Journal of Building Performance Simulation

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tbps20

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JOURNAL OF BUILDING PERFORMANCE SIMULATION
https://doi.org/10.1080/19401493.2025.2452657

A framework for calibrating and validating an HVAC system in Modelica

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ABSTRACT

Using Modelica to simulate the dynamic behaviours of building HVAC systems has gained popularity. Calibration of a Modelica model that represents large and complex HVAC systems involves elaborate and time-consuming determination of hundreds of parameters. This study proposes a systematic framework to calibrate and validate an HVAC system model in Modelica. The framework includes strategies to decouple the model and calibrate it with multi-source data, aiming to efficiently and accurately determine Modelica model parameters that provide a good match between the simulated and real system behaviours. To demonstrate the validity, the framework was applied to calibrate the parameters of a Modelica model representing a real AHU-VAV system with components such as fans, pumps, dampers, valves, chillers, etc. The results show that the simulated results match well with the real system measurement of VAV supply air condition and equipment power consumption within the acceptance criteria.

ARTICLE HISTORY
Received 17 September 2024
Accepted 7 January 2025

KEYWORDS
Building energy simulation; HVAC system model; Modelica; calibration and validation

Introduction

Modelica HVAC system modeling

Modeling heating, ventilation, and air conditioning (HVAC) systems is critical when investigating different aspects of building HVAC systems, such as system design, control strategies, and fault detection and diagnosis. There are three main approaches for modeling HVAC systems: data-driven, physics-based, and hybrid methods (Afram and Janabi-Sharifi 2014). The interpretability of physics-based models is the highest among the three approaches, which helps researchers analyze the simulation results when using the physics-based models. Twenty widely used physics-based building energy simulation tools have been reviewed in the literature (Crawley et al. 2008), including EnergyPlus, TRNSYS, and Modelica/Dymola.[1] Among them, Modelica has become one of the leading tools for system simulation due to its high resolution, accessibility and robustness (Qiu et al. 2024).

Modelica is an open-source, object-oriented, equa tion-based language that models, simulates, and analyzes complex dynamic systems, including mechanical, electrical, electronic, hydraulic, thermal, control, and power systems (Fritzson 2020). Unlike a typical modeling tool, such as EnergyPlus, Modelica can simulate dynamic HVAC systems down to seconds. Due to this benefit, it is becoming an increasingly common tool for dynamic HVAC systems modeling (Li et al. 2014). Modelica models of HVAC systems can be used to simulate energy consumption, thermal comfort, and indoor air quality in buildings, and optimize the performance of HVAC systems (Abugabbara et al. 2020). Modelica provides several libraries specifically for HVAC systems, such as the Modelica Buildings Library and the Modelica HVAC Library (Wetter et al. 2014; Wetter et al. 2015). 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, parameters of pre-built HVAC models need to be customized to accurately reflect actual system performance. Therefore, model calibration is needed to minimize the gap between the simulated results and real system behaviours.

Modelica model calibration

There are a few publications in the literature that discuss how to calibrate specific HVAC system models in Modelica. For example, Fontanella et al. (2012) showed the calibration and validation of a solar thermal system model in Modelica using a single week of monitoring data to adjust the model performance parameters

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/19401493.2025.2452657.

based on an optimization method. Eisenhower, Gasljevic, and Mezi (2012) calibrated an air handling unit with a variable air volume (AHU-VAV) system model containing 25 adjustable parameters using EnergyPlus simulation data and regression coefficients method. Victor (Martinez-Viol et al. 2022) and AnKush (Chakrabarty et al. 2021) used Bayesian optimization to simultaneously calibrate a Modelica model containing an HVAC system and building. The former used 15 days of data collected from the building management system and a Bayesian search method to calibrate the model with 45 parameters related to the building and HVAC system. The latter calibrated a model containing 17 parameters, with the calibration data obtained from simulated data. de la Calle, Bayon, and Too (2018) calibrated a heat exchanger model with 14 parameters using the Modelica optimization library and MATLAB Global Optimization Toolbox.

Based on these references, current HVAC system Modelica model calibration studies tend to include a small number of parameters and focus on limited components or a subset of the systems. There is a lack of a systematic calibration framework or methodology in the literature, especially for larger and more complex HVAC systems. For example, a complete AHU-VAV system contains several fans, dampers, cooling coils, chillers, pumps, etc., where each component involves multiple performance parameters, resulting in hundreds of parameters that need to be calibrated using real operational data. One approach is to calibrate these components separately using calibration methods mentioned in the literature. This requires detailed measurements. For example, damper calibration requires static pressure measurements at the damper inlet and outlet. However, such measurements are usually not available, and they are difficult to measure accurately. In addition, due to coupling effects between the components, it is hard to ensure that the same simulation accuracy can be achieved at the system level and at the separately calibrated component level. For example, in a water loop, the chiller outlet water temperature will affect the cooling coil inlet water temperature, thus affecting the cooling coil outlet air temperature. In that way, when the chiller and coil are calibrated, it is unknown whether those components' simulation errors will result in an acceptable impact on the overall HVAC system. Therefore, such a calibration and validation process is complicated and time-consuming for a large and complex HVAC system.

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 behaviours. This framework includes strategies to (1) decouple the complex HVAC system models for systematic calibration; (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 modeling advantages in the field and 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 an AHU-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) (Pertzborn and Pertzborn 2019).

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 systematic framework for calibrating an HVAC system model in Modelica. Calibration can emphasize different metrics depending on the purpose of the model, but, in general, the calibration of most HVAC system models will focus on the accuracy of the modeling of energy consumption and the zone environmental condition. This focus requires that the calibrated model can accurately simulate 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 sufficient granularity, which are often unavailable. In this paper, the proposed framework strives for a balance between the global and independent approaches. The flowchart of the framework is shown in Figure 1.

First, the entire system is decoupled by dividing it into weakly coupled subsystems based on expert knowledge

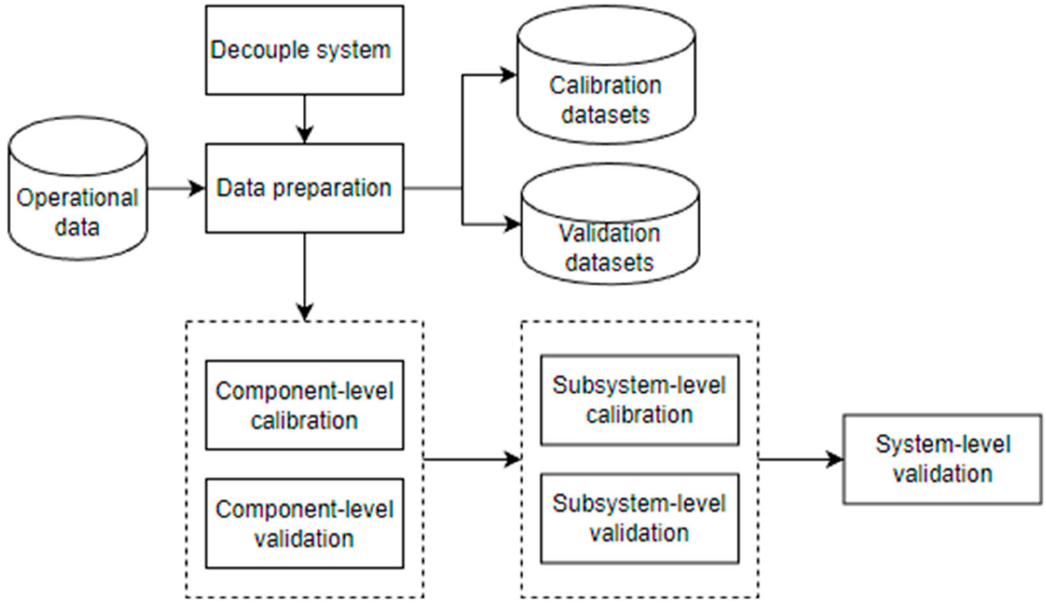

Figure 1. The flowchart of the calibration and validation for an HVAC system model in Modelica.

so that they can be calibrated independently. In HVAC systems, decoupling is typically based on the type of fluid, and each fluid loop can be considered as a subsystem. Calibration of those subsystems focuses on aligning flow distributions between simulations and measurements. And the multiple heat exchange processes collectively form a thermal subsystem. Furthermore, each subsystem is further decoupled into components and secondary subsystems for calibration and validation.

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

Following that, component-level calibration and validation are performed. The components included in this step 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 is primarily influenced by their own performance parameters and not by external conditions.

Subsystem-level calibration and validation are performed after the component-level calibration and validation are completed. 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 subsystem-level calibration, a system-level validation is performed to ensure that the calibrated components and subsystems can achieve the desired system-level performance.

While the notion of component-level 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-level or system-level calibration. The details of this framework will be elaborated in subsequent sections, including the identification of suitable equipment for component-level or subsystem-level calibration, the methods of these calibrations and validations, and the corresponding data requirements.

