Topic 14. Retrofit and optimal operation of the building energy systems

A System-level Incipient Fault Detection and Diagnosis Strategy for HVAC System Based on EWMA Control Chart

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Summary

A new fault detection and diagnosis (FDD) strategy is proposed in this study. The performance indexes (PIs) are used to indicate the health condition of different subsystems. Generally, the residuals between the tested PIs and benchmark PIs are slight at lower severity levels. And also, the higher the sensor noise is, the poorer the FDD performance will be. Both factors make FDD sometimes not effective, particularly when the actual data is used. In the proposed strategy, the exponentially weighted moving average (EWMA) control chart is introduced, which is a statistical strategy with superior capacity to detect small shifts of the deviations. Three typical subsystem faults are considered in this study. Results show that significant improvements are achieved compared with the typical t-statistic based FDD strategy.

INTRODUCTION

In the commercial buildings, about 15% to 30% of the energy is wasted resulted from performance degradation, improper control strategy and malfunctions of heating, ventilating and air conditioning (HVAC) systems (Katipamula 2005). FDD tools are essential to maintain the HVAC system in health status. It is beneficial to equipment life prolonging, indoor environment improvement, as well as savings of building energy and operating costs.

The developments of FDD strategies for HVAC systems have been an active research field in the last decades. Most of publications focused on specific faults within a certain component of HVAC system, such as chiller, AHU, VAV, and etc. The component-level FDD strategies are developed to identify the reasons of faults in the targeted component. In contrast, the system-level FDD strategies are developed to identify the components which contribute to the performance degradation of HVAC system. Comparing with the component-level FDD, the system-level FDD mainly focus on the energy consumptions of the whole systems.

A novel model-based FDD strategy for HVAC Systems was proposed by Zhou et al. (2009). The robustness of such a strategy was improved by implementing a sensor FDD strategy for the corresponding sensors by Wang et al. (2010). The performance indexes were selected to represent the health status of different sub-systems, including cooling tower system, chiller system, secondary pump system before heat exchangers, heat exchanger system, and secondary pump system after heat exchangers. A dynamic simulation platform was used to simulate the faults of different sub-systems and generate data for training and validation. However, the FDD performances were poor for the incipient faults, i.e. the faults occurred in the beginning stage. The main reason was the Type II error. Generally, a fault is detected when the residuals of PIs are outside of the predefined confidence intervals. However, for the incipient faults, the residuals of fault data are still within the confidence interval and considered as normal ones. This is so called Type II error (more details can be found in section *online fault detection using EWMA*).

This study aims to propose a solution to this problem. Firstly, the reference models for generating benchmark PIs are developed by the Support Vector Regression (SVR) algorithm. It is a new machine learning algorithm based on structural risk minimization from statistical learning theory. Secondly, Exponentially Weighted Moving Average (EWMA) control chart is used to detect the deviations caused by faults. It is a statistical based approach with superior capability to detect small shifts of the deviations. This study is based on the framework of the HVAC system FDD strategies proposed by Zhou et al. (2009) and Wang et al. (2010), while the reference models and PIs are improved.

