A framework for calibrating and validating an air loop dynamic model in an HVAC system in Modelica

Yicheng Li[1], Zhelun Chen[1], Jin Wen[1], Yangyang Fu[2], Amanda Pertzborn[3], Zheng O'Neill
[1]Drexel University, Philadelphia, USA
[2]Texas A&M University, College Station, USA
[3]National Institute of Standards and Technology, Gaithersburg, USA

Abstract

The use of Modelica for simulating the dynamic behaviors of building heating, ventilation, and air conditioning (HVAC) systems has gained popularity. Calibration of a model that represents large and complex HVAC systems in Modelica involves the determination of hundreds of parameters using real-world operation data. Considering the coupling effects among various components, such a calibration process is complex and time-consuming. In this study, we propose a systematic framework to efficiently calibrate and validate a complex HVAC system model in Modelica. The framework includes strategies to solicit real-system operation data and to decouple the model. The goal of this calibration framework is to accurately and efficiently determine a set of Modelica model parameters that provide a good match between the simulated and real system behaviors. To demonstrate the validity of the framework, it was applied to calibrate the parameters of a Modelica model of the air loop subsystem of a real AHU-VAV system. The results show that the calibrated model can generate simulated results, including VAV air flow rate, outdoor air flow, and fan power consumption, that match well with the operational data of the real system. The coefficient of the variation of the root mean square error, CV(RMSE), of the air flow rate and power consumption are 14.6 % and 11.5 %, respectively. The results prove that the framework is valid and effective, and it can be used to calibrate other complex HVAC system Modelica models in the future.

Key innovations

- A framework for calibrating and validating a HVAC system Modelica model in a decoupled way.
- Component-level calibration of a fan model in Modelica.
- Subsystem-level calibration of multiple damper pressure resistance models in Modelica.
- Validation of an air loop subsystem in Modelica.

Practical implications

When calibrating a complex model for HVAC systems in Modelica, it is recommended to follow the presented framework for component-level and subsystem-level calibration and verification.

Introduction

Modelica HVAC system modelling

Modeling of heating, ventilation, and air conditioning (HVAC) systems is a critical process when investigating different aspects of building HVAC systems, including system design, control strategies, and fault detection and diagnosis. Modelica is an open-source, object-oriented, equation-based language that can be used to model, simulate, and analyze complex dynamic systems including mechanical, electrical, electronic, hydraulic, thermal, control, and power systems [1]. Due to its potential for simulating dynamic systems, Modelica has also become a commonly-used tool for simulating dynamic HVAC systems [2, 3]. The HVAC systems modeled by Modelica can be used to simulate energy consumption, thermal comfort, and indoor air quality in buildings, and to optimize the performance of HVAC systems [4]. Modelica provides several libraries specifically for HVAC systems, such as the Modelica Building Library and the Modelica HVAC Library [5, 6]. These libraries provide pre-built HVAC system component models, such as air handling units, chillers, and heat exchangers. Due to the variation in performance parameters, pre-built HVAC models often fail to accurately reflect actual system performance. Therefore, model calibration is needed to minimize the gap between the simulated results and real system behaviors.

Modelica model calibration

There are a few publications in the literature that discuss how to calibrate specific HVAC system models in Modelica. For example, Giuliano [7] et al. showed the calibration and validation of a solar thermal system model in Modelica using a single week of monitoring data to adjust the performance parameters in the model. Bryan [8] et al. calibrated an air handling unit with variable air volume (AHU-VAV) system model containing 25 adjustable parameters. Victor [9] and AnKush [10] used Bayesian optimization to simultaneously calibrate a Modelica model containing an HVAC system and building. Calle [11] et al. calibrated the heat exchanger model by using the Modelica Optimization Library. While many researchers mentioned Modelica model calibration in their studies, there is no systematic framework or methodology proposed in the literature. In practice, when calibrating a large and complex HVAC system model in Modelica, hundreds of parameters need

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to be determined using real operational data. Such a calibration process is complex and time-consuming due to the coupling effects among different components.