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 are 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 fan's performance depends primarily on its fan curves, including the pressure curve and the power curve (Liu and Liu 2012). 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 fan's flow rate, power, and differential pressure in an experiment. Therefore, fan models are usually calibrated and validated at the component level. For an 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 dependent on the type of 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, the Modelica fan model can be validated 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. These simulated results are then compared to the measurement in a 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, as well as 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.

Based on the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Guideline 14 (A standard for measurement of energy, demand, and water savings) (American Society of Heating, V., and Air Conditioning Engineers (ASHRAE) 2014; Garrett and New 2016), Federal Energy Management Program (FEMP) criteria (A standard to guide federal agencies in improving energy efficiency, reducing emissions, and adopting sustainable practices) (Webster et al. 2008), and International Performance Measurement and Verification Protocol (IPMVP) (A framework to quantify, report, and verify savings from energy and water efficiency) (Cowan 2002; Ruiz, and C, and Bandera 2017), the common validation metrics include Root Mean Squared Error (RMSE), Coefficient of Variation Root Mean Squared Error (CV(RMSE)), coefficient of determination (R^2), the Goodness-Of-Fit index (GOF), and cost function (f_i). These documents summarize the criteria for validating a calibrated model, for example, CV(RMSE) $<$ 15% (American Society of Heating, V., and Air Conditioning Engineers (ASHRAE) 2014; Garrett and New 2016; Cowan 2002; Payne, Yoon, and Domanski 2017), $R^2 > 0.75$ (Garrett and New 2016; Webster et al. 2008; Cowan 2002), etc. Researchers can select validation metrics that best align with their particular research goals and context. These validation metrics apply not only to the component-level validation but also to the subsystem-level and system-level validation discussed in the following sections.

Subsystem-level calibration and validation

A subsystem is made up of components that cannot be divided because of the strong coupling between them. Such subsystems 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 (to obtain the parameters in the non-calibrated components) and validated as a whole. For example, an air loop model in Modelica has components such as fans, air ducts, and dampers. The goal of the calibration for the air loop model is to simulate the air flow rates that pass through the subsystem accurately. As mentioned before, the fan is usually calibrated at the component level. However, the pressure resistances of the remaining components, such as dampers and ducts, need to be determined. These components need to be calibrated as a subsystem because of the lack of measurements in a typical air loop system that would provide enough granularity for component-level calibration of ducts and dampers.

Subsystem-level calibration involves the calibration of several performance parameters. This can be achieved by formulating it as an optimization problem (Martinez-Viol et al. 2022; Chakrabarty et al. 2021), 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 main steps include: (1) Conversion of the Modelica model to an Functional Mock-up Unit (FMU). This step allows Modelica to be imported by 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 structure, 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) 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 measured values. During optimization, the error of the flow rate should be considered in the objective function. (3) Updating the parameters in the Modelica

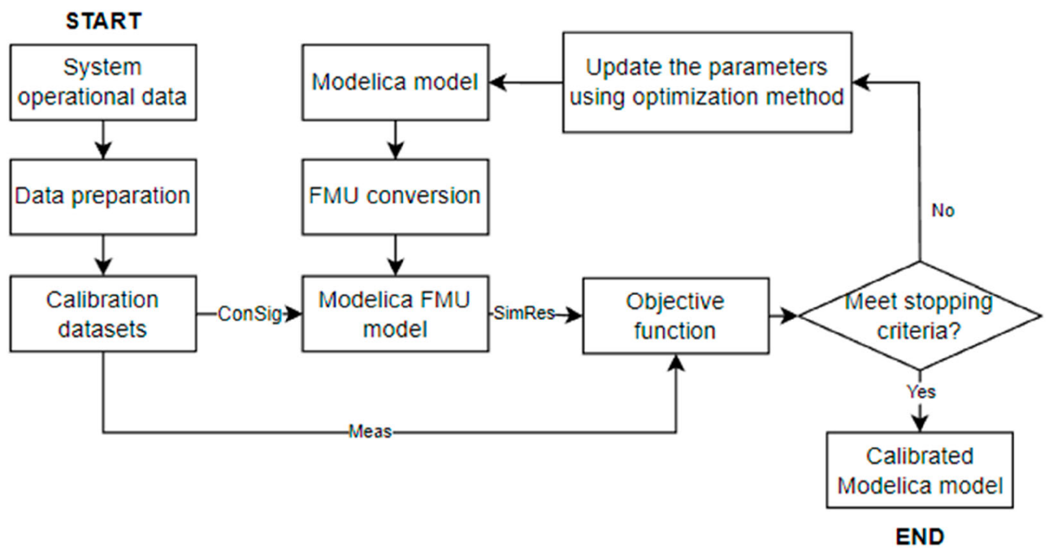

Figure 2. The optimization process for calibrating a subsystem model in Modelica.

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 (Yao and Shekhar 2021).

After the subsystem-level calibration, the calibrated Modelica model is validated at the subsystem level. Similar to the optimization calibration, during validation, the Modelica model uses the same control signals as the real system in an attempt to replicate the behaviour 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 system's behaviour, 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, the air flow rate of each component is checked first during validation. If the air loop contains a component that consumes energy, such as a fan, 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, that component's inlet and outlet fluid temperature should be checked.

System-level validation

After the coupled components and subsystems have been calibrated and validated correspondingly, the last step of the framework is to reassemble them for system-level validation. The system-level validation methods used are the same as those described above for sub system-level validation, i.e. using the same control signals as the real system for the calibrated Modelica model and comparing the behaviour of the critical parts of the model. If the error between Modelica simulation results and the real measurements meets the criteria, then it can be concluded that the calibrated Modelica model can accurately model the behaviour of the real system at the system level. If the system-level validation result is out of the acceptable criteria, it is necessary to check whether the system decoupling is appropriate. The errors at the component level and the subsystem level will eventually propagate into the final system-level errors. Inappropriate decoupling of the system will make this propagation large and difficult to estimate. For example, a wrong decoupling approach will fail the system-level validation due to ignoring the strong association of the decoupled components. The focus of the validation will be different depending on the use of the model. In general, for an entire HVAC system, the system-level validation focuses on system energy consumption and zone supply air conditions (impacting the zone environment), which are the metrics occupants and managers generally care about.

Case study

Description of the case study

The proposed framework was applied to an AHU-VAV system model in Modelica that represents the real subsystem in the IBAL shown in Figure 3. This case study is an extension of a previous conference paper (Li et al. 2023). The IBAL is designed to emulate a small commercial office building. The air system contains the zones and