METHODS

Structure of the FDD Strategy

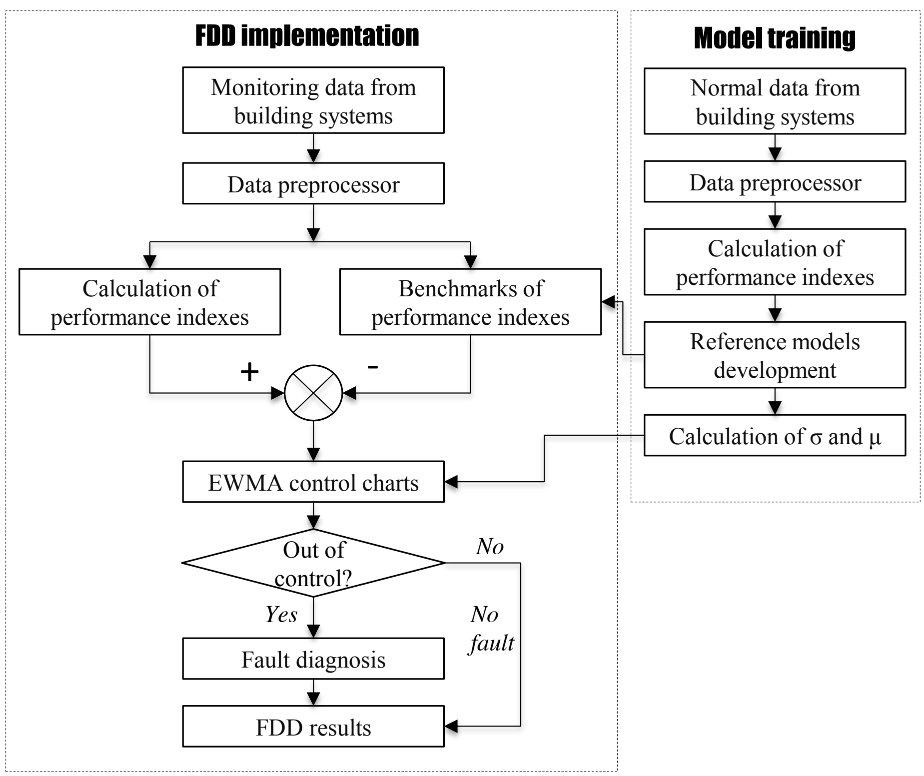

Figure 1. Schematic of the FDD strategy

The structure of the proposed FDD strategy is as shown in Figure 1. It includes two parts, i.e. Model training part and FDD implementation part. The offline model training consists of four steps. In the step of data preprocessing, the obvious outliers and dynamical data are filtered by the outlier detector and steady-state data filter respectively. In the step of calculation of performance indexes, the PIs are calculated based on the filtered data. In the step of reference models development, the SVR approach is used to develop the black-box model to generate the benchmark PIs. In the last step, the statistical characters of the reference models are calculated, i.e. μ (the expectation) and σ (the standard deviation), which are the requirements of the EWMA model.

In the FDD implementation part, the steps of data preprocessing and calculation of PIs are the same as those in the offline model training. The benchmarks of performance indexes are calculated by the reference models. Then the residuals between the current PIs and benchmarks are calculated, which are the inputs of EWMA control charts. A fault will be detected as soon as it is out of the control intervals. At the end, the fault is diagnosed and reported on the basis of the fault rule table.

Description of HVAC systems

The HVAC system concerned in this study is in a new super-rise commercial building in Kowloon, Hong Kong. A dynamic HVAC simulation platform was developed by Ma (2008). The HVAC systems serving the first zone are considered in this study. There are eleven cooling towers, six chillers, two heat exchangers, six constant-speed condenser pumps, six constant-speed primary pumps, one secondary heat exchangers and two secondary variable-speed pumps after heat exchangers. More details can be found in Ma (2008). The fault free data are generated using this simulation platform. The faulty data are gained through simulating various faults on the platform.

Actually, the simulated results do not include the uncertainties (e.g. noises and outliers) which are commonly existed in the measured values. In this study, the normally distributed noises were added to the concerned sensors in the associated models. Such noise introduction is suitable for two reasons: 1) the uncertainties of measured values from a sensor are normally distributed in practice; 2) the uncertainties are introduced into the models instead of the measurement. In this case, it can simulate the effect on control process if the variable is used in control strategy. In this study, two uncertainty levels are considered: Level 1 with the standard deviations 0.2℃ for all temperature sensors and 5% for water flow meters and power meters; Level 2 with the doubled standard deviations.

Three kinds of typical faults are considered in this study, i.e. the fan motor degradation in the cooling tower system, the compressor motor degradation or condenser and evaporator fouling in chiller system, and tube fouling in heat exchanger system. The faults at different severity levels are simulated in the constructed HVAC system. The case studies were carried out to evaluate the proposed strategy.

Performance indexes

The performance indexes represent the health status of the subsystem. Table 1 presents the selected sub-systems, the typical faults concerned, the way to model the faults as well as the formulations of PI.

Table 1. Typical faults and their modelling strategys of HVAC sub-systems and corresponding mathematical PI formulations (Zhou et al. 2009)

Sub-system	Fault	Fault modeling	Selected PI
Cooling tower system	Fan motor degradation	Air flow rate reduction (5%, 10%, 15%, 20%)	$W_{ct} = \sum W_{i_{ct}}$
chiller system	Compressor motor degradation or condenser and evaporator fouling	Increase electromechanical power loss (5%, 10%, 15%, 20%)	$COP = \frac{c_p m_{w,ev}(T_{ecw} - T_{chws})}{W}$
			$W_{chiller}$, Measured value.
Heat exchanger system	Tube fouling or blockage	Decrease in the heat transfer coefficient (5%, 10%, 15%, 20%)	M_{w_bfHX} Measured value.