Goal of the study

In this study, we propose a systematic framework to efficiently calibrate and validate complex HVAC system models. The goal of this calibration framework is to accurately and efficiently determine a set of Modelica model parameters that provide a good match between the simulated and real system behaviors. This framework includes strategies to: 1) decouple the HVAC system models; 2) solicit real-system operational data; 3) calibrate single component models that are weakly coupled with the rest of the system; 4) determine the performance parameters of the components/subsystems that are strongly coupled using an optimization method; and 5) validate the calibration results of the entire system. The calibration-validation framework can be used with different building simulation platforms. Modelica is used in this study because of its flexibility to connect with the external optimizer for optimization purposes. To demonstrate its effectiveness, the framework was used to calibrate the performance parameters of the air loop subsystem of an Air Handing Unit (AHU)-Vairable Air Volume (VAV) system model in Modelica, which represents the real system in the Intelligent Building Agents Laboratory (IBAL) at the National Institute of Standards and Technology (NIST) [12].

The rest of this article is organized as follows: the methodology section offers a thorough explanation of the proposed calibration and validation framework; the case study section demonstrates the application of the proposed framework to a real HVAC system to verify its effectiveness; the discussion section provides an analysis of the results; finally, the conclusion section provides a summary of this paper.

Methodology

Overview of the calibration and validation method

This study aims to develop and demonstrate a framework for calibrating a HVAC system model in Modelica. Depending on the purpose of the model, such as energy forecasting or occupant-centric control, its model calibration might have slightly different emphasis. However, generally speaking, calibration of most HVAC system models should focus on the accuracy of the system energy consumption and zone environmental condition. This requires that the calibrated model accurately simulates the conditions of the fluids passing through the system, such as the fluid flow rate, temperature, and humidity.

For a complex and large HVAC system model in Modelica, it is difficult to calibrate hundreds of parameters in the model simultaneously (global strategy). On the other hand, calibrating each component separately (independent strategy) requires component-level real system measurements with enough granularity, which often are not avaiable. For example, the pressure drop between the inlet and outlet of a damper is typically not known and can be difficult to measure accurately. In this paper, the proposed framework strives for a balance between the global and independent approaches. The flowchart of the framework is shown as Figure 1.

First, decoupling system means that the entire system is divided into subsystems that are weakly coupled with each other based on expert knowledge so that they can be calibrated independently. Each subsystem is further decoupled into components and second-level for calibration and validation.

After that, data corresponding to the decoupled subsystems and components, which are needed for the calibration and validation process, are prepared from the real system operational data.

Following that, <u>component-level calibration and validation</u> are generally conducted first. The components included in this step are those that are weakly coupled with the rest of the subsystem, and hence can be isolated from other components for calibration. This is possible because the performance of such components are primarily influenced by their own performance parameters and not by external conditions.

After the component-level calibration and validation are completed, <u>subsystem-level calibration and validation</u> are performed. Due to the strong coupling relationship with other components and/or a lack of detailed boundary data, some components can only be calibrated and validated at the subsystem level. In a subsystem-level calibration, optimization methods are needed to simultaneously calibrate multiple performance parameters. After finalizing the component-level and the subsystem-level calibration, a system-level validation will be performed to ensure that the calibrated components and sub-systems can achieve desired system-level performance.

While the notion of component- and system-level calibration and validation is well-trodden, the literature often presents a piecemeal approach rather than a unified framework to guide users through the calibration process. This paper addresses this gap by introducing a systematic framework to decide how to implement component- or system-level calibration. The details of this framework will be elaborated in the subsequent sections.

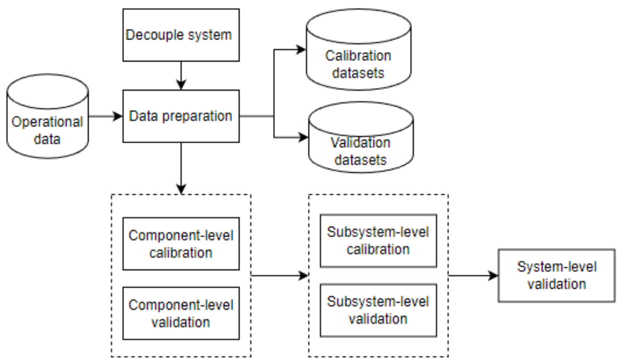

Figure 1 The flowchart of the calibration and validation for an HVAC system model in Modelica

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Component-level calibration and validation