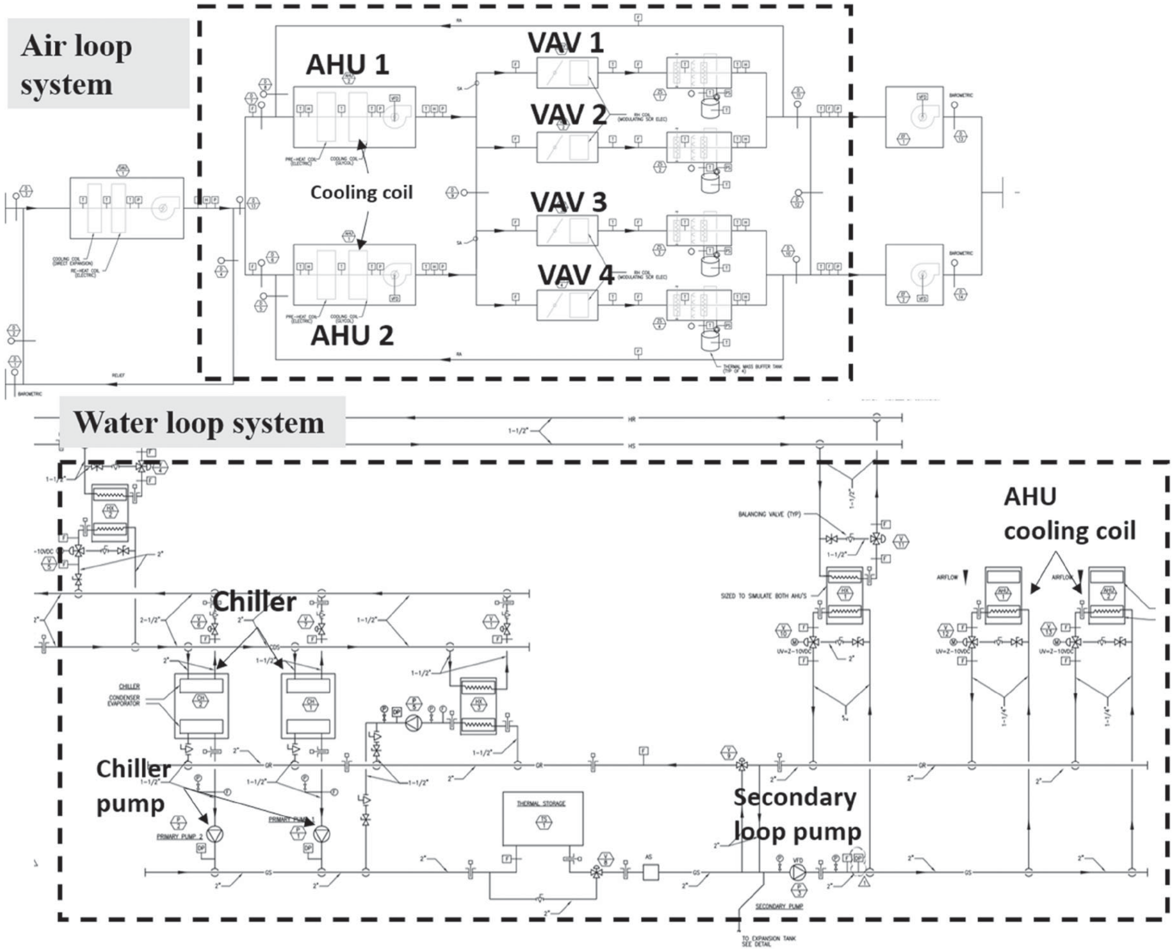

Figure 3. IBAL diagram (Pertzborn and Pertzborn 2019).

the equipment used to condition the air for the zones, while the water loop system contains the equipment used to provide cooling for the air system. The air loop in the IBAL contains zones and equipment, including coils, variable-speed fans, dampers, and ducts. The IBAL has two AHU air loops; each AHU is connected to two VAV boxes, and each VAV box serves one zone. The water loop equipment in the IBAL consists of two variable-speed chillers, four pumps, two valves connected to the coils in the AHUs, and several pipes. In the evaporator loop, the two chillers will be chosen to serve the system based on the cooling load, supplying cold 30% propylene glycol to the cooling coils by the corresponding chiller pump and secondary loop pump. In the condenser loop, a pump supplies chilled water to the chiller.

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 (Chen et al. 2023) and additional experimental tests conducted to supplement the existing data. The operational data include (1) the control signals of the equipment, including fans and dampers, chillers, pumps, and valves, (2) measurements of the system power, including fans, pumps, and chillers, and (3) measurements in the air loop and water loop. Specifically, the supply air temperature to the VAVs, humidity, and flow rate in the air loop, and the chilled water temperature and flow rate through the chillers and cooling coils in the water loop. The resolution of the operational data is one minute. Figure 3 labels the air loop system, the water loop system, and the key components within the systems.

System decoupling

According to the proposed calibration framework, the first step is to decouple the system. Based on the mass balance and energy balance, a typical AHU-VAV system can be divided into an air loop subsystem, a water loop subsystem, and a thermal subsystem. 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 calibration at the component and subsystem levels, the system-level performance is validated for the entire air

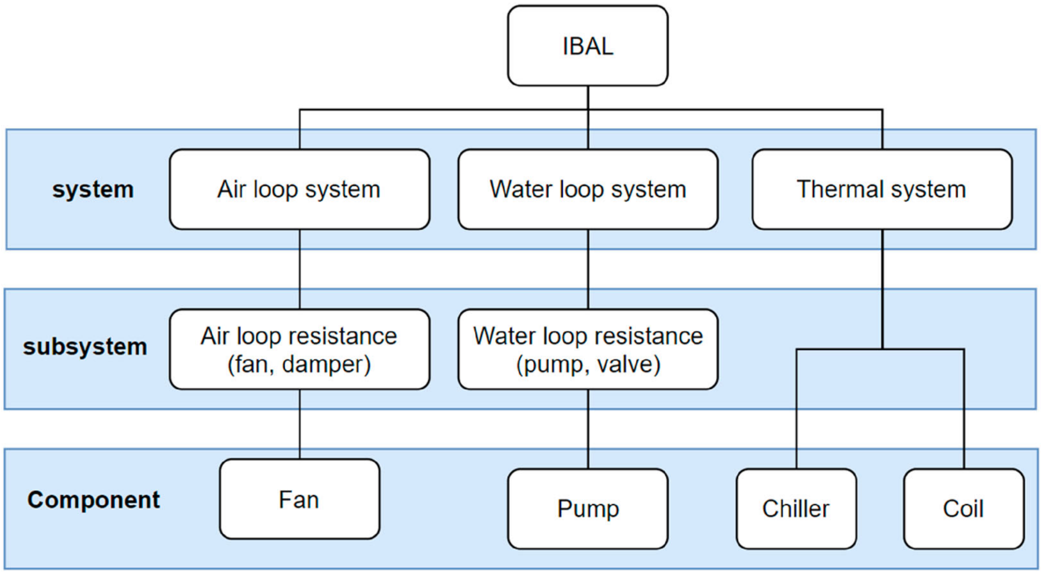

Figure 4. IBAL system decoupling result.

loop subsystem. By the same reasoning, the calibration of the water loop subsystem can be divided into pump component-level calibration and water loop pressure resistance subsystem-level calibration. In the IBAL system, the energy variation occurs mainly in the chillers and coils. Since the performance of those components is primarily influenced by their own performance parameters, these two components will be calibrated at the component level. The IBAL system decoupling result is shown in Figure 4.

Air loop subsystem

There are two AHU air loops in the IBAL system. As the two air loops are weakly coupled to each other, and to avoid content redundancy, the AHU1 loop will be used as an example in the air loop subsystem-level calibration and validation. 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.

Fan component-level 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 (Wetter 2013). 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). Because the complete fan curves are difficult to obtain from normal operational data, they 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 (Wetter 2013; Lu et al. 2005). 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 the two plots in 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 ($R^2 = 0.999$) and the first-order fit to the power fan curve ($R^2 = 0.996$); the solid green points are selected from the fitted curves and used by the Modelica fan model to represent the calibrated fan curves.

The Modelica fan model was also validated at the component level. A simple air loop model was developed in Modelica, which includes the calibrated fan model and pre-built damper and ducts. Pressure rises, energy consumption, and flow rates can be obtained by keeping the fan running at full speed and adjusting the damper opening fraction. The calibrated fan model was validated by comparing the Modelica model simulation results with the curve fitted from the experimental data mentioned before. The red points in 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

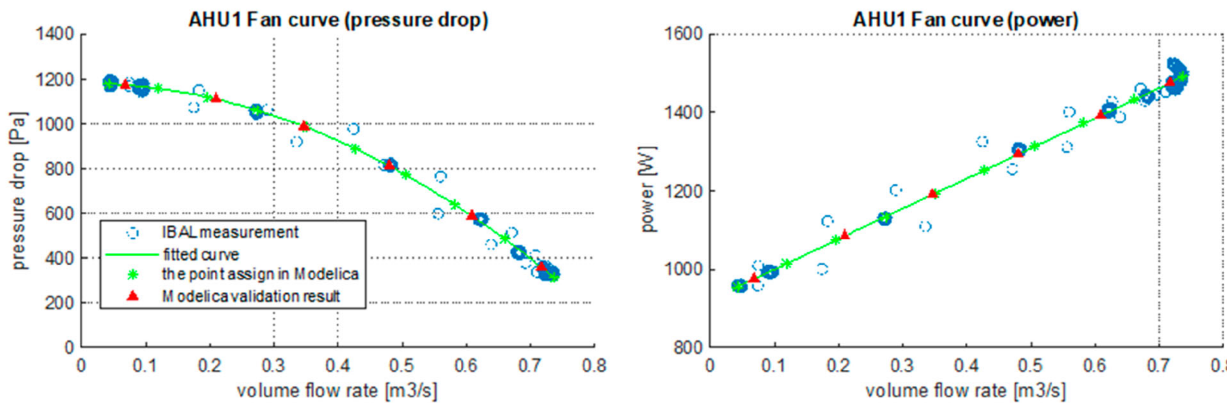

Figure 5. Pressure-drop and power fan curves in fan component-level calibration and validation.

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 those for the fan in AHU1, in which the simulated fan model output agrees well with the measurements.

Air loop resistance subsystem-level 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. Based on observations of operational data, the air damper model with exponential opening characteristics is used in Modelica (Wetter 2009).

