DEVELOPMENT AND ONLINE TUNING OF AN EMPIRICALLY-BASED MODEL FOR CENTRIFUGAL CHILLERS

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ABSTRACT

In this study, we develop a quadratic homogeneous polynomial (QHP) regression model for predicting chillers and present its online tuning strategy. First, sample data is processed using the ordinary least square (OLS) method to obtain the initial QHP model. Second, errors occurred during on-site monitoring are categorized based on which data-processing rules are deduced to filter outliers. Third, we propose an error controller with the sliding window training approach, which will utilize the processed data to automatically tune the regression coefficients so that the updated information can be used in the chiller model. Finally, a case study was performed to validate this procedure. Results show that the model after online tuning can simulate the current operating condition of centrifugal chillers accurately.

INTRODUCTION

With recent development of building performance simulation software, modelling of the building and HVAC&R (Heating, Ventilation, Air-Conditioning and Refrigeration) systems are increasingly popular in the research of building energy efficiency. Chiller systems, accounting for a large portion of energy consumption in buildings, are very important in the simulation of HVAC&R applications. In addition, simulation plays an essential role in performance prediction, function commissioning and FDD (fault detection and diagnosis) strategy of chillers (Ma et al., 2011; Jia, 2002; Cui and Wang, 2005). Developing chiller performance model by using data from chiller manufacturers, laboratory and field measures has been a subject of many studies over last decades (Yik et al., 1998; Hydeman et al., 2002; Swider, 2003).

The coefficient of performance (COP) for chillers is defined as the ratio of the evaporator cooling capacity to the compressor input power. Usually the chiller performance is not only related with surrounding environment, chiller type and sizing parameters, but also affected by real working condition such as load factor, cooling capacity, cooling water temperature and flowrate, chilled water temperature and flowrate, etc. Therefore, it is necessary to analyze these factors and select significant parameters which is convenient to measure for a better accuracy and robustness of prediction models.

Previous empirically-based models for chillers can generally be classified into two categories: gray-box (semi-empirical) and black-box (empirical) models (Lee et al., 2012). For gray-box approach, the functional form allows the parameters be traced to actual physical principles that govern the performance of the modeled chiller. While the functional form of black-box models is developed by either statistical or non-statistical methods.

Empirically-based models usually require a great number of measurements indicating chiller performance characteristics. During the course of operation, chiller performance degrades naturally due to the fouling of heat exchangers, damage of compressors, etc. When the working condition of chillers exceeds the threshold of sample dataset, the developed model may not be useful. In fact, field data can be the best indicator to reflect the current chiller performance. With spread of online monitoring and sensor technology in HVAC system, massive field data of chillers is available for users. Although data-driven model can be significantly effective, it is not an easy job to use the data and analyze the statistical information to update the initial model for online tuning.

In this study, we develop a quadratic homogeneous polynomial (QHP) regression model to predict the centrifugal chiller performance based on the previous evaluations of numerical empirically-based models. The best regression coefficients for the QHP model are derived using ordinary least square (OLS) method. The measurement anomalies contained in the on-site monitoring is analyzed and concluded. A set of rules for processing raw data is deduced from theoretical analyses and we employ the first-order lag filtering algorithm to filter noise data. An error controller is provided and serves to deal with systematic errors and to determine whether the model need update with sliding window training approach for realizing online tuning. Finally, a case study was performed to validate the online tuning strategy for the QHP model.

MODEL DEVELOPMENT

Quadratic homogeneous polynomial regression

The quadratic homogeneous polynomial (QHP) regression is a black-box model. This model has six independent variables which are easy to measure and are able to indicate the health condition of a chiller sy-

$$COP = \beta_0+\beta_1 T_{ei}+\beta_2 T_{eo}+\beta_3 T_{ci}+\beta_4 T_{co}+\beta_5 M_e+\beta_6 M_c+\beta_7 T_{ei}^2+\beta_8 T_{eo}^2+\beta_9 T_{ci}^2+\beta_{10} T_{co}^2+\beta_{11} M_e^2+\beta_{12} M_c^2 \quad (1)$$