Whether the component should be calibrated at the component level depends on: 1) whether the performance of the component is primarily dependent on its own performance parameters; 2) whether there is data available to support component-level calibration; and 3) whether the calibration of the component involves multiple or complicated performance parameters. A fan model, which is a common component in an HVAC system, is used as an example to explain these three requirements. The performance of the fan depends primarily on its own fan curves, including the pressure curve and the power curve [13]. In contrast to other Modelica components that may require calibration for only a few performance parameters, the Modelica fan model requires two fan curves to be calibrated. These fan curves are typically composed of multiple data points that contain information such as flow, differential pressure, and power. As a result, the number of parameters that need to be calibrated for the fan model is much greater than for other components. The fan curves can be obtained by measuring the flow rate, power, and differential pressure of the fan in an experiment. Therefore, fan models are usually calibrated and validated at the component level. For a HVAC system model in Modelica, component-level calibration is also generally appropriate for pumps, chillers, coils, etc.

The performance parameters that need to be calibrated, and the performance indicators that are used to evaluate the calibration result, are dependant on the type of a component model in Modelica. Still using the fan as an example, the Modelica fan model requires fan curves of pressure and power during calibration. After calibration, validation of the Modelica fan model can also be done at the component level. Using a calibrated fan model, the air flow through the fan is the input of the model which can be adjusted to obtain the corresponding differential pressure and power of the fan. The simulation results from the calibrated fan model can be compared with measurements from those in the real system. As another example, the calibration of the Modelica coil model requires the nominal flow rate and differential pressure on the air and water sides, and the thermal conductance. For validation, the temperature and flow rate on the air and water sides can be compared between the simulated values from a calibrated Modelica model and the real measurements.

Subsystem-level calibration and validation

In addition to the isolatable components, a subsystem is made up of components that cannot be further divided because of the strong coupling between them. Such subsystems will need to be considered as a whole for calibration and validation. If the subsystem contains components that can be calibrated at the component level, those components should be calibrated first. After the component level calibration is completed, the entire subsystem, including the calibrated components, is calibrated (for those parameters in other non-calibrated components) and validated as a whole. For example, in an air loop model in Modelica, there are components such as fans, air ducts, and dampers. The goal of the calibration for the airloop model would be to simulate the air flow rates that pass through the subsystem accurately. As mentioned before, the fan would usually be calibrated at the component-level. But the pressure resistances of the remaining components, such as dampers and ducts, need to be determined. Due to the lack of measurements from a typical airloop system that would provide enough granularity for component level calibration for ducts and dampers, these components need to be calibrated as a subsystem.

Subsystem-level calibration involves the calibration of several performance parameters. This can be achieved by formulating it as an optimization problem [9, 10], i.e. by continuously adjusting the performance parameters in the subsystem Modelica model to minimize the error between the subsystem model outputs and the real system measurements. A typical flowchart of the calibration of a subsystem model in Modelica using the optimization method is proposed in this paper, as shown in Figure 2. In addition to data preparation, the steps include: 1) The conversion of the Modelica model to a Functional Mock-up Unit (FMU). This step allows Modelica to be imported to other simulation programs (such as Simulink) for optimization. The input of the FMU is the control signal of the subsystem, and the output is the simulation results for the objects of interest in the calibrations. By using this struture, optimization can be implemented using the same control signals as the real system and the simulation results can be compared directly to the measurements. 2) The calculation of the objective function. Taking the subsystem-level calibration of an air loop Modelica model as an example, the goal is to minimize the error of the flow rate in the air loop between the Modelica model and the real system. During optimization, the error of the flow rate should be considered in the objective function. 3) Updating the parameters in the Modelica model by optimization. During calibration, the optimization process produces new parameter sets. These sets are used to update the Modelica model, which is then converted into a new FMU. This loop continues until the optimization meets its stopping criteria. This is a multivariate global optimization problem and the common optimization algorithms used to solve it include genetic algorithm, particle swarm optimization, and harmony search [14].