Calibration of the air loop pressure resistance requires determination of damper performance parameters, inclu ding the nominal mass flow rate, nominal pressure drop, and damper coefficients. The air loop pressure resistance was 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' and 'kmeans' (Arthur and Vassilvitskii 2006). 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 (Figure 7).
2. Conversion of the Modelica model to an FMU: In this case study, the optimization process was implemented in the MATLAB & Simulink environment. Therefore, the air loop Modelica model was converted into an FMU to interact in this environment using the function of 'Export FMU' (the relevant key settings include: Type: co-simulation using Cvode; Model description filters: Exclude protected variables; and Options: Copy resources to FMU, etc.) (Pazold et al. 2012). 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 & Simu link 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: The 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 (Ruiz, and C, and Bandera 2017), was used to calculate the error between the Modelica simulation result and the measurement. The objective function is shown in Equation (1) below, where *x* is the adjustable parameter set of the dampers; *NumCaliData* is the total number of calibration datasets, which is 5 in this case study; *NumAir_m* is the number of air mass flow rates considered in the

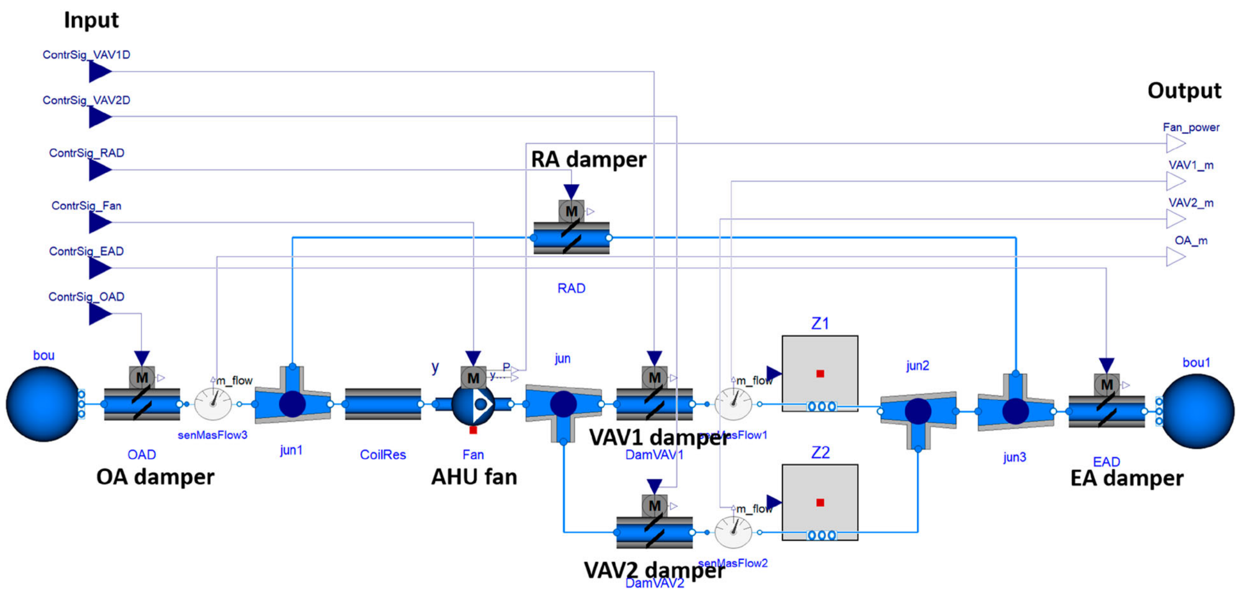

Figure 6. Modelica model of one of the AHU air loops.

objective function, which is 3 (the air in VAV1, VAV2, and outdoor air) in this study. Given the parameter x, the Modelica model will generate the corresponding simulation results, denoted Sim_x. The$Sim_{x,ij}$ and Mea_{ij} represent the simulated and measured values of the air mass flow rate$i$under the calibration dataset j. The mean CV(RMSE) was calculated based on the air flow rate in the VAVs and the OA dampers in the five calibration cases.

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

5. Optimizing model parameters: A genetic algorithm, specifically the MATLAB function 'ga', was 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 that need to be calibrated, **m**, **dp**, **a**, **b**, **K1**, **L**, **yL**, and **yU**. The values of each parameter were constrained by the ranges listed in Table 1. The upper and lower bound selection is based on an estimation based on operational data (such as the damper maximum flow rate and damper pressure drop under fully open) or a reasonable amplification based on the default value (such as the damper coefficients a and b, which range from 0 to twice the default value). 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 is fully open, 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.

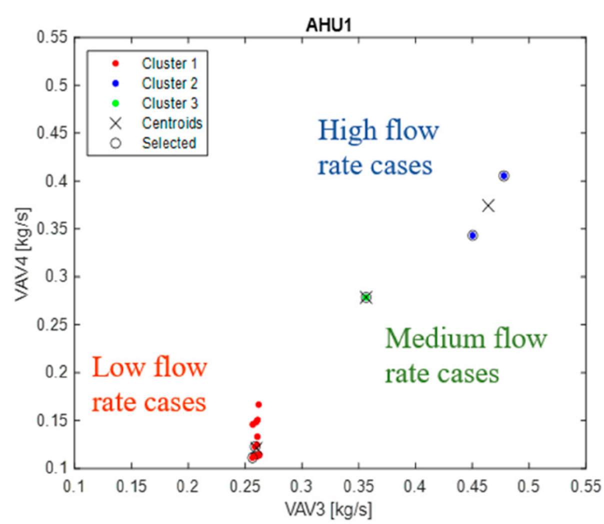

Figure 7. Air loop subsystem-level calibration datasets selection.

6. Optimization termination: The default options of the MATLAB 'ga' function were used in this study, except function tolerance. Based on the observation that the objective function decreases very slowly after reaching about 100 generations, as shown in Figure 8 below, the functional tolerance is adjusted from the default of 10^{-6}–10^{-4} as the stopping criterion. When the stopping criterion was met, the optimization calibration stopped, and the calibrated air loop Modelica model was obtained.

The progress of the optimization using the genetic algorithm in MATLAB is shown in Figure 8. After 149

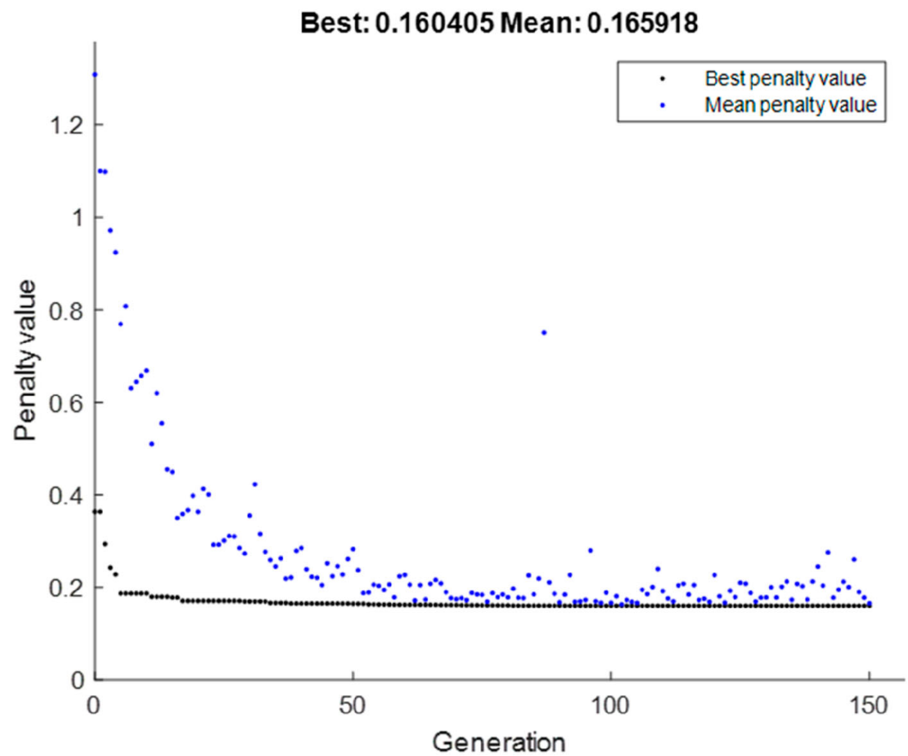

Figure 8. The minimum objective function value for each generation during optimization with GA.

Table 1. The bounds of the parameters of the dampers in the 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 is fully open. The parameter **dp** represents the pressure drop at the maximum flow rate when the damper is fully open. The parameters **a** and **b** are the coefficients for damper characteristics. The parameter **K1** is the loss coefficient when the damper is fully open. The parameter **L** represents damper leakage ratio. The parameters **yL** and **yU** represent the lower and upper values for the damper curve (Wetter et al.2014).

generations, the optimization was terminated by reaching the function tolerance. The optimization program outputs 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 calibration 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 were input to the calibrated Modelica model. Then the simulated fan power and the air flow rate in VAV1, VAV2, and OA dampers were compared to the measurements. The model simulation accuracy was validated by calculating the corresponding RMSE values, which will be discussed in the *Analysis of the validation results* section. The typical thermal load validation case in AHU1 (as shown in Figure 9) 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.