For the cooling tower system, the typical faults are fan motor degradation or heat transfer degradation. These two faults are simulated by reducing the mass air flow rate in this study. The power consumption (W_{ct}) is selected as the PI.

For the chiller system, the typical faults are compressor motor degradation, condenser fouling, and evaporator fouling. The degradations are simulated by increasing electromechanical power loss. The fouling faults are conducted by decreasing the corresponding heat transfer coefficient. When such faults occur, both COP and power consumptions will deviate from the health values.

For the heat exchanger system, the typical faults are tube fouling and blockage. Both of them are simulated by reducing the overall conductance-area. The algorithm of ε-NTU is adopted to simulate the two faults.

Reference models of performance indexes

The reference models are developed to calculate the benchmarks of PIs under fault-free condition. The black-box reference models are as shown in Equation (1).

$$Y = f(X1, X2, X3) + \xi \tag{1}$$

Where, Y is the PI, Y = [COP, W_{ct}, M_{w_bfHX}] in this study. X1, X2, X3 are the variables which determine the unique operating conditions for a certain subsystem. ξ is the model error, $\xi \sim (0, \sigma^2)$.

A non-linear approach named the SVR is adopted to build the reference models. It is a new machine learning algorithm based on structural risk minimization from statistical learning theory. It possesses prominent advantages such as excellent learning capability using limited samples, good generalization ability. It is proved that SVR has outstanding performance according to the comprehensive comparisons of SVR with other regression approaches.

Online fault detection using EWMA

In statistical test theory, there are two kinds of errors, i.e. Type I error and Type II error. Specialized to the FDD in HVAC field, a Type I error occurs when the FDD strategy rejects the normal data (i.e. detects normal data as faulty data). A Type II error occurs when it fails to reject the fault data (i.e. fails to detect faulty data). In the t-statistic based FDD strategies, the confidence intervals are determined to reach a small Type I error to reduce false alarm ratio, e.g. 2σ at 95.45% confidence level. However, these determined confidence ranges may result in failed detection of the incipient errors particularly when a fault occurs at the beginning stage. Hence, the Type II error occurs.

The EWMA was originally proposed by Roberts in 1959 for detecting small shifts as defined in Equation (3) (Roberts 1959).

$$Z_i = \lambda X_i + (1-\lambda) Z_{i-1} \tag{3}$$

Where, Z_i is the statistics of the *i*th observation (EWMA statistics of the *i*th observed value), $Z_0 = \mu_0$. λ ($0 < \lambda \leq 1$) is the weighting applied to the current value. A smaller λ results in that the chart is more sensitive to smaller long-term changes of the process mean. X_i is the *i*th observed value. The control limits are determined using Equation (4) and (5).

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{n(2-\lambda)}} \tag{4}$$

$$LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{n(2-\lambda)}} \tag{5}$$

Where, UCL is the upper control limit. LCL is the lower control limit. L is the width of the control limits, which determines the confidence intervals. In this study, L is 2.5758σ to maintain 99.0% of the data points fall within the control limits in normal conditions.

RESULTS

The FDD performances of the subsystems at two uncertainty levels are illustrated in Table 2. For each subsystem fault at level 1, the FDD performances of 100 samples are as shown in Figure 2-4. It was found that the EWMA-based strategy improved the FDD performance significantly.

For the chiller faults, Figure 2 shows the FDD performance in the case that the electromechanical power loss was increased by 5%. For the t-statistic based strategy, few faulty points were effectively detected. About 4.0% of points were even falsely detected. For the EWMA based strategy, 47.5% of points are correctly detected while the false alarm ratio was 0. For the cooling tower faults, Figure 3 shows the FDD performance in the case that the NTU of cooling tower was reduced by 5%. For the t-statistic based strategy, 52.4% points were correctly detected, while most of them were close to the threshold. For the EWMA based strategy, 87.8% points were correctly detected. Most of the points were far away from the threshold. The EWMA based strategy was more robust. For the heat exchanger faults, the EWMA based strategies effectively detected 63.6% points at level 1, while it is 4.6% for the t-statistic based strategy.