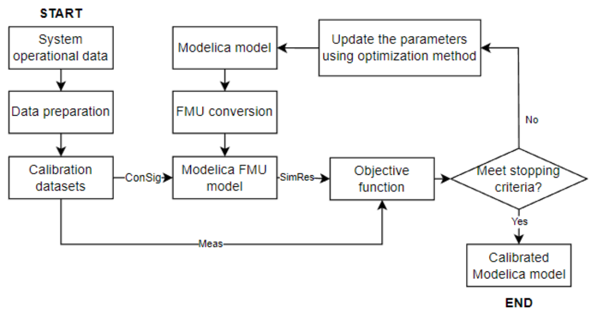

Figure 2 The optimization process for calibrating a subsystem model in Modelica

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After the subsystem-level calibration, the calibrated Modelica model is validated at the subsystem-level. Similar to the optimization calibration, during the validation, the Modelica model uses the same control signals as the real system in an attempt to replicate the behavior of the real system. The validation dataset usually contains a diverse range of data so that the scalability of the calibrated model can be fully verified. When validating at the subsystem level, the behavior of the system, such as energy consumption, fluid flow rate, and fluid temperature within the components, is considered. Continuing with the example of subsystem-level calibration of the air loop, during validation the air flow rate of each component is checked first. If the air loop contains a component that consumes energy, such as a fan, then the energy consumption of that component should be checked. If the air loop contains a component with a heat exchanger, such as a cooling or heating coil, then the inlet and outlet fluid temperature of that component should be checked.

Case study

Description of the case study

To demonstrate the proposed framework, it was applied to an AHU-VAV system model in Modelica that represents the real system in the IBAL. The IBAL is designed to emulate a small commercial building. The air loop in the IBAL contains zones and equipment including coils, fans, dampers, and ducts. In the IBAL, there are two AHU air loops; each AHU is connected to two VAV boxes, and each VAV box serves one zone. The air loop diagram is shown in Figure 3. The data used for the calibration and validation in this study were obtained from two sources: the operational data of a hardware-in-the-loop flexibility load study [15], and additional experimental tests conducted to supplement the existing data. The operational data include: 1) the system control signals of the fans and dampers. 2) measurements of the fan power, the air flow rate in the air loop, and the static pressure after the AHU with one-minute data resolution.

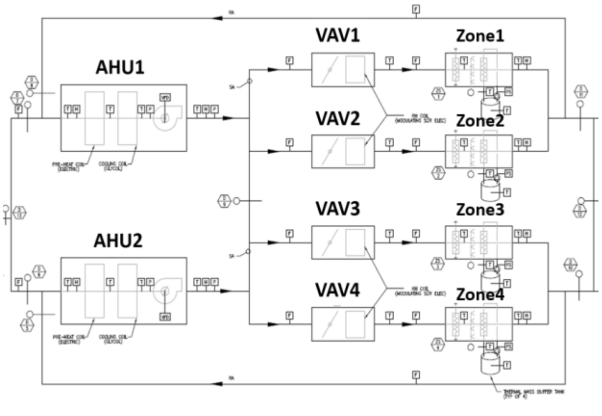

Figure 3 IBAL air loop diagram

A typical AHU-VAV system can be divided into an air loop subsystem, a water loop subsystem, and a thermal subsystem. This case study focuses on the calibration and validation of the air loop subsystem to illustrate the proposed framework and demonstrate its effectiveness. The calibration of the air loop subsystem can be divided into two parts: fan component-level calibration and subsystem-level air loop pressure resistance calibration. After finalizing the calibration at the component level and subsystem level, the system level performance is evaluated for the entire air loop model.

To provide a clear illustration of the calibration and validation process for the IBAL system, it will be presented using the AHU1 loop as an example, as the two air loops are weakly coupled with each other. The overview of the results for the AHU2 loop will be presented, but the details are very similar to those of the AHU1 loop and will not be shown.

Component-level: Fan calibration and validation

As previously described, fans can be calibrated and validated at the component level. The fan model used in Modelica is controlled by normalized speed [16]. The pressure rise and energy consumption of the fan vary with the fan speed control signal and air flow rate.

Calibration of the Modelica fan model requires the complete full-speed fan curves (the curve between volume flow rate and pressure rise and the curve between volume flow rate and power), which were obtained by an additional experiment using the real system. The required fan curves are in a format with a series of monotonically increasing or decreasing operation points. The calibration of the Modelica fan model is therefore a process of fitting the fan curves and selecting the points to assign to the model. A second-order polynomial fit for the pressure rise vs flow and a first-order polynomial fit for the power vs flow are generated from experimental data to obtain the complete full-speed fan curves [16, 17]. After curve fitting, the points were selected from the fitted curves as performance parameters used by the Modelica fan model to complete the calibration. The calibration and validation results of the AHU1 fan are shown in Figure 4 and Figure 5 for the fan curves of pressure drop and power, respectively. In the plots, the blue hollow points are measurement data; the green line is the second-order fit to the pressure drop fan curve (R2=0.999) and the first-order fit to the power fan curve (R2=0.996); the solid green points are selected from the fitted curves and used by the Modelica fan model to represent the calibrated fan curves.