In terms of air flow rate in the VAVs and outdoor air flow for the two AHU air loops, considering the different average flow rates of the various dampers in the air loop, the RMSE is used to evaluate the accuracy of the calibrated model. From the perspective of occupant thermal comfort, an RMSE of 0.059 kg/s (equivalent to 100 CFM) is used as the criterion for validating the model based on ASHRAE Guideline 14 Section 5.3.2 (Garrett and New 2016) and IPMVP Appendix C (Ruiz, and C, and Bandera 2017). Based on the validation criterion, the calibrated model is acceptable for the air flow distribution in the air loop. In terms of energy consumption, the RMSE for

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 (RMSE) in the validation of the AHU1 air loop.

	Mass flow rate [kg/s]			
Validation case	VAV1	VAV2	OA	AHU1 Fan power [W]
Low thermal load	0.019	0.036	0.033	37
Medium thermal load	0.017	0.029	0.030	47
High thermal load	0.019	0.025	0.025	53

the fan power is less than 53 W, which is less than 15% of the average power. This meets the validation criterion according to ASHRAE Guideline 14 (Garrett and New 2016). Considering that the air loop accounts for only about 10% of the total energy consumption of the system, this validation error is acceptable. In conclusion, the calibrated Modelica air loop model can accurately simulate the dynamic behaviour of the real IBAL system under different operating conditions.

Water loop subsystem

Pump component-level calibration and validation

Similar to the air loop subsystem, the water loop subsystem was also divided into a component-level calibration for the pumps and a subsystem-level calibration for water loop pressure resistance. The water system contains four pumps, namely the condenser loop pump, the pump connected to chiller 1, the pump connected to chiller 2, and the secondary loop pump. Based on the operating data, it is observed that the condenser loop pump, the chiller 1 pump, and the chiller 2 pump run in only one operational condition. In other words, these pumps' power and pressure rise are fixed, which can be easily obtained from the operational data. Therefore, this section does not show the component-level calibration and validation work for those three pumps, but the validation results of these three pumps will be included in the system-level validation section. This section will focus on the component-level calibration and validation of the secondary loop pump.

The calibration method for the pump is the same as the fan calibration method mentioned above, in which the calibration object is the device curve between the flow rate and the power or pressure (Wetter 2013). The full-speed pump curves relating the flow rate with the pressure drop and power were obtained using the same system flexibility load study (Chen et al. 2023). After curve fitting, the pump curves were assigned to the pump model in Modelica and validated in a loop with definable boundary conditions in Modelica. Figure 10 shows the secondary loop pump calibration and validation results. The plots show the pump curves fitted from the pump's real data, the points assigned to the pump Modelica model, and the validation point. Because the pump will only operate within the range of the curve during actual operation, the pump curve in Figure 10 is not the full pump curve. In this case, although the R^2 of the curve fits do not meet the general criterion of 0.75 (Ruiz, and C, and Bandera 2017), the validation results, CV(RMSE) (dp) = 4.67% and CV(RMSE) (power) = 3.82%, both meet the criterion of 5%, which is the uncertainty of system measurement (Chen et al. 2023). Therefore, the calibration results meet the requirements.

Water loop resistance subsystem-level calibration and validation

The IBAL system has two water loops, the condenser loop and the secondary loop. The condenser loop is relatively simple, with cold water supplied by the NIST site-wide plant in parallel to the two chillers. The supply water flow is controlled by the valves connected to the two chillers, which will only be in the fully open or fully closed state. It is only needed to calibrate the parameter **m** and **dp** of the valves, which represents the mass flow rate and pressure drop, respectively, at the maximum flow rate when fully open. Both values can be derived from operational data and are not presented here.

Figure 11 shows a Modelica model used to calibrate the secondary loop pressure resistance. In this secondary water loop, two chillers and corresponding pumps are connected in parallel to supply chilled water to two cooling coils connected in parallel. The chilled water flows through the cooling coils are controlled by the secondary pump and the valves. In addition, as safe mechanisms, two loops (bypass loop and heat exchanger loop) are used to equalize the pressure in the secondary water loop. In that Modelica model, the parameters to be calibrated are the resistance parameters, **m** and **dp**, for the bypass

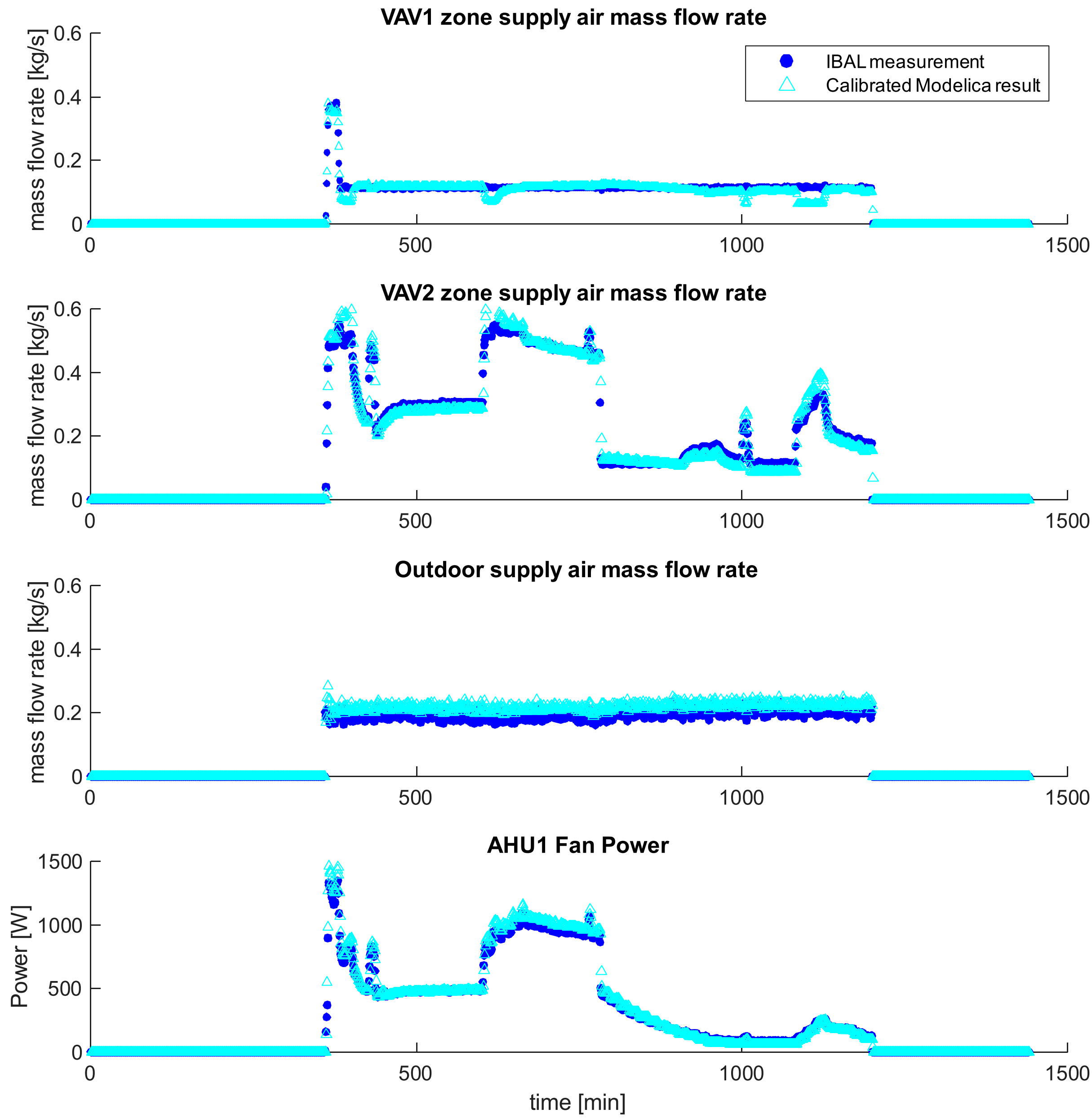

Figure 9. The validation result of the AHU1 air loop using typical thermal load case data.

loop and heat exchanger loop and the parameters, **m**, **dp**, **delta**, and **R**, for the two AHU cooling coil valves. The multivariate optimization method mentioned in the air loop subsystem-level calibration and validation was used to calibrate the parameter set for the secondary loop pressure resistance. The method first identified five calibration datasets representing extreme low/high and typical low/medium/high water flow rates, respectively. Then, an objective function was established to calculate the average CV(RMSE) of the water mass flow rate through the cooling coils and secondary loop pump between the Modelica model simulation results and the calibration datasets. The objective function is shown in Equation (2) below, where x is the adjustable parameter set of the secondary loop resistance; *NumCaliData* is the total number of calibration datasets; *NumWater_m* is the number of water mass flow rates considered in the objective function, which is 3 (the water flow rate through the two valves and the secondary loop pump) in this study. The pressure parameters in the Modelica model were tuned using a genetic algorithm to find the set of parameters that minimize the above objective function. The values of each parameter were selected from the ranges listed in Table 4.

