THE IDENTIFICATION AND OPTIMIZATION OF THE HVAC PARTIAL SUBSYSTEMS IN INTELLIGENT BUILDINGS

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Abstract

This paper presents on modeling of outside air systems (OAS) and air condition systems (ACS) of intelligent buildings (IB). The open loop identification estimation method is adopted for uncorrelated noises between the input and output （I/O） measurements. Analysis of input variables of these two processes verifies the supply water temperature is a significant factor in certain cases. The Variable Decoupling is proposed during processing the measured data. The M-sequence for water valve actuator during measurements is proved to be authentic by its auto-correlative function calculation. An Instrumental Variable method (IV) is used as consistent estimation. A Determinant Ratio method is used for measured data-based model's order estimation. A set of candidate model structures are used for comparison of their properties. Cross Correlation Function calculation between the residuals and input of obtained model shows their validation. All modeling results for several P.R.C IBs have proven their correct, efficient and robust features.

Keywords: Identification of HVAC systems, Modeling, Optimization

1. Introduction

Intelligent buildings are rapidly booming up in P.R.C nowadays, most actively developed regions: Shanghai, Beijing, Guangdong Province and Southeast China, from big to middle cities. So their relative first costs are sharply increased. According to informal statistics, there are more than 3000 IBs in PRC now. But the majority of their operations are unsatisfactory, especially their HVAC systems. Said systems have not good regulations and optimizations, which leads to expensive energy and maintenance costs, due to bout 65% IB's annual energy consumption is paid for HVAC energy. For example, Fig.1 shows two trend curves of OAS operation status, percentage of valve stem travel (VST) and outside air temperature respectively of The Jingying Mansion Shanghai lately. The operating difference of temperature is about ±2℃ and the percentage of VST is 0% to 70%, which shows control parameters tuned are unsuitable. Obviously the wear of actuator

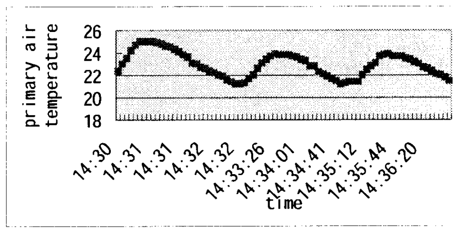
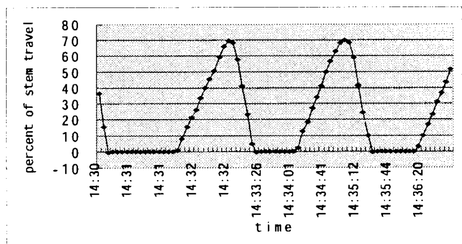


Figure 1 (a). Outside Air Temperature on 2F of Jingying Mansion in Shanghai

and valves are important. Our general investigation of OAS and ACS of various IBs has concluded similar causes. The software products of



(b) Percentage of VST of Jingying Mansion in Shanghai

BAS are all imported from developed countries. Local engineers on the spot are not very experienced in tuning PID parameters and would not like to spend a lot of time to do so.

After analysis of most HVAC systems in IBs, we find all single input-single output system (SISO) and conventional PID control really. We understand that only PID control related to imported BAS software, so required improvement of HVAC system should start from their math models mainly, although PID strategy is a rather simple and well-studied problem. Model-based simulation can utilize MATLAB for required static and dynamic performances. The simulated parameters will be applied to BAS software for validation and make the systems more consistent disturbance rejection as condition is changing.

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Thus we only spend little time to tune PID controls upon spots. By classical and modern control theories we can apply different control strategies and compare results. The mathematical models are also the basis on developing our own BAS software. In this paper we focus on creating the models of OAS and ACS in order to gain multiple benefits: reducing energy and maintenance costs.

2. Selecting Identification Methods

Owing to applications and control loops of OAS and ACS both SISO systems, the unique input is voltage to actuator and output is supply air temperature to OAS or return air temperature to ACS. And supply water temperature of the chillers or boilers has significant effects upon output, which depends on their operation status and variation of thermal loads of IB and weather. For instance, summers high load leads to only 1 to 2℃ variation and winter (when boilers are used) or low load 10℃ even more. So there are really two input variables of the control loop, shown as figure 2.

