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Data Filtering and Fault Detection of VAV System using Wavelet Transform and Machine Learning Model

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Abstract

For efficient operation of HVAC systems by Building Energy Management System (BEMS), accurate and automatic filtering of outlying data and fault detection is crucial. This paper addresses an automated data filtering and fault detection method of a Variable Air Volume (VAV) system. For this purpose, a discrete wavelet transform method and a machine learning simulation model so called Gaussian Process Model (GPM) were applied. To validate the model, three faulty behaviors (sensing errors of temperature and mass flow rate, wrong operation of outdoor air damper, malfunction of coil valve) were tested. In the paper, it is concluded that the data filtering and fault detection model provides accurate prediction for daily building operation.

Keywords – Fault detection, Data filtering, Machine learning, Wavelet transfrom, Variable Air Volume

1. Introduction

Advanced building simulation techniques, e.g. whole building dynamic simulation tools, parameter estimation, optimal controls, can be used for the Building Energy Management System (BEMS). However, the efficient operation of BEMS can fail to achieve optimal energy saving and maintain comfortable indoor environment when outlying sensor data or malfunction of building systems deteriorate prediction by simulation tools. To avoid this, the automated data filtering and fault detection should be properly introduced. Unfortunately, most of data filtering and fault detection are being made manually, requiring hands-on involvement of building operators.

This paper addresses a data-driven strategy to automatically capture faulty behavior of a Variable Air Volume (VAV) system. The data-driven approach is advantageous since its computation is faster compared to whole building simulation tools. For this study, a wavelet transform and a machine learning based on Gaussian Process Model (GPM) were used to filter out outlying data and to provide accurate prediction. For validation purpose, three fault scenarios were chosen and tested.

2. Data driven approach for data filtering and fault detection

2.1 Fault detection methods

Fault behaviors of VAV systems consist of sensor errors, malfunction of system components, and incorrect control logics, etc. Firstly, the sensor errors with regard to temperature, humidity, mass flow rate of air and water, pressures are caused by unstable current or power supply, or deteriorated sensor devices. Secondly, the malfunctions of system components are such as stuck or leaking outdoor air (or exhaust air) dampers, clogged air filers/coils, wrong opening ratio of coil valves, poorly performing supply/return fans, clogging inside the pipes and ducts, etc. Thirdly, incorrect control logics are as follows: ad-hoc intervention with regard to outdoor air damper, coil valve, fan, VAV terminal damper, etc.

In general, there are three methods for fault detections: rule-based, model-based, and data-driven [1].

The rule-based method uses experts' rules. House et al. [2] and Schein et al. [3] showed that this method is useful for detecting various faults embedded in air handling units. But, the accuracy and reliability of the rule-based fault detections depend on experts' rules. If experts' rules were biased, the rule-based fault detection is misled into incorrect fault alarms.

Secondly, the model-based method identifies faults by predicted outputs of simulation models. Basarkar et al. [4] indicated that whole-building simulation models can be used to identify the faults of HVAC equipment. However, it is not easy to develop an accurate simulation model due to uncertain sources (e.g. aleatory or epistemic uncertainty). To reduce the uncertainty, the stochastic calibration techniques (e.g. Bayesian calibration) can be used. However, such calibration technique requires extensive computation time, in-depth expertise and effort.

The data-driven method uses Principle Component Analysis [PCA], Fast Fourier Transfer [FFT], or wavelet transform combined with machine learning based inverse models such as Artificial Neural Network (ANN), Support Vector Regression (SVR), and Gaussian Process Model (GPM). Fan et al. [5] showed that this hybrid strategy (e.g. wavelet transform and ANN technique) can detect sensors or system faults in control loop of an air handling unit. Yan et al. [6] also presented that a hybrid fault detection technique by FFT and SVR is suitable for solving HVAC system fault problems. The hybrid strategies are advantageous compared to the model-based approach since it doesn't require in-depth knowledge of first principles and significant modeling time and effort.

In this study, a hybrid strategy by wavelet transform and GPM was developed to find sensor or system faults in a VAV system.

2.2 Wavelet transform and Gaussian Process Model

Wavelet transform is used to analyze the frequency of the signals (stationary or non-stationary signal) in a time-frequency domain. The mathematical formulation is as shown in (1).

$$f(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \psi^* \left(\frac{x-b}{a} \right) f(x) dt \quad . \tag{1}$$

where a is a scale parameter, b is a translation parameter, ψ is a mother wavelet, * is a complex conjugate.