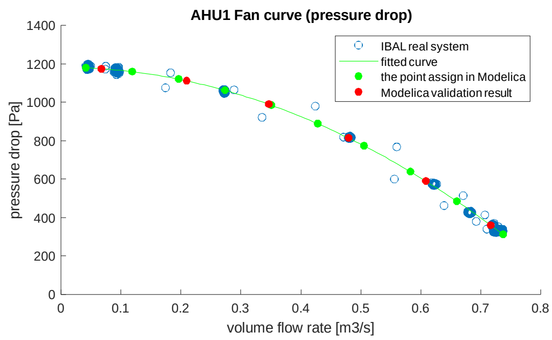

Figure 4 Pressure-drop fan curve in component-level calibration

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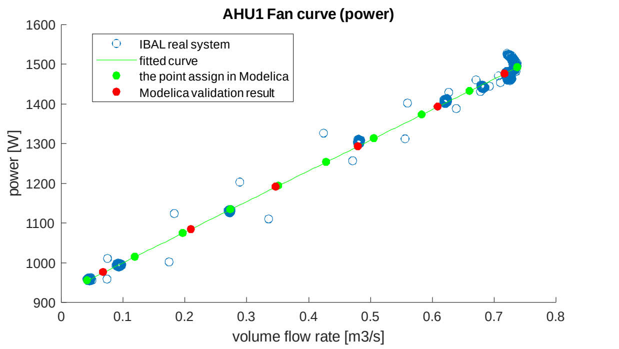

Figure 5 Power fan curve in component-level calibration

The Modelica fan model is also validated at the component level. A simple air loop model is developed in Modelica, which includes the calibrated fan model and pre-built damper and ducts. By keeping the fan running at full speed and adjusting the damper opening fraction, pressure rises, energy consumption, and flow rates can be obtained. The calibrated fan model is validated by comparing the Modelica model simulation results with the curve fitted from the experimental data mentioned before. The red points in Figure 4 and Figure 5 are the validation results of the calibrated Modelica fan model. The red points are completely on the green fitted curve, which indicates that the calibrated fan model matches the performance of the fan in the real system.

For the fan in AHU2, the pressure drop fan curve is fitted with R^2=0.999 and the power fan curve is fitted with R^2=0.998. The validation results are the same as the fan in AHU1, in which the simulated fan model output agree well with the measurements.

Subsystem-level: Air loop pressure resistance calibration and validation

The air loop of the IBAL AHU-VAV system is comprised of dampers, ducts, tees, coils, and other components in addition to the fan. The remaining components were calibrated at the subsystem level due to the strong coupling effects among them. Preliminary testing data shows that the pressure resistance in the air loop primarily comes from the dampers. Therefore, the pressure resistance of the dampers is considered in this study. The dampers in the air loop of the IBAL include an outdoor air (OA) damper, a recirculating air (RA) damper, an exhaust air (EA) damper, and two VAV dampers. Figure 6 shows the IBAL AHU air loop model in Modelica. Air damper models with exponential opening characteristics are used in Modelica [18].

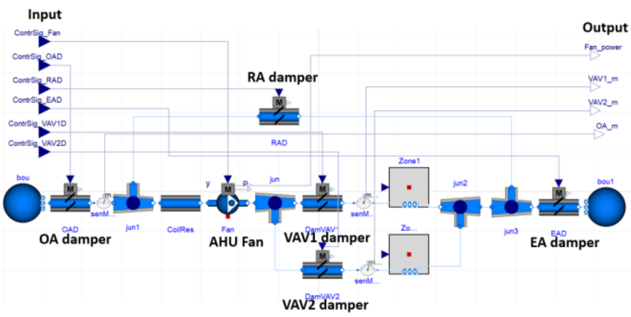

Figure 6 Modelica model of one of the AHU air loops

Calibration of the air loop pressure resistance requires determination of the damper performance parameters including the nominal mass flow rate, nominal pressure drop, and damper coefficients. The air loop pressure resistance is calibrated using the optimization method mentioned in Figure 2. This method is used to find a set of damper parameters that minimizes the errors between the Modelica model simulation and the calibration operational data for the air flow rates in VAV1 and VAV2, and the outdoor air flow at the OA damper. The specific steps of the calibration method include:

