A Case Study of Simulation-Based PID Tuning Method For A Room Temperature Controller Using Uncertainty Analysis

Qiujian Wang[1], Yiqun Pan[1,*], Zhizhong Huang[2], Wangda Zuo[3], and Peng Xu[1]

[1] School of Mechanical Engineering, Tongji University, Shanghai, China
[2] Sino-German College of Applied Sciences, Tongji University, Shanghai, China
[3] Department of Civil Environmental and Architectural Engineering, University of Colorado Boulder, Boulder, United States

ABSTRACT

PID controllers are still prevailing in building environmental control due to its easy deployment and acceptable performance. However, it is common in practice that the PID controllers are not tuned properly because of the limited time for commissioning and the inexperienced practitioners. This study proposes a simulation-based method to provide instructions for on-site tuning. Due to the uncertainties within both the physical problem and modelling process, the uncertainty analysis method is adopted. The transfer functions of local temperatures are identified and then used to calculate the PID parameters of the controller. A simple room with variable supply airflow rate is selected as a use case, in which seven types of uncertainty factors are addressed. The entire simulation process is conducted with CFD and Modelica modelling sequentially. From the histograms of the PID parameters, the values with the highest probabilities can be identified with the control performance verified to be acceptable.

KEYWORDS

Simulation-based commissioning, uncertainty analysis, PID tuning, transfer function identification, Modelica modelling

INTRODUCTION

The control of the heating, ventilation, and air-conditioning (HVAC) systems plays a very important role in the mission of accomplishing the goal of building energy conservation and thermal comfort maintenance. The most prevalent control law used in today's HVAC control industry is still PID (Salsbury 2005). The performance of PID control is highly dependent on the quality of the tuning work. However, the conventional way of on-site PID tuning is often time-consuming as Bi et al. (2000) stated that the tuning process for an air pressure loop could last for 1-3 days and it could be even longer for a temperature loop. In addition, the tuning results are usually related to the conditions under which the parameter identification is performed. Due to the limited time for tuning, which is common in practice, it is almost impossible to perform the model identification under multiple conditions. This also partially results in the insufficient robustness and sometimes the sluggish or oscillatory control performance. What's more, in the industrial practice, not all of the on-site practitioners are experienced enough to deliver the high-quality work, which furtherly exacerbates the unsatisfying performance.

With the development of modeling techniques, simulation can assist in providing precedent knowledge for decision making and serve as a guidance for actual work. As for applying modelling technique in the PID tuning, simulations can be used to provide a reasonable initial guess of the PID parameters. Since the operating conditions can be easily manipulated during simulations (within the reasonable ranges), the result becomes more robust in terms of considering multiple scenarios. The on-site tuning work can be guided accordingly so that an acceleration of the process and a better control performance could be expected. It is the main motivation of this paper.

In order to demonstrate the idea of the simulation-based PID tuning, we take the PID control for the room temperature as an example. The method of uncertainty analysis is adopted to handle the uncertainties within the process and identify a proper combination of the controller parameters under the influences of multiple uncertainty sources. The following sections will be arranged as methodology, results and conclusion.

METHODOLOGY

Figure 1 shows the workflow of the proposed simulation-based PID tuning method, where TFI stands for transfer function (TF) identification. Unlike many of the other uncertainty analysis researches feeding all the uncertain inputs into one simulation tool, the proposed framework consists of two steps of simulations to handle different uncertainty factors separately. As show in Figure 1, the CFD simulation and the subsequent HVAC simulation are coordinated with each other through the intermediate transfer function models, which are identified from the transient CFD results. The final transfer function models are identified using the results from the HVAC simulation and then used to determine the PID parameters.

The case (M. Wang and Chen 2009) that we use to demonstrate the proposed approach is a simple cubic room (2.44m × 2.44m × 2.44m) with a cubic box (1.22m × 1.22m × 1.22m) right in the centre of the room, as shown in Figure 2. The box inside is to mimic the internal heat source, like the equipment or occupants. The supply airflow rate is controlled by a variable air volume (VAV) terminal, whose controller is the one to be designed through the proposed approach.

