuracy of detection (%)	Precision	Recall	F1-score
1	Linear	99.172	9.181	99.172	99.177
2	RBF	99.793	99.794	99.793	99.794
3	Polynomial	99.796	99.794	99.795	99.796
4	Sigmoid	99.792	99.794	99.793	99.793