1. Data preparation: Based on the zone supply air flow rate, the operational data were divided into stable 60-minute low-, medium-, and high-flow datasets using the MATLAB functions “findchangepts” [19] and “kmeans” [20]. To ensure that the calibration dataset is representative and covers a wide range of scenarios, a total of five datasets (i.e., datasets with extreme low/high and typical low/medium/high flow rate) were selected as calibration datasets.
2. Conversion of the Modelica model to FMU: In this case study, the optimization process is implemented in the MATLAB & Simulink environment, so the air loop Modelica model is converted into an FMU to interact in this environment. The inputs of the FMU are the control signals for the fan and dampers, and the outputs are the VAV supply air flow rates and outdoor air flow rate.
3. Modelica model simulation: In the MATLAB & Simulink environment, the converted FMU ran with the control signal from the calibration datasets and simulated the air flow rate in the air loop.
4. Objective function formulation: Objective function used for the subsystem-level calibration aims to match the air flow rate at three critical locations in the subsystem, i.e., VAV1, VAV2, and outdoor air. In the objective function, J(x), the Coefficient of Variation Root Mean Squared Error, CV(RMSE), a typical and commonly used error metric [21], was used to calculate the error between the Modelica simulation result and the measurement. The objective function is shown below, where x is the adjustable parameter set of the dampers; $\#CaliData$ is the total number of calibration datasets, which is 5 in this case study; $\#Air\_m$ is the number of the air mass flow rate considered in the objective function, which is 3 (the air in VAV1, VAV2, and outdoor air) in this study. The mean CV(RMSE) was calculated based on the air flow rate in the VAVs and the OA dampers in the five calibration cases.

$$J(x) = \frac{\sum_{j=1}^{\#CaliData} \sum_{i=1}^{\#Air\_m} CV(RMSE)_{(Sim_{x,ij},\, Mea_{ij})}}{\#CaliData \times \#Air\_m}$$

5. Optimizing model parameters: A genetic algorithm, specifically the MATLAB function "ga" [22], is used to determine the optimal parameter sets of the dampers in the air loop model in Modelica. Each damper in the Modelica model has eight performance parameters

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that need to be calibrated, including m, dp, a, b, k1, L, yL, and yU. The values of each parameter were constrainted by the ranges listed in Table 1, which were determined based on reasonable assumptions. Note that **m** and **dp** together determine the resistance of a damper, therefore, only one of them needs to vary in the calibration. Of these two parameters, **m**, the maximum air flow rate when the damper fully opening, can be obtained from the operational data. By continuously adjusting the parameter set of the dampers and calculating the objective function, the genetic algorithm minimized the error between simulation and measurement.

Table 1 The bounds of the adjustable parameters of the dampers in air loop subsystem-level calibration

Damper	OA	RA	EA	VAV1	VAV 2
m [kg/s]	0.6	0.88	0.36	0.55	0.5
dp [Pa]	[1, 100]				
a	[-3.02, 0]				
b	[0, 0.21]				
K1	[0, 0.9]				
L	[0, 0.0002]				
yL	15				
yU	55 or 65				

Note: The parameter **m** *represents the maximum flow rate when the damper fully opening. The parameter* **dp** *represents the pressure drop at the maximum flow rate when the damper fully opening. The parameters* **a**, **b**, **k1**, *and* **L** *are all damper coefficients. The parameters* **yL** *and* **yU** *represent the lower and upper values for the damper curve* [18].

6. Optimization termination The default options of the MATLAB "ga" function were used in this study, except function tolerance, which was set to 10^{-4} as a stopping criteria based on observations. When the stopping criteria was met, the opitimization calibration stopped, and the calibrated air loop Modelica model was obtained.

The subsystem-level calibration of the air loop pressure resistance was performed following the steps above using an Intel(R) Xeon(R) CPU E5-2699 v4 @ 2.20 GHz. The progress of the optimization is shown in Figure 7. After running 149 generations, which took about 60 hours, the optimization was terminated by reaching the function tolerance. The optimization program output the minimum value of the objective function and the associated parameter set of the dampers. The minimum value of the objective function is 16.04 %, which is the mean CV(RMSE) of the air flow rate in VAV1 and VAV2 and the OA dampers in the five calibrations cases. Table 2 shows the calibrated parameter sets of the five dampers in the AHU1 air loop. As for AHU2 air loop calibration, the optimization stopped at 158 generations with a minimum mean CV(RMSE) of 19.16 %.