$$COP = \beta_0+\beta_1 T_{ei}+\beta_2 T_{eo}+\beta_3 T_{ci}+\beta_4 T_{co}+\beta_5 M_e+\beta_6 T_{ei}^2+\beta_7 T_{eo}^2+\beta_8 T_{ci} +\beta_9 T_{co}^2+\beta_{10} M_e^2 \quad (2)$$

$$COP = \beta_0+\beta_1 T_{ei}+\beta_2 T_{eo}+\beta_3 T_{ci}+\beta_4 T_{co}+\beta_5 T_{ei}^2+\beta_6 T_{eo}^2+\beta_7 T_{ci}+\beta_8 T_{co}^2 \quad (3)$$

stem. This model is applicable to centrifugal chillers with variable chilled and cooling water flow, as shown in Figure 1.

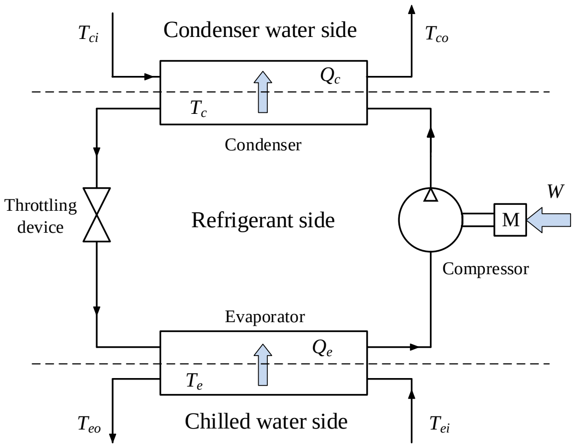

Figure 1 Schematic of a centrifugal water chiller

In real condition, the cooling capacity (Q_e) cannot be measured directly, but can be calculated through evaporator water flow (M_e) and evaporator inlet/outlet water temperature (T_{ei}/T_{eo}). Meanwhile, T_{ei} and T_{eo} can reflect the impact of evaporation temperature on COP. Besides, the condenser water flow (M_c) and condenser inlet/outlet water temperature (T_{ci}/T_{co}) are selected as parameters. The functional form of the QHP model is presented as Equation (1). When the evaporator water flow is variable while the condenser water flow is constant, the model can be simplified as Equation (2). If both the evaporator water flow and the condenser water flow are constant, the model can be further simplified as Equation (3).

In previous study (Tian et al., 2014), the multivariate polynomial (MP) regression model (Reddy et al., 2002) has a better suitability in the simulation of chillers with constant water flow than that with variable water flow. The Gordon-Ng model (Gordon and Ng, 1995) has a good prediction accuracy for simulation of chillers with variable evaporator water flow, but it works extremely bad for simulation of chillers with variable condenser water flow. The DOE-2 model (1980) must separate full-load and part-load data before calibrating the regression coefficients based on the design condition of chillers, indicating a complicated datasets training process. Besides, the DOE-2 model employs the same functional form for chillers with variable condenser water flow or variable evaporator water flow. In comparison, the QHP model has achieved extremely good prediction accuracy after including the evaporator and condenser water flow, showing that the evaporator and condenser water flow can affect the performance of variable water chillers significantly. Therefore, the QHP model considers more variables than the MP, Gordon-Ng and DOE-2 models as well as achieves a better prediction ability for simulation of chillers with variable evaporator water flow or with variable temperature difference. Compared with the DOE-2 model, the QHP model is easier to establish and has no need to separate full-load and part-load data. The larger the operation datasets become, the better accuracy the QHP model can achieve. In this paper, we select the QHP model to simulate the centrifugal chiller for online tuning study.

Ordinary least square method

The general functional form for the QHP model in this study can be written as follows:

$$y_i = \beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\ldots+\beta_z x_{iz}+\varepsilon_i = \hat{y}_i + \varepsilon_i \quad (4)$$

where y_i is the output dependent variable of the true measurement, $\hat{y}_i$ is the output dependent variable of the prediction, x is the independent variable, β_i is the unknown regression coefficients and ε is the residual. The subscript i denotes the number of input dependent variables (i=1,…,n).