According to wavelet orthogonality, the wavelet transform is divided into Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). The DWT decomposes the signal into mutually orthogonal set of wavelets. Thus, the DWT is more appropriate for real observed signals than CWT since the observed ones are discrete [5]. In this study, the DWT was selected.

Gaussian Process Model (GPM) can be used for stochastic predictions [7, 8]. When time-series inputs/outputs are given such as a dataset measured from the BEMS, the GPM can be constructed using Bayesian approaches (e.g. Maximum A Posteriori (MAP), Markov Chain Monte Carlo (MCMC)) and Gaussian Process as shown in (2)-(4).

$$k(x_i, x_j^{'}) = \begin{bmatrix} C(x_1, x_1) & \cdots & C(x_1, x_p) \\ \vdots & \ddots & \vdots \\ C(x_p, x_1) & \cdots & C(x_p, x_p) \end{bmatrix} \tag{2}$$

$$f(x_i) \sim gp(m(x_i), k(x_i, x_j^{'})) \tag{3}$$

$$y_i = f(x_i) + \varepsilon_i \tag{4}$$

where k is a kernel matrix, x are inputs, y are outputs, C is a covariance function, gp is a Gaussian Process, m is a mean function, ε is a Gaussian noise.

3. Target building and fault scenarios

A 5-storey office building was chosen and modelled by EnergyPlus 8.0 (Fig. 1). Due to lack of real measured data, it was assumed that simulation inputs and outputs were measured from the BEMS. Simulation inputs including thermal properties of construction materials, internal load density [people, lights, and equipment], infiltration, HVAC system, and plant were determined based on [9, 10]. In this study, simulation runs were made only for a cooling period (July).

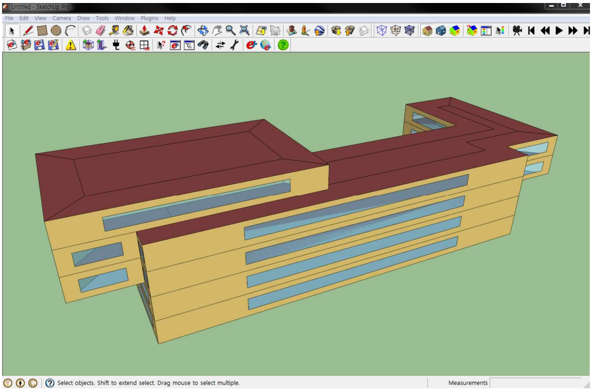


Fig. 1 Target building (displayed in OpenStudio)

Fig. 2 shows mechanical components (damper, supply/return fans, air filter, heating/cooling coils, humidifier, and controller) in the VAV system as well as sensor location of temperature/mass flow rates. The inputs for the GPM are as follows: respective mass flow rates and temperatures of return air, outdoor intake, and mass flow rate of the chilled water loop. The output for the GPM is outlet temperature of the supply fan.

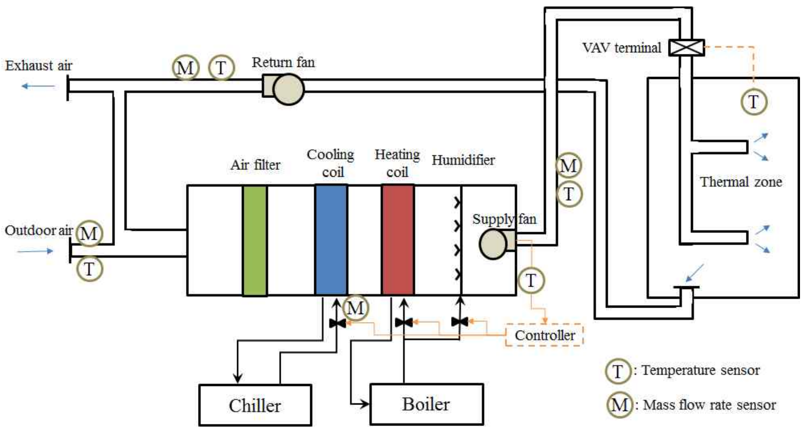


Fig. 2 VAV system

Three fault scenarios were assumed as shown in Table 1. To generate the malfunction of coil valve control and stuck outdoor air damper, the schedules of pump flow rate and outdoor air rate were arbitrarily changed in the EnergyPlus model.