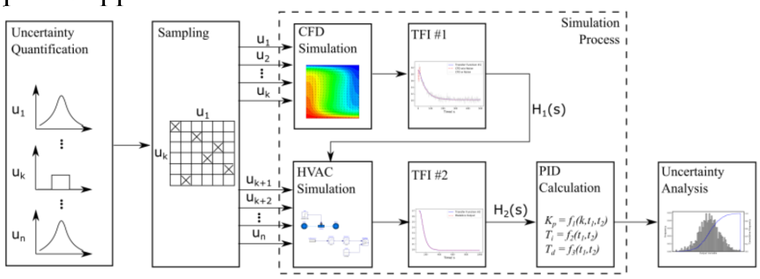

Figure 1. *Workflow of simulation-based PID tuning for room temperature controller*

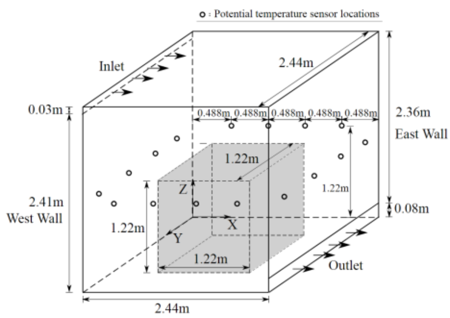

Figure 2. *Schematic of a simple room with a box inside*

Table 1 lists all the uncertainty factors, the distributions they follow, and how they are implemented in the simulations. The ranges of the inputs are estimated based on literature review, product leaflets, and engineering experiences. The supply air temperature varies from 14 ºC to 16 ºC indicating that it is controlled at 15 ºC with the accuracy of ±1 ºC. The interior thermal load varies from 16 W/m^2 to 40 W/m^2, which is to introduce a heat source of 120 W to 300 W after multiplying the surface area of the box. The rise time of the damper is estimated from the product's leaflets. The error of the damper's PLC model means the calculated value may have an error within ±40% compared to the real case (Ai and Mak 2013). The reason why we choose the uniform distribution for the aforementioned variables is that the uniform distribution generates the highest level of uncertainty of the inputs, which could be utilized to test the robustness of the proposed method. The measurement error follows a normal distribution with the average of zero and the standard deviation of 0.55 (L. Wang and Haves 2014). At last, 16 different locations are selected as the potential candidates (see Figure 2). The sensors are positioned with 5 centimetres away from the vertical walls, at the height of 1.22m, and evenly distributed along the horizontal direction.

Table 1*. Uncertainty factors addressed in the case study*

#	Uncertainty factors	Distribution
1	Supply air temperature, °C	Uniform (14, 16)
2	Interior thermal load (heat flux of the box), W/m^2	Uniform (16, 40)

3	Inner surface temperature of wall, ℃	Uniform (20, 30)
4	Inner surface temperature of ceiling, ℃	Uniform (20, 30)
5	Inner surface temperature of floor, ℃	Uniform (20, 25)
6	Rise time of damper, s	Uniform (90, 120)
7	Damper's PLC error, %	Uniform (-40, 40)
8	Temperature measurement error, ℃	Normal (0, 0.55)
9	Sensor locations	16 discrete alternatives
Note: For the uniform distribution (a, b), a and b are the lower and upper limit. For the normal distribution (a, b), a and b represent the average value and the standard deviation, respectively.		

To improve the simulation efficiency, the LHS method is used (Hyun, Park, and Augenbroe 2007). The uncertainty factors #1 ~ 7 are involved in the sampling process and reflected in different simulation scenarios. 100 scenarios are generated accordingly as the minimum number of cases is 10 (calculated by 4k/3, where k is the number of dimensions (Hyun, Park, and Augenbroe 2007)).

The uncertainties of the room boundary conditions are implemented in the CFD simulation. Different CFD cases are generated according to the sampled values of those uncertainty factors. The influence of the measurement error is introduced by directly adding the noise to the transient temperature results of CFD during the TFI process #1. To take the uncertainties of the rise time and PLC error into account, different HVAC simulation cases are generated with the corresponding TF #1 embedded in. As for the sensor location, all the 16 local temperature data are recorded from the CFD simulation and then used in the TFI process #1. Therefore, the CFD and HVAC simulations are conducted sequentially.