$$J(x) = \frac{\sum_{j=1}^{NumCaliData} \sum_{i=1}^{NumWater\_m} CV(RMSE)_{(Sim_{x,ij}, Mea_{ij})}}{NumCaliData \times NumWater\_m} \tag{2}$$

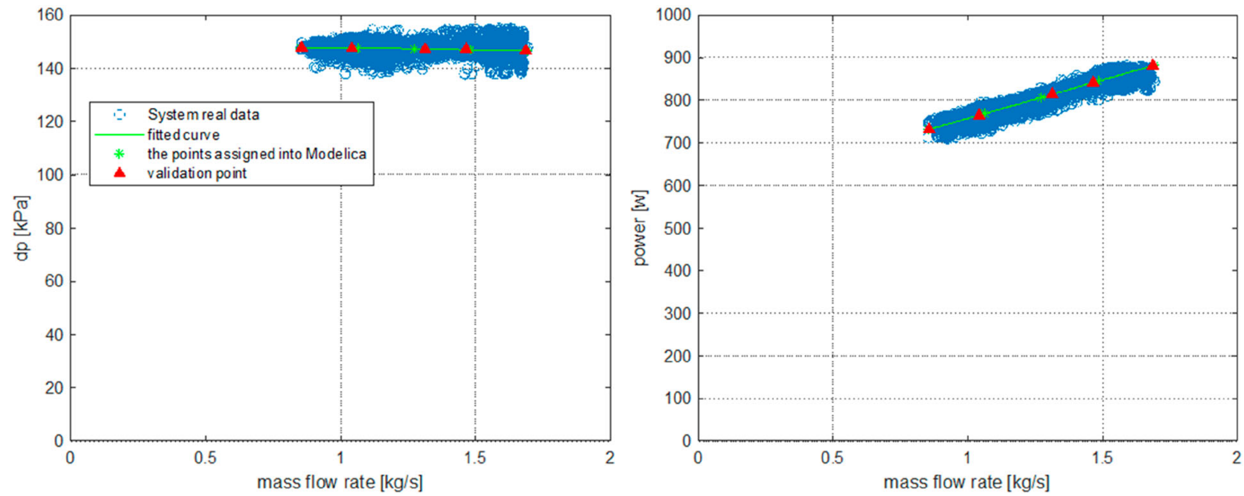

Figure 10. Secondary loop pump calibration and validation results (left: pump pressure drop curve; right pump power curve).

Table 4. Parameter ranges for secondary loop calibration.

Object	m [kg/s]	dp [$\times 10^5$ Pa]	L	delta	R
Bypass resistance	0.50	[0.1, 3.4]		NA	
HX resistance	0.60	[0.1, 6.2]			
AHU1 valve	0.45	[0.1, 6.2]	[0, 0.0002]	[0, 0.02]	50 or 100
AHU2 valve	0.65				

Note: The parameter **m** represents the nominal mass flow rate. The parameter **dp** represents the nominal pressure drop of the fully open valve. The parameters **L** represents the valve leakage. The parameters **delta** represents the range of significant deviation from the equal percentage law. The parameters **R** represent the rangeability of the valve (Wetter et al.2014). NA is not applicable.

Table 5. Summary of validation error (RMSE) of secondary loop Modelica model.

	Mass flow rate [kg/s]		
Validation case	AHU1_f	AHU2_f	SL_Pump_power [W]
Low thermal load	0.0296	0.0279	33
Medium thermal load	0.0365	0.0579	37
High thermal load	0.0449	0.0605	38

Three datasets were selected from the system flexibility load study representing low, medium, and high thermal load cases to validate the model. The control signals for the chillers, pumps, and valves were used as inputs, and the simulated secondary loop pump power and the water mass flow rate through the cooling coil were the outputs of the model. The validation results are shown in Figure 12, which compares the Modelica model simulated results with the actual measurements at medium thermal loads. Table 5 summarizes the full validation results. The acceptance criteria for the validation results are 0.063 kg/s (equivalent to 1 GPM) for the water flow RMSE and 50 W (5% of the average power) for the power RMSE, which are met, so the calibrated IBAL water subsystem Modelica model is accepted.

Thermal subsystem

As the equipment where primary heat exchange between fluid mediums occurs, the two components, chiller and cooling coil, are the components that need to be calibrated in the thermal subsystem. They are very weakly coupled with each other, and, therefore, both were calibrated at the component level.

Chiller component-level calibration and validation

The DOE2 electric chiller model was used in the Modelica model and calibrated using the method proposed by Hydeman and Gillespie Jr (2002). The method can be summarized as calculating the curve coefficients for the CAPFT (the available capacity function), EIRFT (the full-load efficiency function), and EIRFPLR (part-load ratio efficiency function) functions by applying standard least squares linear regression using the chiller data in full-load and part-load conditions. These data were provided by additional chiller testing. After the calibration, data from the system flexibility load study representing low-, medium-, and high-thermal load cases were also used for validation in a loop with definable boundary conditions in Modelica. In the validation, the inputs were condenser and evaporator inlet water temperature and mass flow rate, and the evaporator outlet water temperature

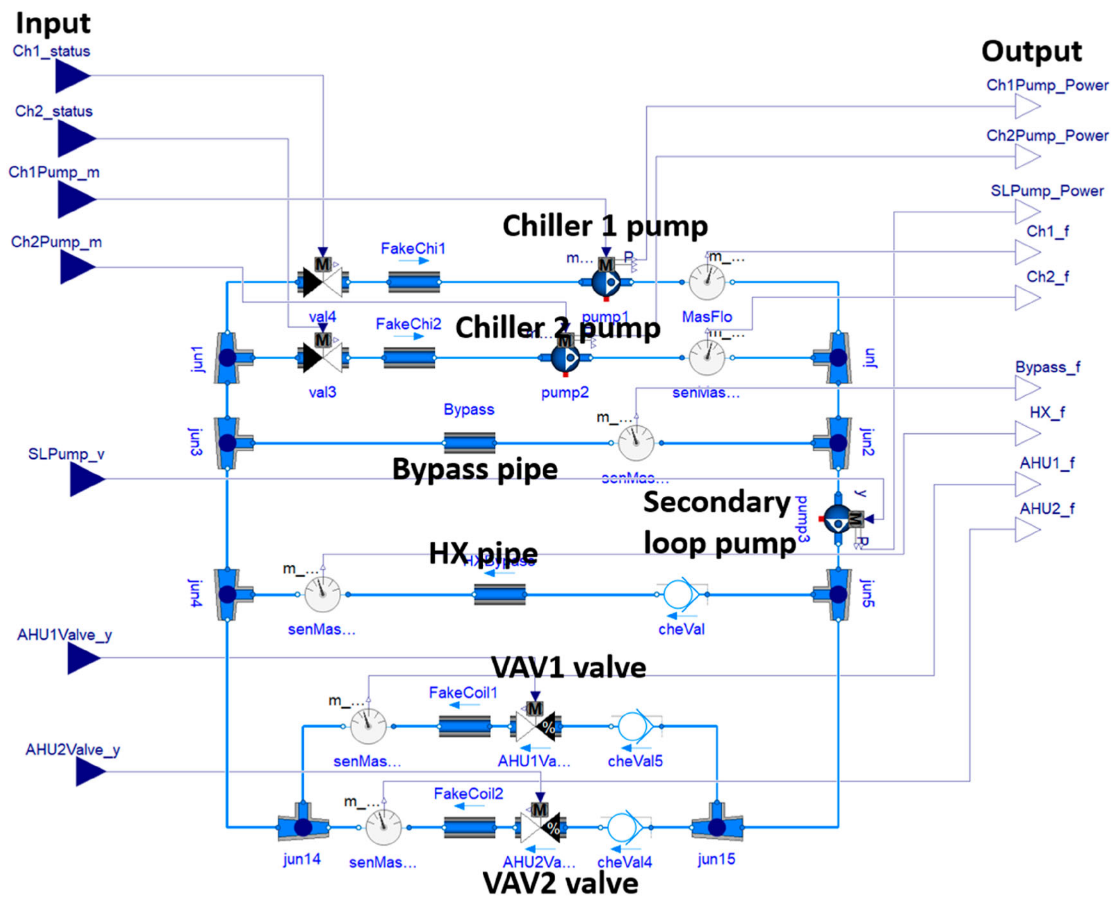

Figure 11. Modelica model of the secondary water loop.

Table 6. Summary of chiller power validation error (RMSE) of the Modelica models.