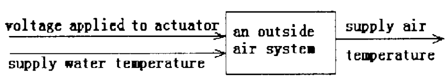

Figure2. I/O Variables of OAS

Because of the disturbance of the supply water temperature it is hard to gain two complete equal curves when repeat step-response experiments. The middle temperature-time curve shows a bit bulge, which leads to a higher-order calculated transfer function. It indicates difficulties of MATLAB simulation and controls. We also can not use Artificial Neural Networks for modeling, as we can not link them with the imported BAS software. At last we choose modern mathematic methods for modeling. Open-loop identification estimation is selected for the uncorrelated noises between I/O measurements. The operating conditions on the spot permit breaking the control loop.

3. Choosing Input Signal for Measurements

The input signal for measurements should guarantee the identification. All identified dynamic status at least should be thoroughly and continuously stimulated by the input in order to let data simply contain sufficient information[1]. In other words, the frequency spectrum of input must completely cover that of process. Furthermore the selected input signal should lead to modeling more accurate one, i.e. the pseudorandom signals are ideal ones.

M-sequence signal(MSS).

The M-sequence pseudorandom signal has been shown the properties similar to traditional Gaussian White Noise. The M-sequences generator (MSG) made by linear feedback shift registers is used as experiment system's input. The MSG is made by us, so its auto correlative function (ACF) and spectrum density are calculated for reasonable results, which are shown partially in Fig. 3.

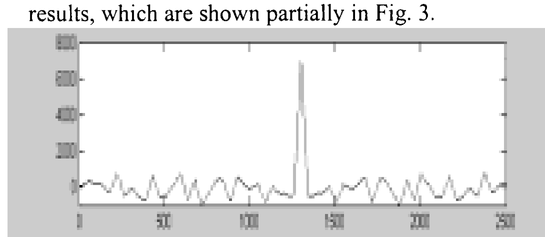

Figure 3. ACF of Designed Real Signal

Compared Fig.3 with Fig.4, the theoretic ACF wave of MSS, they both are triangle wave, so we conclude that the designed signal is an authentic one.

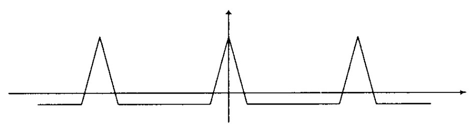

Figure 4. Theoretic ACF Wave of MMS

M-sequence parameters determination.

The cycle period N_p of MSS is in term of order p, its width of the shift pulse Δt, system's transition time Ts and maximum frequency $f_{\max}$. We have

$$N_p = 2^p - 1, \quad \begin{cases} \dfrac{1}{3\Delta t} \ge f_{\max} \\ (N_p - 1)\Delta t \ge T_s \end{cases} \qquad (1)$$

Assume a step signal to the researched system (here is Honeywell ML7984 electrical valve actuator) then T_s is estimated and $f_{\max}$, input sinusoid signals of different frequencies is obtained.

4. Subsystem Modeling Procedures

Measured data-based dynamic system modeling has following procedures.

Data processing.

Because dynamic models do not explain the actual levels of the I/O signals, but describe how changes in the input give changes in the output, their mean value should firstly be removed. Second, there commonly are linear or nonlinear trends of the signals generated by disturbances, which is mainly the supply water temperature and should be canceled for increasing of estimated model's accuracy. Fig.5 shows a set of input-output measurements without mean value and trends.

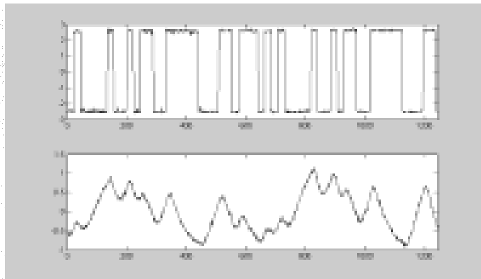

Figure 5. I/O Measurements by Removing Mean Value and Trends

Selecting model structure.

There are no standards and secure routes to good models in system identification. We have to select and define a model structure within a set of candidate system descriptions known as output-error (OE) models, ARMAX models, and Box-Jenkins (BJ) models and so on. The most used model structure is the simple linear difference equation ARX.[2]

Once you have a feel for suitable delays and dynamics orders, it is often useful to try out ARMAX, OE, and/or BJ with these orders. Especially for poorly damped systems, the OE structure is suitable. When the true noise term in the ARX model structure is not white noise and the order of its output is nonzero, the estimate does not give a correct model. It is then better to use ARMAX, BJ, IV4, or OE. While an IV method with arbitrary instruments is selected, it is not sensitive to the color of the noise term in the model equation[3].