The open-loop step tests are used in both of the CFD and HVAC simulations to obtain the responses of the local temperatures to their respective excitation signals. As in this case, the temperature is maintained by varying the supply airflow rate. Therefore, a step signal of the inlet mass flow rate is chosen as the excitation in the CFD simulation, while the damper's control input is chosen for the HVAC simulation.

During the CFD simulation, a steady state simulation is performed first at the inlet mass flow rate of 0.018 kg/s. Once the calculation is converged, the transient simulation is initiated from the converged solution and the inlet mass flow rate is changed to 0.24 kg/s. The transient results of the 16 local temperatures are recorded from now on. The time step size and the number of iterations per time step are set as 1 second and 200, respectively. The total simulation time of the transient simulation is 500s, which is proven to be long enough for all the local temperatures to reach a new steady state. All the CFD simulations are conducted using Fluent version 19.0.

To include the uncertainties within the HVAC components, i.e. the rise time and PLC error of the damper, we adopt the models from the Modelica Buildings Library (LBNL 2018) and run the simulations on the platform of Dymola. ***Figure 3*** shows the diagram of the Modelica models used for HVAC simulation. On the left side, two "FixedBoundary" models are used to represent the upstream of the damper and the room with a constant pressure difference of 28 Pa between each other. The value of the pressure difference equals to the nominal pressure drop of the terminal damper at its maximum flow rate of 0.24 kg/s and 100% open position. As for the damper, we take the "VAVBoxExponential" model from the Buildings Library with a slight revision of the embedded filter module. The revised filter module could regulate the damper to move at the constant speed of $\frac{1}{riseTime}$, so that the actual length of transitional period would be dependent on the movement range. In addition, the nominal parameters of the damper model are selected from the product leaflet after sizing, as the nominal flow rate and pressure drop are 0.24kg/s and 28 Pa, respectively. More details of the damper model could be found in the document of Modelica Buildings Library (LBNL 2018). While on the right side is the TF #1 of the room's local temperature, which is presented as a second-order model. The "realExpression" model in between transfers the flow rate signal to the TF #1. Then the output of TF #1 will be used for TFI #2.

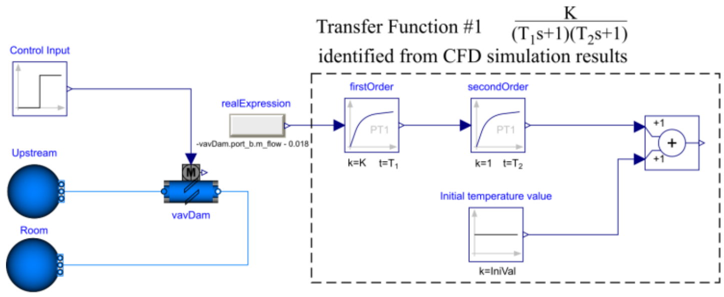

***Figure 3**. Diagram of Modelica models for HVAC simulation*

Within the simulation process, two rounds of TFI are involved. In this case study, we use the Particle Swarm Optimization (PSO) algorithm with the linear dynamic inertia weight (Wetter 2003) to search for the optimal combination of the TF parameters. The transfer functions that we select for the TFI #1 and TFI #2 are the second-order model and the second-order-plus-delay model, respectively. Since we are going to fit the time series data of the temperature to the transfer functions, the transfer functions in time domain are used, as shown in equation (1) (for TFI #1) and equation (2) (for TFI #2) with the step input signals included.