	Variables	
Validation case	Chiller1_power [W]	Chiller2_power [W]
Low thermal load	124	109
Medium thermal load	134	169
High thermal load	165	155

setpoint; the outputs were chiller power and evaporator outlet water temperature. The validation was concluded by comparing the Modelica simulated chiller power with the measurement from the real data. As an example, Figure 13 shows the validation result of chiller 1 in low-thermal load conditions. The validation results for both chillers are summarized in Table 6. The maximum RMSE for chiller 1 and chiller 2 power in the validation cases is 135 and 169 W, respectively, which are both less than 5% of the average power and, therefore, acceptable.

Cooling coil component-level calibration and validation

For the cooling coil Modelica model, it is necessary to calibrate the parameters $\mathbf{m_a}$, $\mathbf{m_w}$, and ϵ, which represent the nominal air mass flow rate, water mass flow rate, and heat transfer effectiveness, respectively. Among them, $\mathbf{m_a}$ and $\mathbf{m_w}$ can be obtained from the operational data, and ϵ can be calculated by the method proposed by Wetter M (Wetter 1999). The validation method is the same as the method described above for the chillers. The validation compared Modelica simulated results with the measurement from the real data by inputting air loop and water loop inlet fluid mass flow rate, temperature, and humidity ratio to the Modelica coil model, and outputting the outlet fluid temperature and humidity ratio. Figure 14 shows the AHU1 cooling coil validation results for outlet water temperature (T_{w-out}), outlet air temperature (T_{a-out}), and outlet air humidity ratio (w_{a-out}) under the medium-thermal load case. Table 7 summarizes the cooling coil validation results in the three validation cases. The RMSE of outlet air temperature and humidity ratio and the outlet water temperature all met the error criteria of 0.56 °C (1 °F) and 4.5×10^{-4} $kg_{water}/kg_{dry-air}$ (5% of the average outlet air humidity ratio), respectively, in the validation of the cooling coils of AHUs 1 and 2.

System-level validation

As described above, the subsystem-level calibration and validation of the air loop, water loop, and thermal

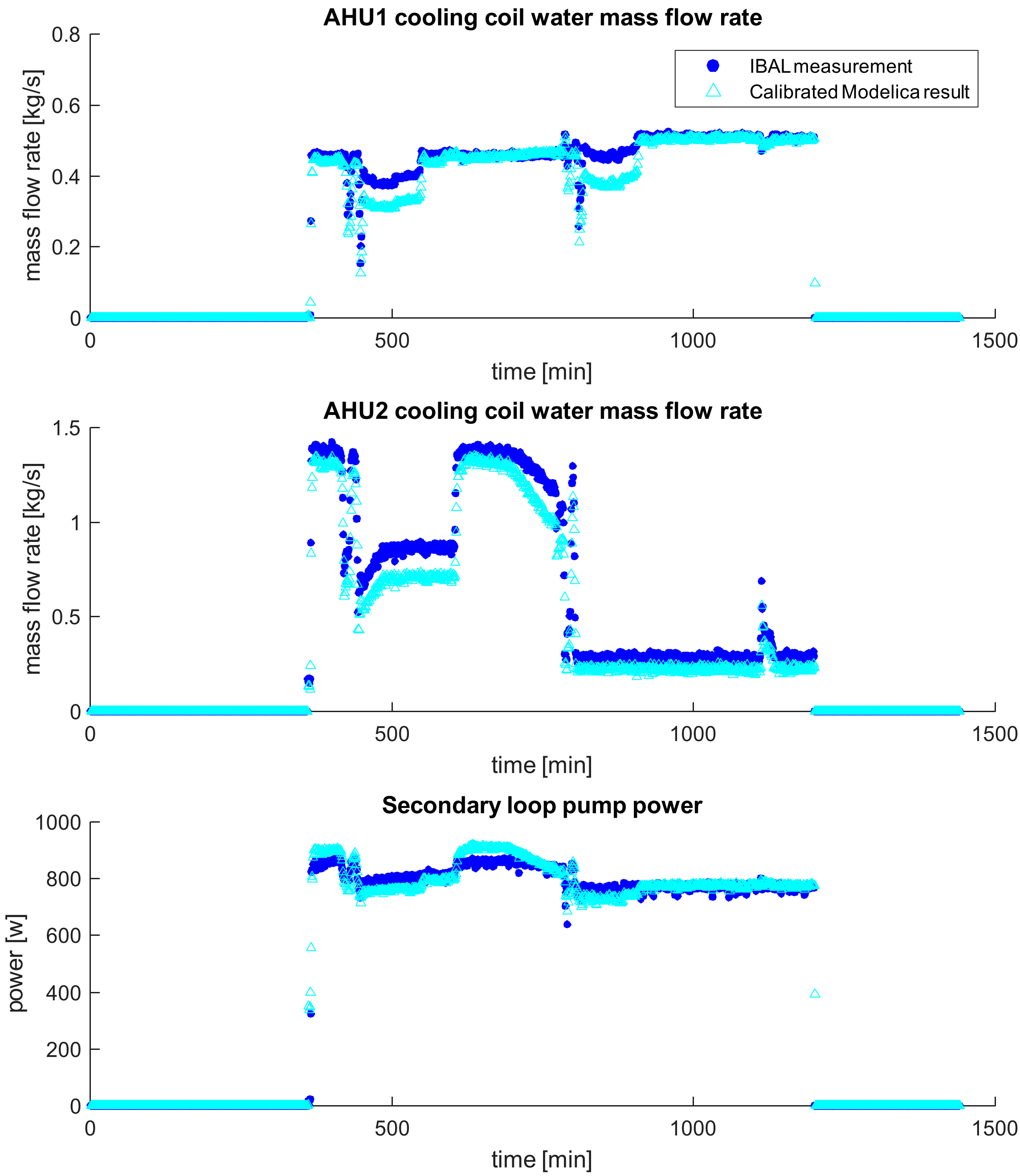

Figure 12. Validation result of secondary loop Modelica model in medium thermal load case.

Table 7. Summary of cooling coil validation error (RMSE).

Validation case	Variables					
	$T_{w-out-coil1}$ [°C]	$T_{a-out-coil1}$ [°C]	$w_{a-out-coil1}$ [$kg_{water}/kg_{dry-air}$]	$T_{w-out-coil2}$ [°C]	$T_{a-out-coil2}$ [°C]	$w_{a-out-coil2}$ [$kg_{water}/kg_{dry-air}$]
Low thermal load	0.51	0.38	3.3×10^{-4}	0.48	0.40	4.0×10^{-4}
Medium thermal load	0.56	0.34	4.3×10^{-4}	0.48	0.41	3.7×10^{-4}
High thermal load	0.32	0.33	3.5×10^{-4}	0.52	0.44	3.5×10^{-4}

subsystems were successfully completed. Subsequently, these three subsystems were integrated for the whole system-level validation of the IBAL. Again, three datasets representing low, medium, and high thermal load cases were selected from the system flexibility load study (Chen et al. 2023). In system-level validation, the Modelica

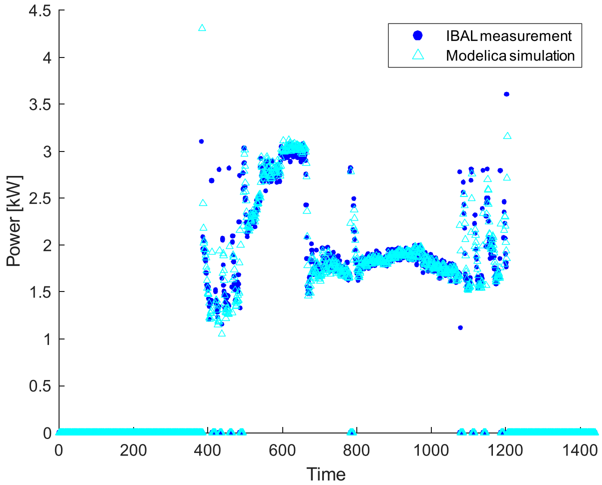

Figure 13. Chiller 1 validation result in low-thermal load case.

model receives control signals for various components, including chiller, pump, valve, fan, and damper. Additionally, it considers boundary conditions like plant inlet water temperature, outdoor air conditions, and zone cooling loads. The primary aims of this validation are the power consumption of the equipment in the system and the zone supply air condition. Consequently, the outputs from the Modelica model are the power of the pumps (condenser loop pump, secondary loop pump, chiller 1 and 2 pumps), chillers (chiller 1 and 2), and fans (AHU1 and 2 fans), as well as the supply air conditions (temperature, mass flow rate, and humidity ratio) of the four zones. Figure 15 shows the validation results of the medium-thermal load case. Table 8 and Table 9 summarize the RMSE values under all validation cases. From this result, the validation results in supply air condition are all within the error criteria of 0.059 kg/s for flow, 0.56 °C (1 °F) for temperature, and 4.5 x 10^{-4} $kg_{water}/kg_{dry-air}$ for humidity. Considering the power error criterion of 5% of average power (about 8 kW), so the RMSE of the power satisfies this criterion. In conclusion, the calibrated IBAL Modelica model can accurately simulate the dynamic behaviour of the real IBAL system under different operating conditions.