Table 2. The strategy performance comparison for different subsystems at two uncertainty levels

Subsystem	strategy	uncertain level	The ratio of correctly diagnosed points			
Chiller	**Power loss ratio**		**1.05**	**1.1**	**1.15**	**1.2**
	EWMA	Level 1	52.7%	90.9%	99.2%	100.0%
		Level 2	47.5%	65.5%	91.1%	98.6%
	t-statistic	Level 1	12.0%	23.7%	38.6%	52.7%
		Level 2	3.6%	9.1%	33.5%	61.4%
Cooling tower	**NTU ratio**		**0.95**	**0.9**	**0.85**	**0.8**
	EWMA	Level 1	91.4%	92.7%	99.2%	1.0%
		Level 2	87.8%	97.4%	96.0%	100.0%
	t-statistic	Level 1	60.8%	78.1%	90.2%	95.7%
		Level 2	52.4%	64.8%	80.3%	87.1%
Heat exchanger	**UA ratio**		**0.95**	**0.9**	**0.85**	**0.8**
	EWMA	Level 1	63.6%	99.1%	100.0%	100.0%
		Level 2	48.2%	92.7%	95.0%	98.6%
	t-statistic	Level 1	4.6%	30.6%	72.1%	91.9%
		Level 2	0.9%	1.8%	39.4%	75.0%

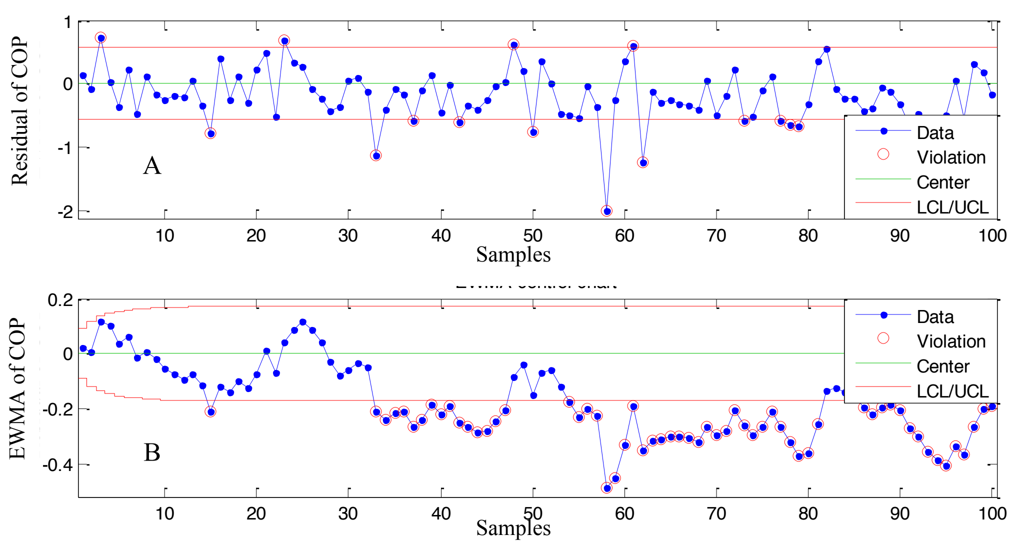

Figure 2. Comparison of the FDD performances using the t-statistic based strategy (A) and EWMA based strategy (B) by increasing electromechanical power loss 5%

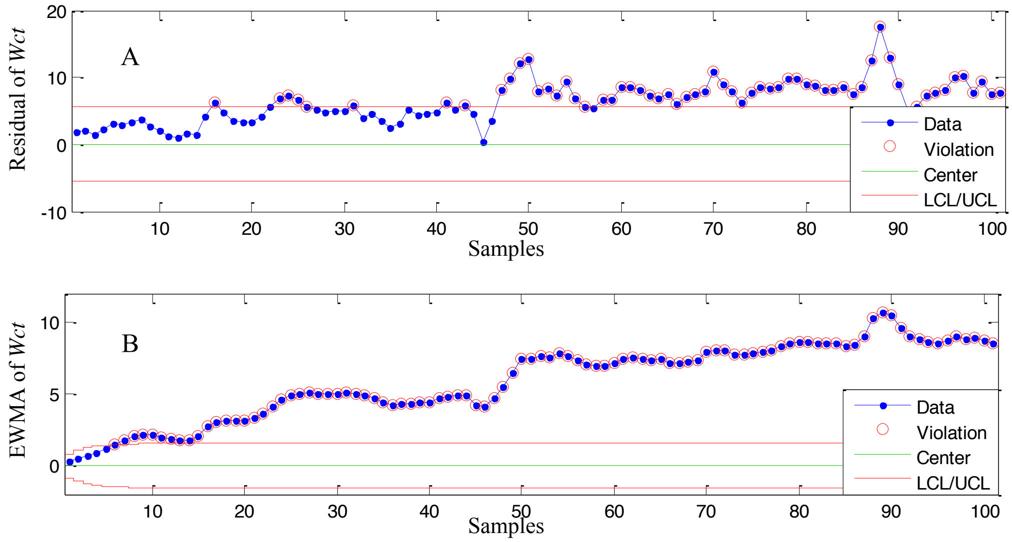

Figure 3. Comparison of the FDD performances using the t-statistic base strategy (A) and EWMA based strategy (B) by reducing NTU of cooling tower at 5%