$$G(t) = step \cdot K \cdot \left(1 - \frac{e^{\left(-\frac{t}{T_1}\right)} \cdot T_1}{T_1 - T_2} + \frac{e^{\left(-\frac{t}{T_2}\right)} \cdot T_2}{T_1 - T_2}\right) + IniVal \tag{1}$$

$$\begin{cases} G(t) = IniVal, & t < D \\ G(t) = step \cdot K \cdot \left[1 + \frac{T_1 \cdot T_2}{T_1 - T_2} \cdot \left(\frac{e^{-\frac{t-D}{T_1}}}{T_1} - \frac{e^{-\frac{t-D}{T_2}}}{T_2}\right)\right] + IniVal, & t \geq D \end{cases} \tag{2}$$

where the *step* is the size of the step signal, *K* is the gain, T_1, T_2 are the first and second order time constants, *D* is the delay, *IniVal* is the initial value of the variable. Since the (1 and (2**Error! Reference source not found.** assume the step signal starts from zero, the initial supply airflow rate (0.018 kg/s) should be subtracted from the input of TF #1 (see in ***Figure 3***), and the initial control input signal (lower limit of damper position, 0.1) should be subtracted from the input of TF #2 (see in Figure 4).

During the optimization, the sum of squared error (SSE) is selected as the objective function, which is calculated as:

$$SSE = \sum_{i=1}^{n} [M(t_i) - G(t_i)]^2, \tag{3}$$

where $M(t_i)$ is the value calculated by the models and $G(t_i)$ is the value calculated by the transfer function. The time series data is sampled with the interval of one second.

The configuration parameters for PSO are listed in ***Table 2***. To accelerate the optimization process, the process gain K is determined manually to reduce the dimensions of the problem. The value of K is calculated as the ratio of the output variation range to the input range. When the artificial noise is added, the new steady-state value of the output is obtained by averaging the data over the last 50 seconds. While the other TF parameters, i.e. the time constants and delay (if applicable), will be determined by PSO. The bounds and the constraint are also presented in ***Table 2***.

***Table 2.** Configuration parameters, variable bounds, and constraint of PSO*

PSO configuration parameters			
Swarm size	20	Maximum iteration	1000
Initial inertia weight	0.9	Final inertia weight	0.4
Cognition acceleration factor	1.5	Social acceleration factor	1.2
Bounds of variables			
1st-order time constant, T1/ sec	[0, 500]		
2nd-order time constant, T2/ sec	[0, 500]		

Delay time, θ/ sec	[0, 100]
Constraint	T1 > T2

After all the transfer functions #2 are identified for all the different scenarios and sensor locations, the PID parameters can be calculated accordingly. From the formulas mentioned in the methodology section, we select the SIMC-PID tuning method (Skogestad 2001). The formulas to calculate the parameters of an ideal PID controller for a second-order-plus-delay process are as follows:

$$
T_1 \leq 8D: \quad \begin{cases} K_c = \dfrac{0.5}{K}\dfrac{T_1+T_2}{D}\,; \\ T_i = T_1 + T_2\,; \\ T_d = \dfrac{T_2}{1+\dfrac{T_2}{T_1}}\,; \end{cases} \qquad T_1 > 8D: \quad \begin{cases} K_c = \dfrac{0.5}{K}\dfrac{T_1}{D}\left(1+\dfrac{T_2}{8D}\right); \\ T_i = 8D + T_2\,; \\ T_d = \dfrac{T_2}{1+\dfrac{T_2}{8D}}\,; \end{cases} \tag{4}
$$

where K_c, T_i, and T_d are the PID parameters.

For some cases, the delay time of TF #2 is identified as zero and the process becomes a second-order one. For those cases, the above formulas cannot be applicable because of dividing by zero. As suggested by Skogestad (2001), the second-order process can be approximated as a first-order-plus-delay process ($T_2 = 0$) by using the "half rule". The new parameters can be calculated as

$$
\begin{cases} K' = K; \\ T_1' = T_1 + 0.5T_2; \\ D' = 0.5T_2; \end{cases} \tag{5}
$$

where K', T_1', and D' is the parameters of the new process model. Then Equation (4) can be applicable again. Only the original PID controller becomes a PI controller since $T_2 = 0$ and $T_d = 0$ accordingly.