Table 1. Fault scenarios in the VAV system

Scenario	Fault	Implementation
1	Malfunction of coil valve control	Exchange of pump flow rate schedule - wo/ faults: 100% (00:00-24:00) - w/ faults: less than 30% (08:00-18:00) after July 19
2	Stuck outdoor air damper	Exchange of outdoor air rate schedule - wo/ faults: 30% (08:00-18:00), 0% (00:00-08:00, 18:00-24:00) - w/ faults: less than 20% (08:00-18:00) after July 11
3	Malfunction of coil valve control + stuck outdoor air damper	Exchange of pump flow rate schedule - wo/ faults: 100% (00:00-24:00) - w/ faults: less than 30% (08:00-18:00) after July 19 Exchange of outdoor air rate schedule - wo/ faults: 30% (08:00-18:00), 0% (00:00-08:00, 18:00-24:00) - w/ faults: less than 20% (08:00-18:00) after July 11

4. Fault detection

Fig. 3 shows the approach used in this study. The data passed through wavelet transform were used to construct the GPM as well as regarded as the filtered measured data. The filtered residuals, which are defined as the differences between the filtered measured data and predicted outputs of the GPM, were compared to the error threshold value. If the filtered residuals are less than the error threshold value, the system is diagnosed as normal. Otherwise, the system is detected as malfunctioning.

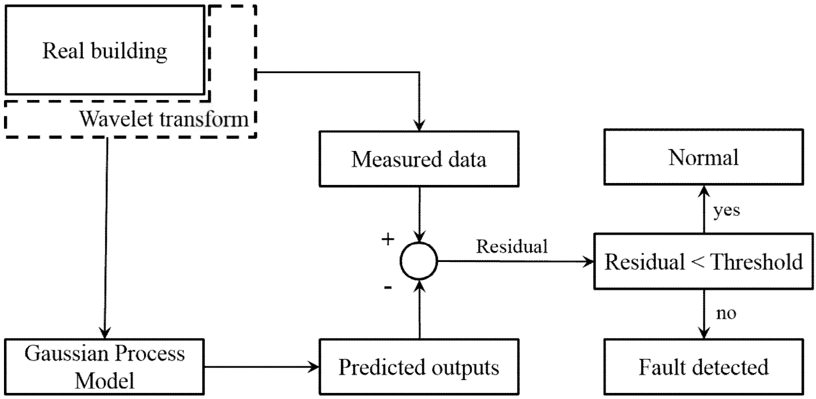
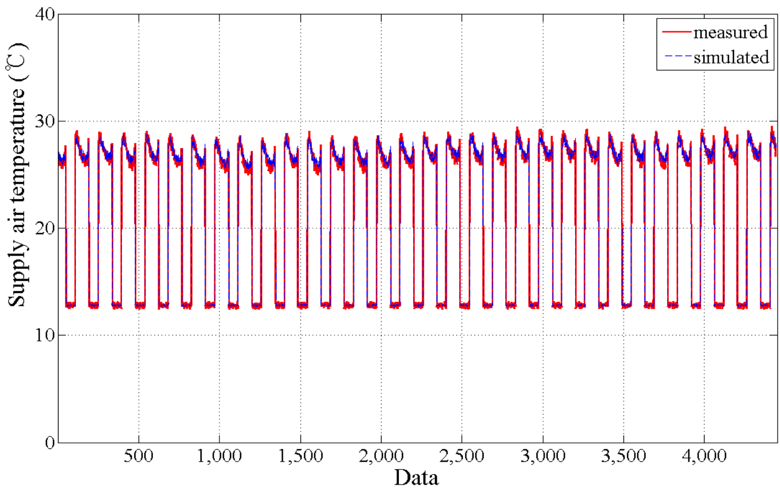
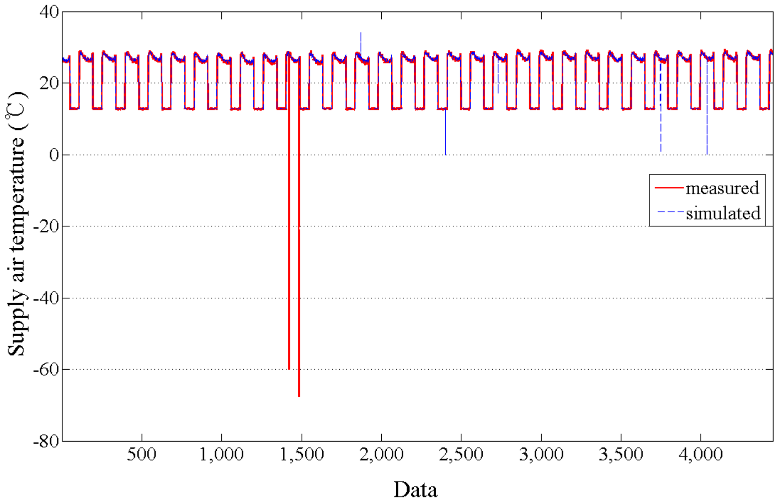