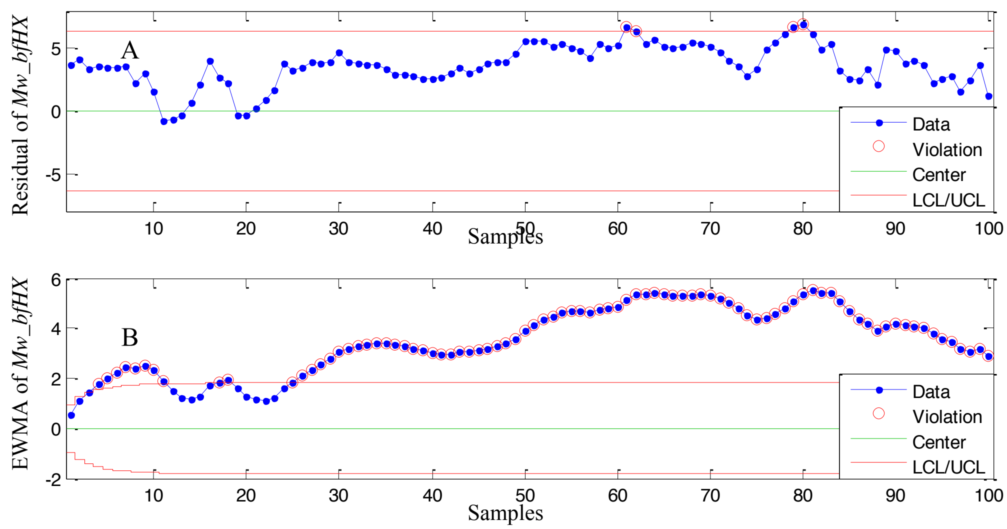

Figure 4. Comparison of the FDD performances using the t-statistic base strategy (A) and EWMA based strategy (B) by reducing UA of heat exchanger at 5%

DISCUSSION

For the t-statistic based strategies, the ratios of correctly detected points reduced significantly when the uncertainties were increased from level 1 to level 2. However, the ratios of the EWMA based strategies were still higher. It was mainly because that the EWMA control chart handled the faulty data in the statistic way. Although the uncertainties were increased, the the exponentially weighted moving average EWMA value was still able to identify the deviations when a fault occurs. Therefore, the EWMA control chart is a good candidate to handle the uncertainties of sensors in the FDD process.

The selections of X1, X2, X3 in Equation (1) are important to the FDD performance. The variables are able to determine the unique operating conditions for a certain subsystem. Meanwhile, they cannot be the variables which are directly affected by the faults.

The faulty data is usually not available in the actual systems due to the reason that the owners are not willing to introduce such faults and the associated risks to their systems. In this study, the faulty data is generated by introducing fault to a HVAC simulation platform. The normal distributed sensor noises were added to the model. It shows that the faulty data are reasonable and can represent the uncertainties of measurement in practice. In this study, only three typical PIs were used to represent the health status of the subsystems. Actually, more PIs can be introduced to diagnose the faults and improve the robustness. This strategy can also be applied to both HVAC system-level FDD and component-level FDD.

CONCLUSIONS

A system-level incipient fault detection and diagnosis strategy was proposed in this study. Comprehensive comparison was made with the t-statistic strategy using simulation data. The FDD performance was improved significantly, particularly for the incipient faults. The PIs were adopted to represent the health status of HVAC subsystems by regressing the properly selected variables which determine the unique operating conditions. The EWMA control chart takes into account the time series information using the weighting factor λ. In this way, the Type II error is reduced while keeping the detection ratio of Type I error unchanged. Comparing to the t-statistic-based strategy which only uses the information of current data, this feature makes it relatively insensitive to small shifts in the process. Therefore, the ratios of correctly detected points of EWMA based strategy were obviously higher than that of the t-statistic based ones, particularly for the incipient faults in systems which have higher uncertainties at the measured values. The proposed strategy can be used to develop FDD tools for the whole HVAC system.

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