Equation (4) shows that there are (z+1) parameters to be estimated when the model includes the intercept. For convenience, this study uses m=(z+1) and assume that n>m. The empirical model can be written in matrix notation as follows:

$$\mathbf{Y} = \mathbf{XB} + \mathbf{e} = \hat{\mathbf{Y}} + \mathbf{e} \quad (5)$$

or

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1z} \\ 1 & x_{21} & \cdots & x_{2z} \\ 1 & x_{31} & \cdots & x_{3z} \\ \vdots & \vdots & & \vdots \\ 1 & x_{n1} & \cdots & x_{nz} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_z \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \hat{y}_3 \\ \vdots \\ \hat{y}_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix} \quad (6)$$

Under general conditions, the training datasets (m) should be larger than the number of regression coefficients (n). This study uses the ordinary least square (OLS) method that minimize the sum of squared residual to get estimate parameters. This method is given as follows:

$$Minimize - \mathbf{e} = \frac{1}{2}\left(\mathbf{Y} - \mathbf{XB}\right)^2 \quad (7)$$

ONLINE TUNING STRATEGY

In the initial stage, the centrifugal chillers mostly work under the sample condition. However, as time goes on, the real performances of chillers may change and deviate from the initial model results due to equipment aging, fouling of heat exchangers, component damage,

Table 1 Value range of monitored data

T_{eo}	$\lvert T_{ei}-T_{eo}\rvert$	M_e	ELECTRIC CURRENT PERCENTAGE
5~13 ℃	0.1~7 ℃	< Rated flow×1.2	30%~100%
T_{ci}	$\lvert T_{ci}-T_{co}\rvert$	M_c	
20~34 ℃	0.1~8 ℃	< Rated flow×1.2	

Table 2 Value range of cooling capacity, COP and power

COOLING CAPACITY (Q_e)	COP	POWER (P)
20%~110%×Rated cooling capacity	1~10	< Rated power×1.2
Relationship of heat rejection, cooling capacity and power		$\lvert Q_c - Q_e - P\rvert / P < 30\%$

seasonal changes, etc. As the operational data accumulates, the newly collected measurements can describe the current performance of chillers better. So we should use the newly measured data to update the previous model online.

Once a set of data from BMS (Building Management System) interfaced with chiller control panels pass through a data processor consisting of a steady-state and outlier filter, the measured and predicted COP at this sampling instance are calculated. The difference between them may be caused by random errors or by the changes of chillers' working condition. An error controller is then used to identify these two errors in order to find whether the model need update. When the difference between the measured and predicted COP is lower than the error threshold, the initial model is considered to be useful and the data will continue to be collected, processed and stored. Otherwise, the newly stored real-time data will be used with sliding window training approach to tune the coefficients and update the model. Finally, the tuned model is selected as the current model to replace the initial one until the next validation. These processes are performed in real-time online, as illustrated in Figure 2.

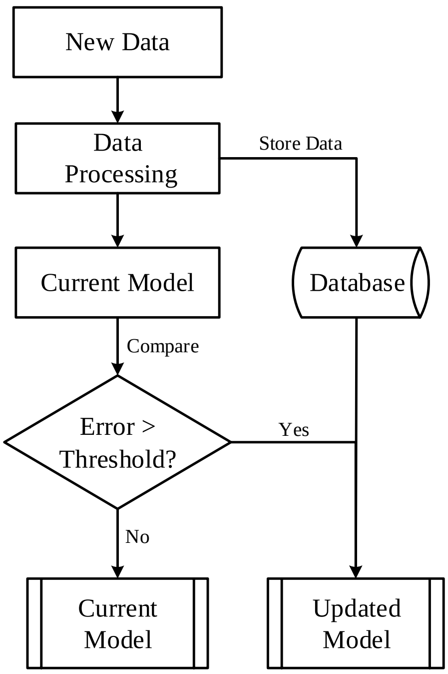

Figure 2 Model online tuning process

Data processing

The measured data from a real environment may be lost or wrong during the collection, transmission and storage. In addition, the chillers may work in non-steady states during the process of overload, load-on and load-off. These test anomalies may make it more challenging to produce highly accurate prediction results. So before the model establishment, the raw data should be first processed and converted into the desired information. The possible reasons causing errors during the collection, transmission and storage can be concluded into the following 3 types: 1) data with wrong format, 2) unreasonable data and 3) non-steady data. Corresponding rules should be deduced from theoretical analyses in order to maintain the completeness and fidelity of data in turn.