Fig. 3 Approach for sensor filtering and fault detection

Before attempting the selected fault scenarios (Table 1), the GPM was tested. The predicted outputs by the GPM is very similar to the BEMS data filtered by the wavelet transform (Fig. 4(a)). On the other hand, the prediction by the GPM was decreased when the wavelet transform was not applied (Fig. 4(b)). In other words, the prediction accuracy of the GPM is sensitive to the quality of the BEMS data. If the data filtering is not applied to the raw measured data, it is likely that the approach could regard simple sensor errors as system faults.



(a) Measured data vs. predicted outputs by GPM (when wavelet transform is applied)

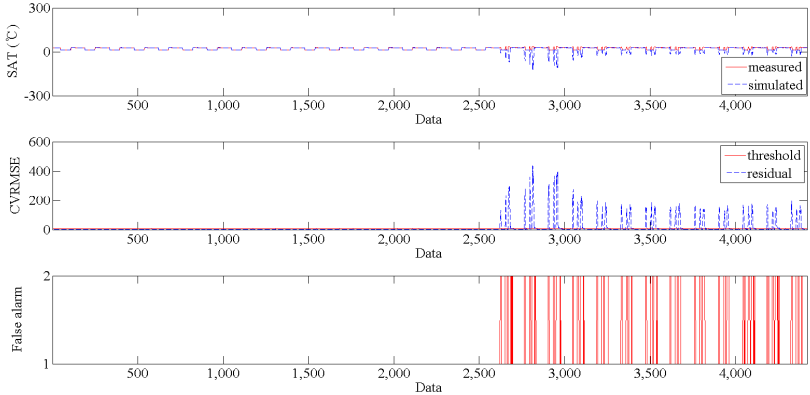


(b) Measured data vs. predicted outputs by GPM (when wavelet transform is not applied)

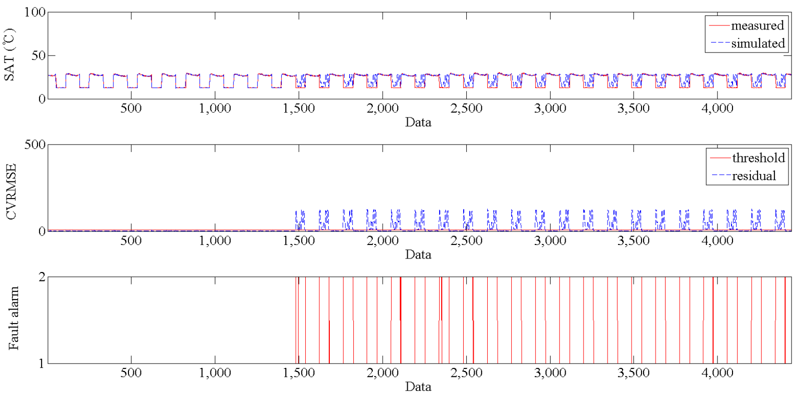
Fig. 4 Testing of the GPM

Fig. 5 shows fault detection results. An error threshold value was set to be 5 times as much as the value of a Coefficient of Variation of the Root Mean Square Error (CVRMSE). The CVRMSE was calculated using the BEMS data and prediction results by the GPM.