To validate the subsystem-level calibration results, three datasets, representing low, medium, and high thermal loads were selected from the operational data as validation datasets. The control signals for the fan and dampers in the validation data are input to the calibrated Modelica model. Then the simulated fan power and the air flow rate in VAV1, VAV2, and OA dampers are compared to the measurements. The model simulation accuracy is validated by calculating the corresponding CV(RMSE) and RMSE values [23]. The typical thermal load validation case in AHU1 (as shown in Figure 8) is used as an example to demonstrate the validation result. In general, the calibrated model captures the performance of the real IBAL system. The results of the three validation cases for the AHU1 air loops are summarized in Table 3. The results will be discussed in the next section.

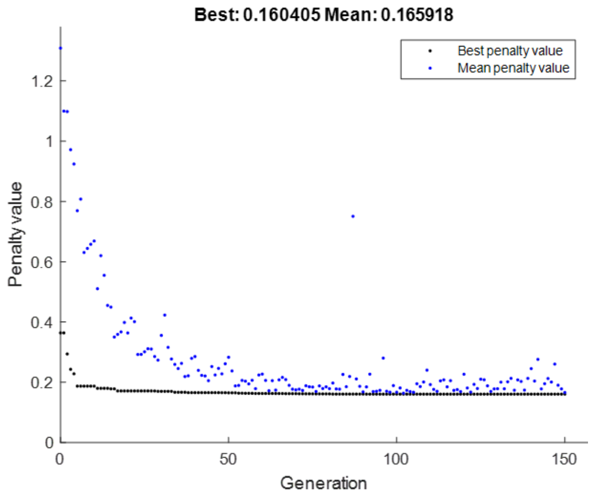

Figure 7 The minimum objective function value for each generation during optimization with GA

Table 2 The calibrated parameters in the AHU1 loop

Damper	OA	RA	EA	VAV1	VAV 2
m [kg/s]	0.39	0.77	0.36	0.55	0.50
dp [Pa]	34	21	38	35	83
a	-0.60	-0.24	-1.90	-0.54	-1.17
b	0.117	0.051	0.089	0.08	0.101
K1	0.51	0.25	0.49	0.72	0.33
L	$0.5*10^{-4}$	$1.1*10^{-4}$	$1.4*10^{-4}$	$0.7*10^{-4}$	$0.9*10^{-4}$
yL	15	15	15	15	15
yU	55	55	55	65	65

Table 3 The error in validation of the AHU1 air loop

	VAV1_m	VAV2_m	OA_m	Fan1_Power
Low thermal load	CV(RMSE) [%]			
	16.34	16.23	16.12	12.38
	RMSE [kg/s for m, W for power]			
	0.019	0.036	0.033	37
Medium thermal load	CV(RMSE) [%]			
	14.56	11.32	15.10	10.05
	RMSE [kg/s for m, W for power]			
	0.017	0.029	0.030	47
High thermal load	CV(RMSE) [%]			
	13.86	8.12	14.10	11.14
	RMSE [kg/s for m, W for power]			
	0.019	0.025	0.025	53

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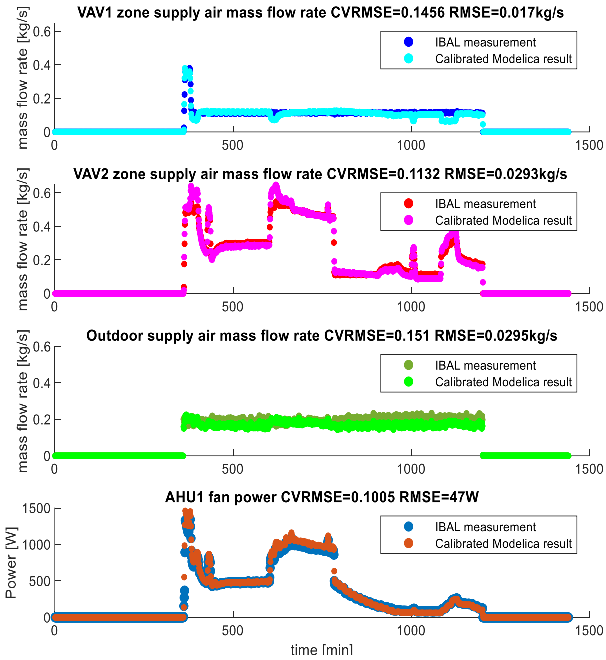