As for the data monitoring of chillers, the value of temperature, electric current and flowrate should be numerical and larger than zero. So *data with wrong format*, such as non-numerical data and data with values below zero, should be discarded.

After filtering the data with wrong format, we can do simple calculations for effectiveness validation. Each monitored physical variable should be set a suitable value range to filter the *unreasonable data*, as shown in Table 1. After processing the original data, we can calculate the cooling capacity, power and COP of chillers for further validation. Reasonable requirement for chillers' capacity, COP, heat rejection capacity and power is illustrated in Table 2.

When in non-steady state, the temperature and power of chillers fluctuate rigorously. The operational data cannot depict the steady-state working condition and thus cannot be used to develop the steady-state model. Therefore the *non-steady data* should be identified and discarded.

As for the overload situation, the electric current percentage can be selected as an indicator. When the electric current percentage exceeds 100%, the data should be discarded.

As for the load-on situation, there are two cases. The first one is the load-on situation after the chillers open abruptly. When the chillers start, the outlet water temperature will go up to the set point gradually, indicating that the ON/OFF status and the outlet water temperature can be selected for identification. If the difference between the evaporator outlet water temperature at two consecutive times is lower than 0.5ºC, the chillers are working in steady state and the data before should be discarded. The other one is the load-on situation after one of the chillers is closed suddenly. When one of the chillers is switched off, the electric current of working chillers will significantly increase, indicating that the increase rate of electric current can be selected for identification. If the difference between the electric current percentage at two consecutive times is larger than 10%, the data should be discarded.

As for the load-off situation, there are also two cases. The first one is the load-off situation when the chillers are closed abruptly. The electric current of chillers can be used to identify the time when the chillers are switched off, after which the data should be discarded. The other one is the load-off situation after another chiller turns on suddenly. Likewise, the decrease rate of electric current can be selected as an indicator. If the difference between the electric current percentage at two consecutive times is larger than 10%, the data should be discarded.

When the temperature set point of chillers suddenly changes, the chillers will work for a short time in load-on or load-off state, which is also the non-steady state. Such process can be identified through observing the change of evaporator outlet water temperature. When the difference between the evaporator outlet water temperature at two consecutive times exceeds 0.8ºC, the data should be discarded.

Data filtering

During the monitoring process, the following situations may happen: 1) instrument precision errors and mechanical tooling errors, 2) surrounding temperature fluctuations and mechanical vibrations, 3) circuit noise, and 4) interference signals from surrounding electric and magnetic field. These situations will result in some irregular and unpredictable random noise in the sample data. These outliers may affect the quality of the measured raw data as well as further influence the model performance evaluation and parameter optimization. It is necessary to filter outliers in the collected data for a better effectiveness and reliability of models.

In real applications, the first-order lag filtering algorithm and the moving filtering algorithm are often employed to process data with big dataset, long-term sampling period and real-time requirement. The first-order lag filtering method has a good filtering effect for slowly changed random variables. The current and last data samples are usually selected to calculate weighted mean, as given by Equation (8).

$$\mathbf{F}_i = (1 - \alpha)\mathbf{S}_i + \alpha\mathbf{F}_{i-1} \quad \alpha = t/(t+T) \tag{8}$$

where $\mathbf{F}_i$ is the current filtered data, $\mathbf{S}_i$ is the current sample data, $\mathbf{F}_{i-1}$ is the last filtered data, α is the filtering coefficient, t is the time constant and T is the sampling period.