At last, to verify the usability of the proposed method, we select the most probable combination of the PID parameters and test the control performance of it. The identical PID parameters are applied to control the local temperatures at the 16 sensor locations under all the different scenarios. To do so, we build another Modelica model to perform the verification thoroughly. Figure 4 shows the diagram of the models.

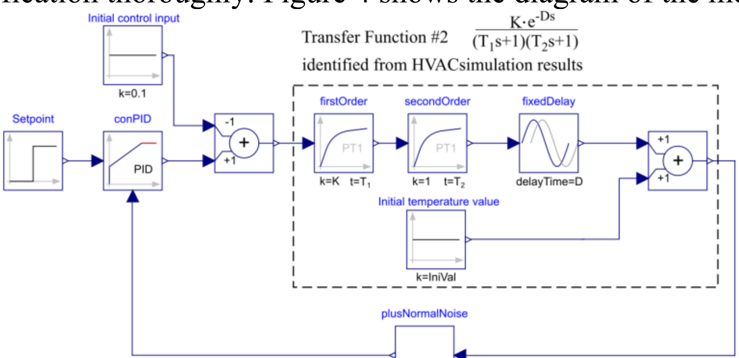

Figure 4. *Diagram of Modelica models for PID control performance validation*

The models surrounded by the dash-line rectangle are implementation of TF #2. The output of TF #2 will plus the noise first and then be sent to the controller. During the simulation, the TF parameters will be read from an external txt file for all the scenarios and sensor locations. Since the local temperatures are significantly different from place to place. It is not reasonable to use the same setpoint signal for all the scenarios. Thus, we use the temperature difference from the initial temperature of each case as the setpoint. During the control performance test, the local temperature will be first controlled to a temperature lower than its initial value by 1 ºC. After the local temperature reaches the new steady state, the setpoint will experience a step change of -

3 ºC. Then the dynamics of the local temperature from now on will be used to evaluate the control performance.

RESULTS

Firstly, the TF #1 under the step signal of mass flow rate is identified from the CFD results. To demonstrate the fitness of the identified TF, the identification process of one local temperature is selected as an example. Figure 5 (a) compares the output of TF #1 with the CFD result without noise and the CFD result with noise. As we can see, although the noise signal is added to the raw data, the lines of the TF #1 output and the CFD result without noise overlap with each other for most of the transitional period, only except for the short period of oscillation at the very beginning. With the help of the manual selection for the gain K, the identified TF could reach the almost identical new steady state. Additionally, the dynamics of the identified TF is almost the same as the raw CFD data without noise. It means the identified time constants, T_1 and T_2 are also appropriate.

Likely, the TF #2 is identified from the Modelica results under the step signal of the damper's control input. Figure 5 (b) compares the output of TF #2 with the Modelica result. As the damper's actuation process is considered, a short delay time is identified during TFI #2. Similarly, a good fitness is also achieved by the proposed identification method as in TFI #1.

(a) (b)

Figure 5*. Comparisons between the outputs of the identified transfer functions and CFD results (a), Modelica results (b)*

Since we have 100 samples generated by LHS method and 16 different alternative locations for the temperature sensors, 1600 different combinations of the transfer function #2 and the corresponding PID parameters are obtained in total. The histograms of the PID parameters are presented in Figure 6. The number of bins is set as 30. As can be seen in the sub-figures, we highlight the values between the 5th and 95th percentile with different color to identify the probable range of the variables, which means the variable would be within this range by 90% chance. In addition, the most probable combination of the PID parameters is annotated in Figure 6.

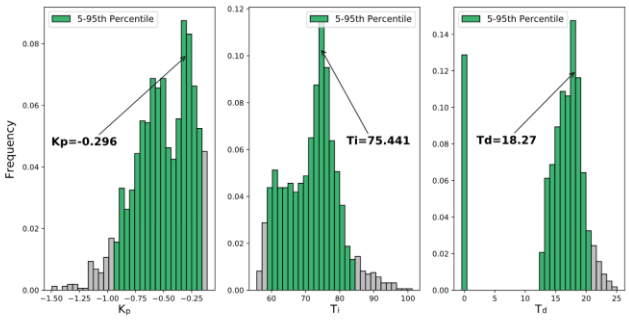

Figure 6*. Distributions of PID parameters for all sensor locations and scenarios*