Figure 8 The validation result of the AHU1 air loop using typical thermal load case data

Discussion

Analysis of the validation results

In terms of air flow rate in the VAVs and outdoor air flow for the two AHU air loops, the maximum CV(RMSE) is 22.06 % and the maximum RMSE is 0.036 kg/s. Differences in the average air flow rate of the dampers can result in a situation where a large CV(RMSE) does not always correspond to a large RMSE, and vice versa. Although the CV(RMSE), as a typical error metric, was used in the objective function to optimize the parameter set of the dampers in the pressure resistance calibration, considering the different average flow rates of the various dampers in the air loop, the RMSE is a better metric to evaluate the accuracy of the calibrated model. An RMSE of 100 CFM (0.059 kg/s) is used as the criteria for validating the model because the impact on system energy consumption and occupant's comfort is acceptable at this level. The criteria is in accordance with the value recommended by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) and the International Performance Measurement and Verification Protocol (IPMVP) [24]. Based on the validation criteria, the calibrated model is acceptable for the air flow distribution in the air loop.

In terms of energy consumption, the CV(RMSE) is below 14 % and the RMSE is below 53 W in the overall air loop validation. The energy consumption of the Modelica fan model has been validated at the component level. It can be inferred that the error in fan energy consumption is mainly due to the error in the simulated air flow through the fan. As supplementary information, the average energy consumption of the entire IBAL system is around 10 kW. Considering that the energy consumption of the air loop only accounts for around 10 % of the whole system total energy consumption, the CV(RMSE) of 14 % or the RMSE of 53 W in the air loop energy consumption is an acceptable error.

In conclusion, the calibrated Modelica air loop model can accurately simulate the dynamic behavior of the real IBAL system under different operating conditions.

Recommendations for optimization

In this case study, CV(RMSE) was used in the objective function, as recommended in the literature [21]. However, due to the different air flow rates of the components in the air loop, relying solely on the CV(RMSE) to assess error may not accurately capture the air flow distribution within the loop. In this context, RMSE might be a better metric. In future studies, the use of mean or maximum values, CV(RMSE) or RMSE in the objective function needs to be carefully considered to assess the error in the air flow distribution in the air loop.

In the calibration of pressure resistance, this paper focuses on introducing an optimization process and does not explore which optimizer to use or how quickly the optimization can be achieved. In this study, using the MATLAB GA optimizer (GA) with its default function tolerance of 10^{-6}, the optimization ran for 80 hours without finishing. Even with a relaxed tolerance of 10^{-4}, it still required about 60 hours to complete the optimization. The optimization settings and other optimization algorithms should be explored to improve the efficiency of this calibration framework. Other global optimization algorithms, such as Particle Swarm Optimization and Harmony Search, and different GA parameters may be investigated in the future. In addition, parallel computing may be considered to further improve the speed of optimization.

Conclusions

This paper presents a systematic framework for calibrating and validating HVAC system models in Modelica. The framework consists of decoupling strategy for a complex system, and calibrating/validating approaches for each de-coupled subsystem, using real system measurements. To demonstrate the effectiveness of the proposed framework, a case study showing the calibration process of an AHU-VAV system air loop model in Modelica was presented. The calibration of this air loop system was decoupled into the calibration of the AHU fan at the component-level and the calibration of the pressure resistance of other components at the subsystem-level. A multivariate optimization method was demonstrated in the pressure resistance calibration process. After calibrating the fan component and the air loop pressure resistances, the air loop system was validated as a whole for fan energy consumption and air flow rate in the air loop. The study demonstrates the feasibility of using the proposed framework to calibrate and validate a complex HVAC system in Modelica. In this study, we only completed the calibration of the air loop subsystem of an AHU-VAV system. Further calibration of the remaining subsystems, including the water loop subsystem and the thermal system, will be performed using the same proposed framework in the future. This will further demonstrate the scalability of the framework.

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