The first-order lag filtering method has disadvantages of phase lag and bad sensitivity, but it can strongly inhibit periodic interference with less time and better reaction. The phase lag extent and smoothing effect depend on the filtering coefficient α, which is related to the time constant and sampling period. In this paper, the filtering coefficient α is 0.7 for the case study.

Error control

The prediction accuracy is an important criterion to examine the predicting capabilities of models. This study uses the difference between the predicted and measured COP as an indicator to evaluate how well a regression model can fit the observations or the predictions, defined as follows:

$$Error_{abs} = COP_p - COP_m \tag{9}$$

$$Error_{rel} = (COP_p - COP_m)/COP_m \tag{10}$$

where $Error_{abs}$ is the absolute error, $Error_{rel}$ is the relative error, COP_p is the predicted COP from the QHP model and COP_m is the measured COP.

Errors are divided into random errors and systematic errors. There are no regular rules about the value, direction and frequency of random errors, but in general, random errors are Gaussian distributed with mean zero and standard deviation.

Systematic errors are caused by fixed or regular factors. Systematic errors change regularly, such as fixed change, linear increase and periodical change, so that the correctness of measurement results may be affected directly. During the operation of chillers, regular factors are interpreted as follows:

- As time goes on, the real performances of chillers may be inferior to the model results due to equipment aging, fouling of heat exchangers and component damage.
- The seasonal load changes will cause big fluctuations of operational performances.
- The real performances of chillers may be superior to the model results due to repair and maintenance of chillers as well as cleaning of heat exchangers.
- The empirical model is developed based on data-driven methods with available measurements, which may result in undesirable data redundancy and big fluctuations of errors.

These factors will make the real chiller performances largely deviate beyond the simulation results with regular changing errors. Thus during the validation of simulation accuracy, the systematic error between the measured and predicted value should be filtered. Identification of systematic errors is based on the following three rules: 1) Errors deviate in the same direction, 2) Mean of errors is not zero, and 3) Errors deviate for a continuous time. Figure 3 illustrates the principle of the error controller. Given the time T and reasonable threshold of relative mean error ERR%, the

$$COP = 11.057+0.924T_{ei}+0.182T_{eo}-0.528T_{ci}-0.235T_{co}+0.0287M_e+0.0129T_{ei}^2+1.27\text{E-}03T_{eo}^2 +0.0139T_{ci}^2-0.00313T_{co}^2-5.16\text{E-}05M_e^2 \tag{11}$$

$$COP = 18.281+4.27T_{ei}-7.331T_{eo}-2.682T_{ci}+1.905T_{co}-4.68\text{E-}04M_e+0.418T_{eo}^2+0.054T_{ci}^2 -0.146T_{ei}^2-0.039T_{co}^2+7.83\text{E}05M_e^2 \tag{12}$$

error controller can identify and filter the systematic errors. If the relative mean error is larger than ERR% during the time T, the current model is considered to be inaccurate with big errors and need to be updated. The tuned model is then selected as the current model to replace the initial one until the next validation.

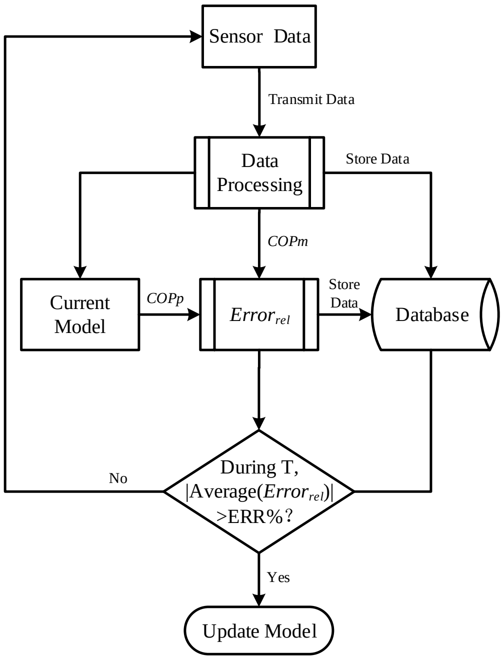

Figure 3 Schematic of the error controller

Sliding window training

In an offline static prediction model, one tries to establish the model in advance and estimate the parameters using historical data. Once the model is built, it is rarely changed even though the presence of significant errors identified by the error controller may indicate that the model is no longer valid. To address this problem, this paper evaluates the performance of the chiller model that can be constantly updated as new operational data becomes available.