As for the control performance validation, 1600 dynamic responses of local temperatures are generated considering the 100 scenarios and 16 sensor locations. Figure 7 shows all the responses of local temperatures. The maximum dynamic deviation is about 1.2 ºC and it takes about 300s for the temperature to reach in the $\pm$0.5 ºC error zone of the new steady state. After that the local temperature could be maintained near the new setpoint with a small error due to the interference of the measurement error. Therefore, the control performance is generally acceptable when the most probable PID parameters are identified from all the results of different scenarios and sensor locations.

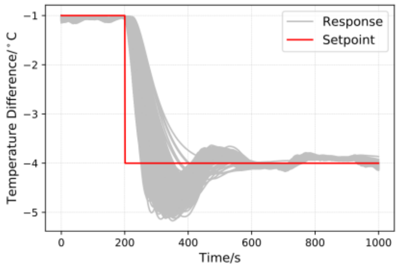

***Figure** 7. Control performance at all sensor locations tested under all scenarios*

CONCLUSION

This paper proposed a simulation-based PID tuning method for the room temperature control using uncertainty analysis. The main workflow is by a use case. The indirect-coupling strategy is used to link the CFD and HVAC simulation together, which is performed by conducting the two types of simulations sequentially. Two separate processes of identifying the transfer functions of the room temperature are involved. In the case study, seven types of uncertainties are accounted to evaluate their impacts on the final PID parameters. The application of the proposed method can even go beyond the scope of the case study, depending on the specific configuration of the HVAC system. From the results of the case study, the uncertainties within the PID tuning process are clearly illustrated, as the parameters spread over a wide range. The most probable PID parameters could be identified from the histogram results. The control performance is generally acceptable when the most probable parameters are applied under all the scenarios. To enhance the practicality of the proposed method, the future works of the simulation-based PID tuning could be focused on the simplification of the implementation procedure and the reduction of the computational cost.

ACKNOWLEDGMENT

This research was supported by the U.S. National Science Foundation under Award No. IIS-1802017.

REFERENCES

Ai, Z. T., and C. M. Mak. 2013. "Pressure Losses across Multiple Fittings in Ventilation Ducts." *The Scientific World Journal* 2013.

Bi, Qiang, Wen Jian Cai, Qing Guo Wang, Chang Chieh Hang, Eng-Lock Lee, Yong Sun, Ke Dian Liu, Yong Zhang, and Biao Zou. 2000. "Advanced Controller Auto-Tuning and Its Application in HVAC Systems." *Control Engineering Practice* 8 (6): 633–644.

Hyun, Se-hoon, Cheol-soo Park, and Godfried Augenbroe. 2007. "Uncertainty and Sensitivity Analysis of Natural Ventilation in High-Rise Apartment Buildings." In *Building Simulation 2007*, 1013–1020.

LBNL. 2018. "Modelica Buildings Library Version 5.0.0." *Http://Simulationresearch.Lbl.Gov/Modelica/.*

Salsbury, Timothy I. 2005. "A Survey of Control Technologies in the Building Automation Industry." *IFAC Proceedings Volumes (IFAC-PapersOnline)* 16: 90–100.

Skogestad, Sigurd. 2001. "Probably the Best Simple PID Tuning Rules in the World." In *The Proceedings of AIChE Annual Meeting*. Reno, NV, USA.

Wang, Liping, and Philip Haves. 2014. "Monte Carlo Analysis of the Effect of Uncertainties on Model-Based HVAC Fault Detection and Diagnostics." *HVAC and R Research* 20 (6): 616–627.

Wang, Miao, and Qingyan Chen. 2009. "Assessment of Various Turbulence Models for Transitional Flows in an Enclosed Environment (RP-1271)." *HVAC and R Research* 15 (6): 1099–1119.

Wetter, Michael. 2003. *GenOpt(R) Generic Optimization Program User Manual Version 2.0.0*. Berkeley, CA.