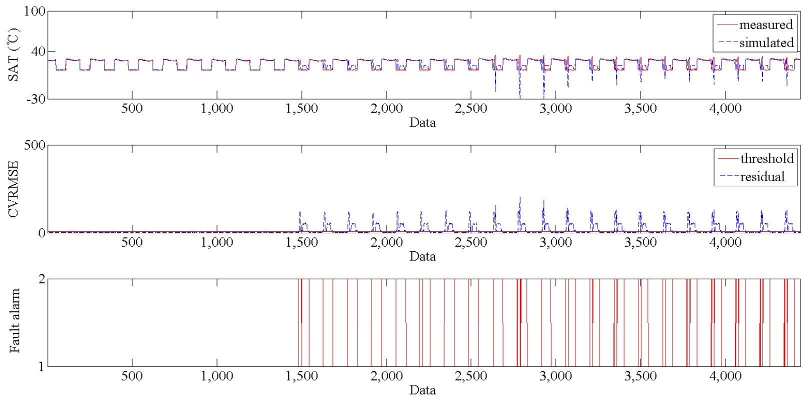
If the fault alarm is 1.0, it means no fault (normal). If the alarm is 2.0, it means malfunctioning. A malfunction of coil valve control (Scenario #1 in Table 1) and a stuck outdoor air damper (Scenario #2 in Table 1) were identified around 2,592 data (= 18 [day] × 24 [hour/day] × 6 [time step/hour]) and 1,440 data (= 10 [day] × 24 [hour/day] × 6 [time step/hour]), respectively. Two concurrent faults (Scenario #3 in Table 1) were also identified around 1,440 data as Scenario #2. The approach (wavelet transform + GPM) developed in this study can identify the faults of the coil valve control and stuck outdoor air damper in the VAV system. The approach can assist building operators with fault alarms.



(a) Scenario #1



(b) Scenario #2



(c) Scenario #3

Fig. 5 Fault detection results (SAT: Supply Air Temperature, output of the GPM)

5. Conclusions

This paper addressed an approach for automatic system fault detections. The approach was based on the wavelet transform and the data-driven model. The wavelet transform was used for filtering of outlying sensor data. Three fault scenarios were made and the simulation inputs and outputs were assumed as the measured dataset. To emulate malfunctioning of the system behavior, pump flow rate and outdoor air intake rate were randomly changed.

The prediction of the GPM is influenced by sensor errors. Thus, the GPM must be developed using appropriate data filtering. The approach (wavelet transform + GPM) presented in this paper can identify malfunctioning of the system and a control logic problem. The approach can improve daily building operation by providing valuable system information in real time.

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References

[1] Z. Du, B. Fan, J. Chi and X. Jin. Sensor fault detection and its efficiency analysis in air handling unit using the combined neural networks. Energy and Buildings. 72 (2014) 157-166.

[2] J.M. House, H. Vaezi-Nejad and J.M. Whitcomb. An expert rule set for fault detection in air-handling units. ASHRAE Transactions. 170 (1) (2001) 858-871.

[3] J. Schein, S.T. Bushby, N.S. Castro and J.M. House. A rule-based fault detection method for air handling units. Enegy and Buildings. 38 (2006) 1485-1492.

[4] M. Basarkar, X. Pang, L. Wang. P. Haves and T. Hong. Modeling and simulation of HVAC faults in EnergyPlus. Proceedings of the 12th IBPSA Conference, November 14-16, Sydney, Australia, pp.2897-2903.
[5] B. Fan, Z. Du, X. Jin, X. Yang and Y. Guo. A hybrid FDD strategy for local system of AHU based on artificial neural network and wavelet analysis. Building and Environment. 45 (2010) 2698-2708.
[6] X.B. Yang, X.Q. Jin, Z.M. Du, Y.H. Zhu and Y.B. Guo. A hybrid model-based fault detection strategy for air handling unit sensors. Energy and Buildings. 57 (2013) 132-143.
[7] C.E. Rasmussen and C.K.I. Williams. Gaussian Processes for Machine Learning. the MIT Press, 2006, ISBN 026218253X.
[8] Managing Uncertainty in Complex Models. 2016. http://mucm.aston.ac.uk/MUCM/MUCMToolkit/index.php?page=MetaHomePage.html, (accessed January 2016)
[9] ASHRAE. ASHRAE Handbook Fundamentals. Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2013.
[10] DOE, EnergyPlus 8.0 Input/Output Reference: The Encyclopedic Reference to EnergyPlus Input and Output, US Department Of Energy, USA, 2013.