The size of the training data set can be kept constant and new measurements are added while some of the oldest data are dropped from the training set. This approach can be graphically viewed as periodically sliding a time window across a time series of measurements to select the training data (Yang et al., 2005). Therefore, the QHP model in this study can be updated online using the newest data with the sliding window training approach.

RESULTS AND DISCUSSION

The data used to validate the developed QHP model and the proposed online tuning strategy were collected from a single-stage centrifugal chiller system of a stadium in Shenzhen (China). The chillers use variable frequency compressors with variable evaporator water flow and constant condenser water flow. First, the initial model was established based on sample data from manufacturers, as shown in Table 3.

Table 3 Descriptive statistics of the sample data

Rated cooling capacity (kW)	2813.5
Refrigerant	134A
Variable frequency?	Yes
Variable evaporator water flow?	Yes
Variable condenser water flow?	No
Sample number	2797
Input power (kW)	567
T_{eo} (℃)	6.67~11.7
$\lvert T_{ei}-T_{eo}\rvert$ (℃)	0.76~5.54
T_{ci} (℃)	18.33~36
$\lvert T_{ci}-T_{co}\rvert$ (℃)	0.76~5.13
M_e (L/s)	42.5~75.7
Load factor	15%~100%
COP	3.67~8.54

The QHP model was developed using Equation (2). The mathematical form of the model is shown as Equation (11). The goodness of fit is $R^2 = 0.975$ and the F-test value is $F = 11050$.

The electric current, evaporator inlet/outlet water temperature, evaporator water flow and condenser inlet/outlet water temperature were monitored continuously. The sampling interval was two minutes. Model validation was carried out based on the data monitored during 20 days. Table 4 illustrates the collected data which was filtered and processed based on the rules above.

Table 4 Descriptive statistics of the processed data

BEFORE DATA-PROCESSING		14462 sets
AFTER DATA-PROCESSING		10230 sets
VARIABLE	**MINIMUM**	**MAXIMUM**
M_e (L/s)	114	194
T_{eo} (℃)	6.1	10.6
T_{ei} (℃)	7.6	15.6
T_{co} (℃)	22.9	35.6
T_{ci} (℃)	21.8	31.3

The first-order lag filtering method was used to filter the noise data, which then was used to calculate the measured and predicted COP. In the error controller, set T=72h and ERR%=5%. Prediction results of the initial QHP model are shown in Figure 4. Figure 5 depicts the comparison of the measured and predicted COP. The relative errors of the initial model prediction