We tried out a number of different model structures and compared the properties of the obtained models.

Determining model order.

Determinant Ratio Method (DR) based on the measured I/O data is applied to estimate the model order [4, 5]. When Signal-to-Noise Ratio is good, DR shows a bigger increase in the order of the system with the order changing. Consider the model with colored-noise term e (k):

$$\begin{cases} z(k) + \sum_{i=1}^{n} a_i z(k-i) = \sum_{i=1}^{n} b_i u(k-i) + e(k) \\ e(k) + \sum_{i=1}^{m} c_i e(k-i) = v(k) + \sum_{i=1}^{m} d_i v(k-i) \end{cases} \qquad (2)$$

Here u (k) and z (k) are the input and output signals respectively and v (k) is uncorrelated noise with zero mean value and σ_v^2 variance. Build equations of matrix $H_{n,m}$

$$Z_n = \begin{bmatrix} z(n) & z(n-1) & \cdots & z(1) \\ z(n+1) & z(n) & \cdots & z(2) \\ \vdots & \vdots & & \vdots \\ z(n+L-1) & z(n+L-2) & \cdots & z(L) \end{bmatrix} \qquad (3)$$

$$U_n = \begin{bmatrix} u(n) & u(n-1) & \cdots & u(1) \\ u(n+1) & u(n+2) & \cdots & u(2) \\ \vdots & \vdots & & \vdots \\ u(n+L-1) & u(n+L-2) & \cdots & u(L) \end{bmatrix} \qquad (4)$$

$$E_m = \begin{bmatrix} e(n) & e(n-1) & \cdots & e(n-m+1) \\ e(n+1) & e(n) & \cdots & e(n-m+2) \\ \vdots & \vdots & & \vdots \\ e(n+L-1) & e(n+L-2) & \cdots & e(n-m+L) \end{bmatrix} \qquad (5)$$

$$V_m = \begin{bmatrix} v(n) & v(n-1) & \cdots & v(n-m+1) \\ v(n+1) & v(n) & \cdots & v(n-m+2) \\ \vdots & \vdots & & \vdots \\ v(n+L-1) & v(n+L-2) & \cdots & v(n-m+L) \end{bmatrix} \qquad (6)$$

$$H_{n,m} = [Z_n \quad U_n \quad E_m \quad V_m] \ldots\ldots (7)$$

Software based on equations (2)-(7) is used to calculate DR

$$DR(\hat{n}) = \frac{\det[H_{11}(\hat{n})]}{\det[H_{11}(\hat{n}+1)]} \quad \ldots\ldots (8)$$

And Fig. 6 shows the variation of DR (n) of ACS where n=2 is obviously clearer than others. So the order of the measured system is 2.

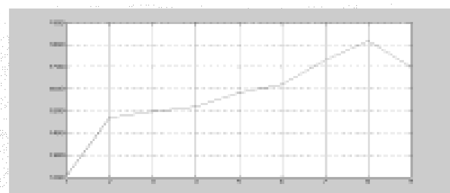

Figure 6. Variation of DR of the Data Set

Table 1 Comparison of FPE and Fits of Five-model Structures

Structure	ARX	IV4	BJ	OE	ARMAX
FPE	0.00105026	0.00135251	0.00135968	0.0496148	0.000995275
FIT	82.79	83.21	80.8	46.68	79.36

The identification of systems.

The identification of an air-condition subsystem.

MATLAB system identification toolbox offers a variety of commands to create different models based on observed I/O data. They are:

arx (data, Mi) for estimating an ARX model, iv4 (data, Mi) for estimating an ARX model with Instrumental Variable, armax (data, Mi) for estimating an AMAX model, bj (data, Mi) for estimating a BJ model, oe (data, Mi) for estimating OE model and so on, where Mi is defined as a vector of the model structure.

They all are tried out to estimate the models of ACS in Jingyin Mansion. The results are listed in table 1.

Comparing their Akaike Final Prediction Error (FPE) and the fits between measured output and model output we select the IV4 command for its best fit and the consistent parameter estimation.

IV4 estimates the parameters of an ARX model using an approximately optimal four-stage instrumental variable (IV) procedure[6].

Then the model can be described as following when n=2

$$z(k)+a_1z(k-1)+a_2z(k-2)=b_1u(k-1-d)+b_2u(k-2-d)+e(k) \quad (9)$$

Here u (k) and z (k) are the input and output signals respectively, d is the pure time-delay (the dead-time) in the system and e (k) is a colored noise.

The parameters of the identification data set are the following: $\Delta t = 110$s, sampling period are 5s, total sample points are 1248, total sampling time is 104 minutes. The calculated parameters are summarized in table 2.

Table 2 Computed Model Parameters of ACS

L	a_1	a_2	b_1	b_2
782	-1.889	0.891	-0.0015	0.00074
882	-1.838	0.840	-0.0016	0.00051
982	-1.9381	0.939	-0.0043	0.0031
1248	-1.9367	0.938	-0.0027	0.0017

The identification of an outside air subsystem.

The identification of OAS is similar to the ACS. Using Determinant Ratio Method we determine its order also equals 2. Estimating the model of the OAS in the second floor of Jingyin Mansion with IV least square method we obtain its transfer function as the form

$$k(s+z1)(s+z2)e^{-\tau}/(s+p1)(s+p2)\ldots\ldots(10)$$

The validation of models.

Model validation is the process of gaining confidence in a model. Following two criteria are used in this paper to validate the process.

(1) The model will be reliable as the data length during estimation is increased and loss function value does not change. Table 2 shows all coefficients do not change when lengths L is larger than 982.

(2) If the residual error ε (k) (RE) between the obtained model and process output can be considered as white noise sequence with zero mean, then the model is accurate.

Calculating RE and its cross correlation function $\rho_\varepsilon(l)$[7], we obtain

$$E\{\varepsilon(k)\}=-1.7167e-005 \approx 0\ldots\ldots(11)$$

$$|\rho_\varepsilon| \le \frac{1.98}{\sqrt{L}} = 0.056 \quad \ldots\ldots (12)$$

Because $\rho_\varepsilon(l)$ does not go significantly outside the confidence region we conclude that RE sequences are white noise one so obtained model is reliable. Fig. 7 shows comparison of model output with realistic measurement output.

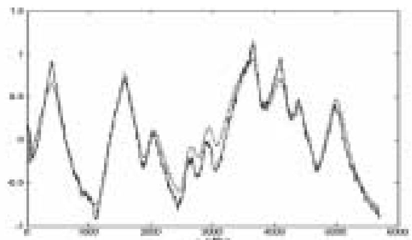

Figure 7. Comparison of Model Output and Measured Output

5. Application and Conclusion

Based on the obtained models we can simulate systems by means of MATLAB according to the requirements of the static and dynamic performances. All P, I, D parameters obtained are implemented to BAS software of Shanghai Jingying Mansion efficiently. The control performances of OAS and ACS are greatly optimized. The percent of valve stem travel is averaged about 46-60% and the error of the temperature controlled is only ±0.3℃. See Figure 8.

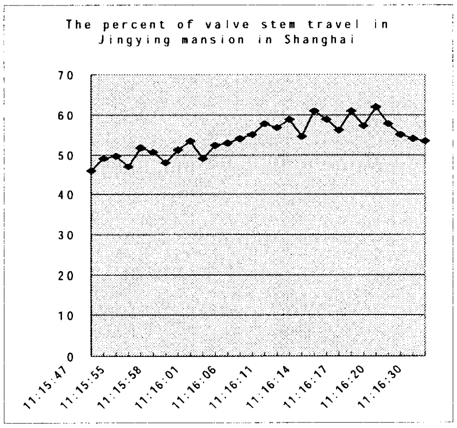

Figure 8. The Percent of VST in Jingying Mansion in Shanghai

At last, we employ the obtained models in several buildings, one of them is Shanghai Futures Tower with only a slight tuning. The percent of valve stem travel is stable even in 17% and error of the temperature controlled is also greatly improved, which indicates that all the systems have been optimized and the models give a good picture of robustness. The improvements of control performances yield large, multiple benefits reducing energy consumption and maintenance costs.

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