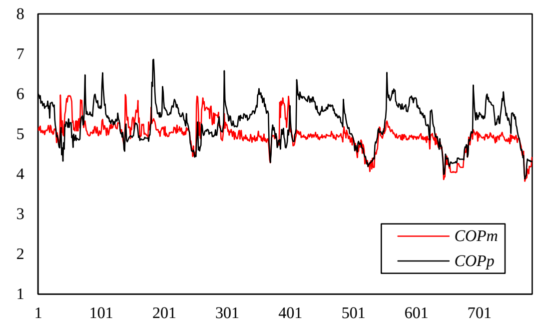

Figure 4 Prediction results of the initial QHP model

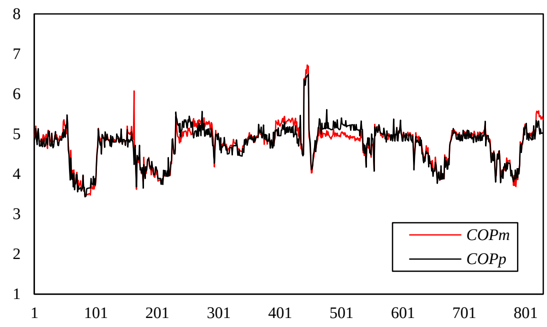

Figure 7 Prediction results of the updated QHP model

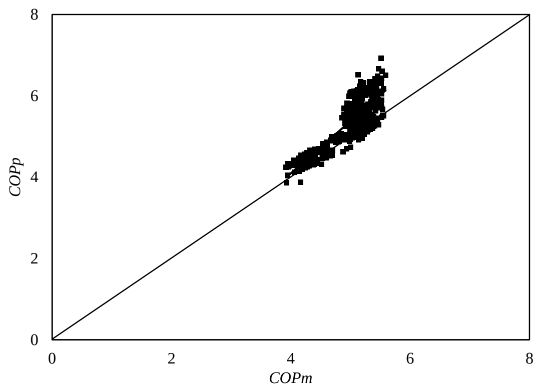

Figure 5 Comparison of the measured and predicted COP (initial model)

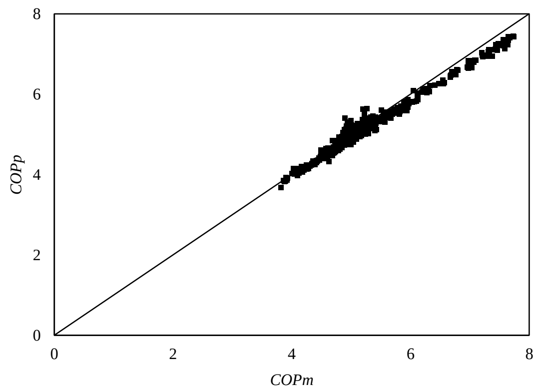

Figure 8 Comparison of the measured and predicted COP (updated model)

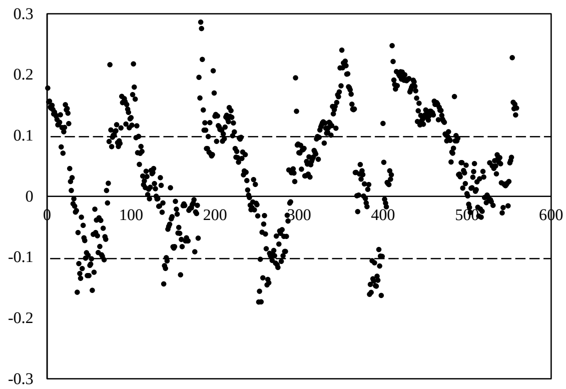

Figure 6 Relative errors of initial model prediction

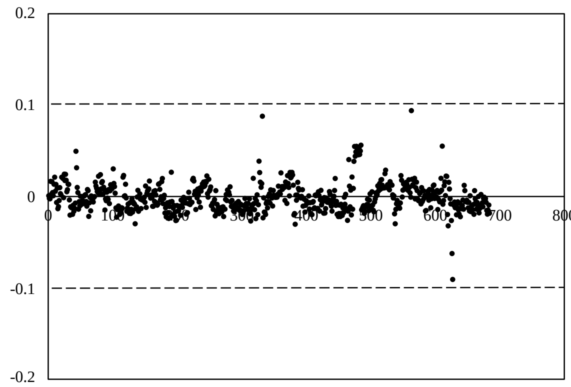

Figure 9 Relative errors of updated model prediction

Table 5 Descriptive statistics of errors (initial model)

ERROR	MAXIMUM	MINIMUM	MEAN	STD. ERR.
Absolute error	1.56	-0.99	0.37	0.384
Relative error	48.3%	-18.6%	0.0435	0.0652
FREQUENCY (-5%< $Error_{rel}$ <+5%)			63%	
FREQUENCY (-10%< $Error_{rel}$ <+10%)			86.6%	

Table 6 Descriptive statistics of errors (updated model)

ERROR	MAXIMUM	MINIMUM	MEAN	STD. ERR.
Absolute error	0.81	-0.54	-0.003	0.14
Relative error	16.2%	-9.5%	0.0002	0.028
FREQUENCY (-5%< $Error_{rel}$ <+5%)			92.7%	
FREQUENCY (-10%< $Error_{rel}$ <+10%)			99.7%	

were calculated using Equation (10), as shown in Figure 6. It is found that the predicted COP values tend to increase significantly compared with the measured COP values, thus the initial model has systematic errors needed to be filtered.

Totally 14462 sets of data were monitored in 20 days, which were processed, filtered and sent to the error controller. When the 9985th set of collected data was investigated, the relative mean error of the data from former 72h was larger than 5%, indicating that the initial model should be updated. Then the newest 5000 sets of processed data were used to reestablish the QHP model by Equation (2). The mathematical form of the newly calculated model is shown as Equation (12). The goodness of fit is $R^2 = 0.935$ and the F-test value is $F = 9881$.

The data after the 9985th set of data continued to be selected, processed, filtered and validated by the rebuilt model. The rest 3035 sets of effective data were used to calculate the predicted COP through Equation (12). Prediction results of the new QHP model are shown in Figure 7. Figure 8 depicts the comparison of the measured and predicted COP. The relative errors of the updated model prediction were calculated using Equation (10), as shown in Figure 9.

Figures 4 and 7 compare the measured and predicted COP for each monitored dataset before and after the model updating, respectively. In Figures 5 and 8, the horizontal axis represents the measured performance of the centrifugal chiller, while the vertical axis represents the predicted performance. Each dot (■) in Figures 5 and 8 represents one dataset result, and the central diagonal solid line represents the most ideal situation, where predicted values are equivalent to measured values. The calculated relative errors before and after model updating are compared in Figures 6 and 9, where each dot (●) represents the relative error in one set of data and the dotted lines represent an acceptable range of 10%. It is found from Figures 4-9 that the prediction values of the updated model almost fall within the range of 10% while the initial model preduced many predictive accuracy values exceeding 10%, indicating that the updated model has achieved an extremely good prediction accuracy. For the rest 3035 sets of data, the errors were statistically analyzed using the initial and updated model, as shown in Tables 5 and 6. It can be observed from comparison that the relative mean error decreased from 0.0435 to 0.0002 after model updated, indicating that the systematic errors have been effectively filtered. In addition, the frequency ($|Error_{rel}|<10\%$) increased from 86.6% to 99.7%, showing a better prediction performance. The results discussed in the case study reveal that the online tuning strategy is an effective way to predict centrifugal chiller performances.

The growing complexity of current BMSs has become a great challenge for field technicians to troubleshoot problems manually, which calls for automated smart systems to perform FDD approaches. As for fault detection, one of the fundamental issues is to identify an accurate reference model of the system performance, representing its fault-free behavior (Cui and Wang, 2005). Each residual for the performance index calculated from the measurements available on BMS is generated by comparing the actual measured value with its benchmark provided by the reference models. Such residual is then compared with its threshold to determine which component is faulty and how the fault can be diagnosed by the fault classifier. So the accuracy and reliablity of the reference model significantly affect on-line FDD applications. Since the developed QHP model in this study has proven to achieve a good accuracy for the operating condition and to capture the behavior characteristics of centrifugal chillers, it is suitable to predict the expected sensor measurements on-line for use in FDD of the HVAC chiller, which is expected to be further investigated in the future.

CONCLUSION

The accuracy of data-driven simulation depends on the quality and quantity of datasets. Advances in online monitoring and sensor technology in HVAC system have made it easy to obtain the operational data of chiller system. In this paper, a quadratic homogeneous polynomial (QHP) regression model and its online tuning strategy are presented for predicting the centrifugal chiller performance. Results show that:

(1) The low quality of measured raw data makes it difficult to design, train and test the QHP model. Reasonable rules should be deduced from basic physical knowledge to discard data with wrong format, unreasonable data and non-steady data in a real environment. In addition, the first-order lag filtering algorithm is a valid method to filter noise data and smooth the data.

(2) The prime concern of error control is to filter systematic errors. Given the time T and reasonable threshold of relative mean error ERR%, the error controller can identify and filter the fixed or regular errors. Finally the QHP model can be updated online with the sliding window technique to simulate the current operating condition of centrifugal chillers accurately.

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