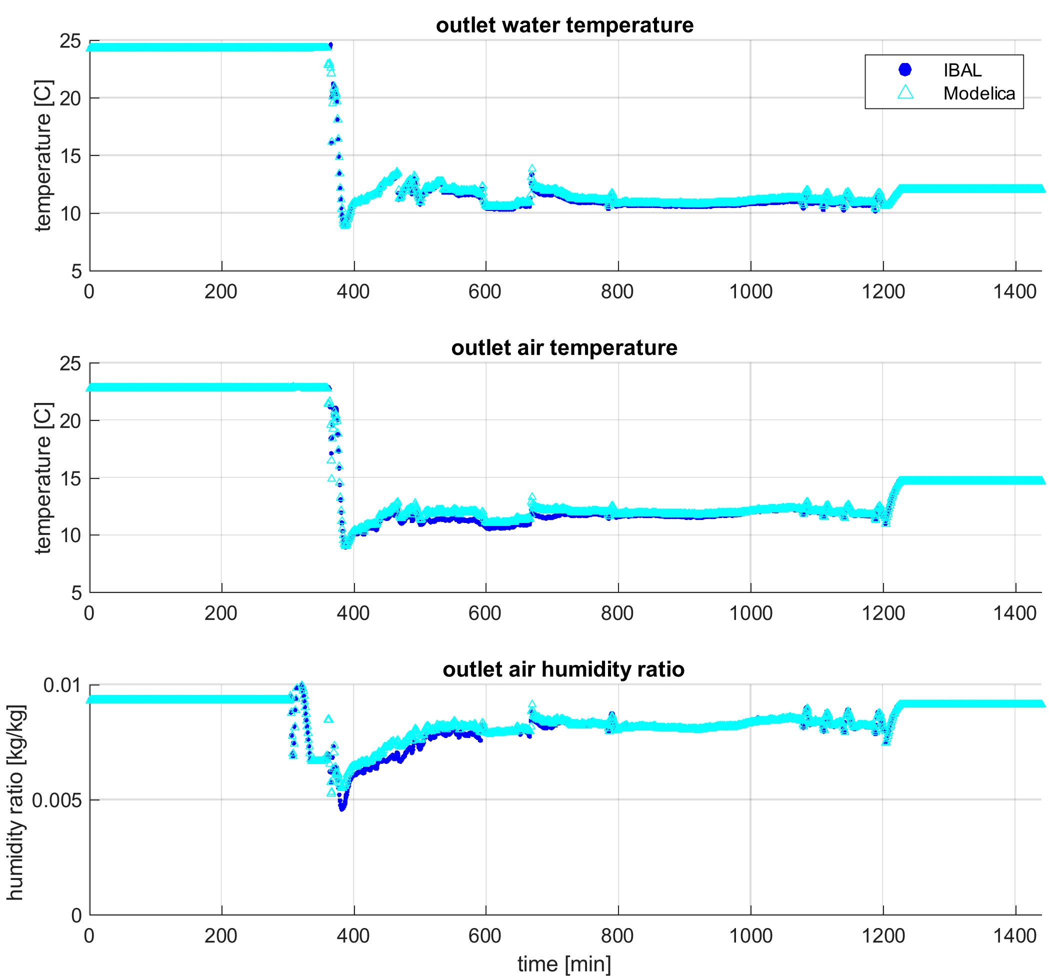

Figure 14. AHU1 cooling coil validation result at medium thermal load case.

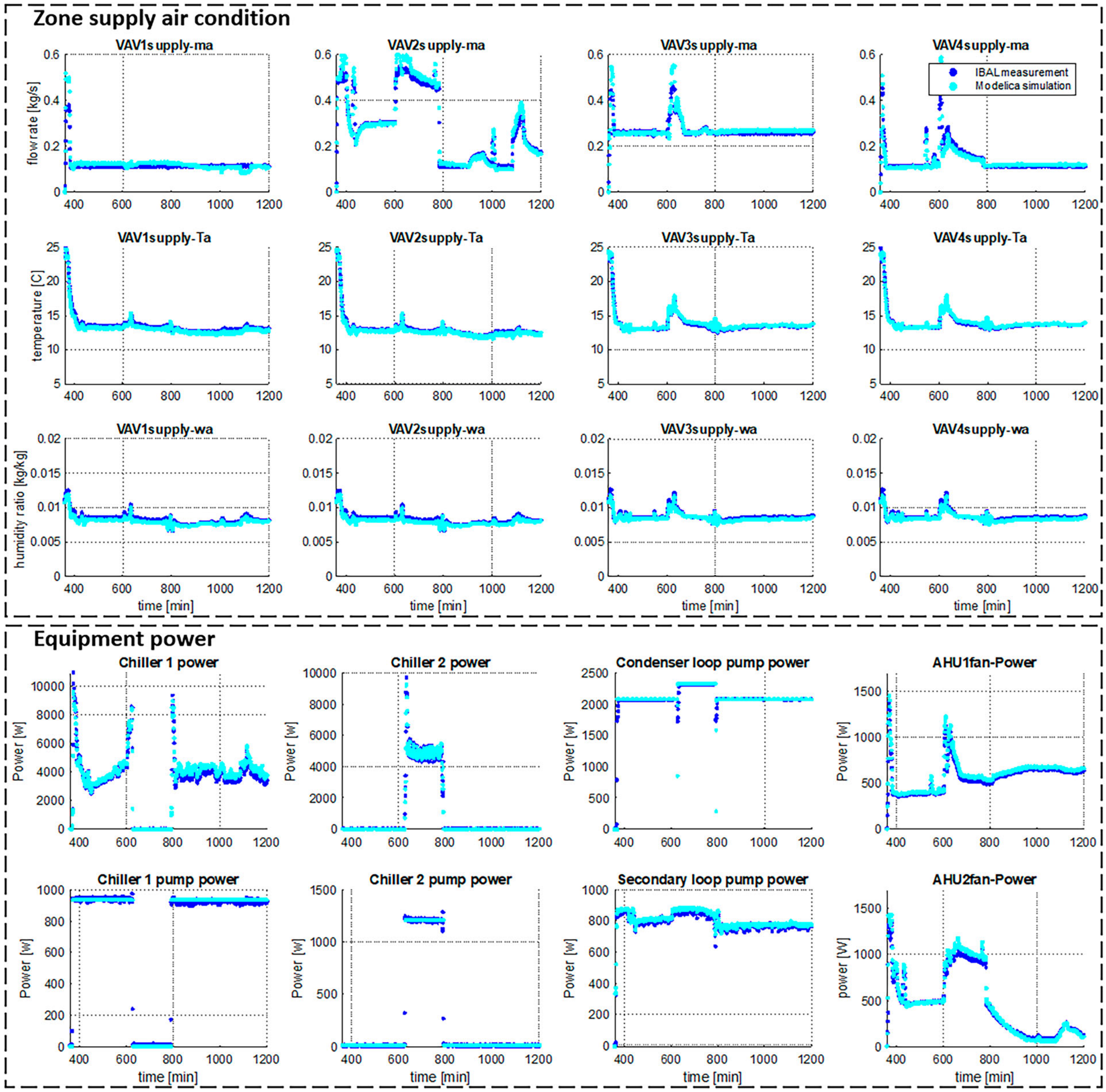

Figure 15. IBAL Modelica model system-level validation result.

Table 8. Summary of the validation errors (RMSE) in zone supply air condition.

Validation case		Zone supply air condition		
		m [kg/s]	T [°C]	w [$\times 10^{-4}$ $kg_{water}/kg_{dry-air}$]
Low-thermal load case	VAV 1	0.018	0.46	3.5
	VAV 2	0.024	0.38	3.2
	VAV 3	0.008	0.14	2.7
	VAV 4	0.006	0.16	2.9
Medium-thermal load case	VAV 1	0.022	0.39	3.0
	VAV 2	0.025	0.30	2.8
	VAV 3	0.019	0.19	2.5
	VAV 4	0.018	0.18	2.7
High-thermal load case	VAV 1	0.027	0.46	4.1
	VAV 2	0.028	0.41	4.1
	VAV 3	0.028	0.29	3.0
	VAV 4	0.031	0.27	3.1

Table 9. Summary of the validation errors (RMSE) in component power.

Validation case	Power [W]								
	chiller 1	chiller 2	pump 1	pump 2	pump 3	pump 4	AHU1 fan	AHU2 fan	Total
Low-thermal load case	166	25	13	5	29	60	41	27	176
Medium-thermal load case	204	101	42	55	27	85	47	39	341
High-thermal load case	173	145	68	85	27	103	36	46	390

Discussion and conclusions

Analysis of the validation results

In the case study chapters, the validation results at the component level, the subsystem level, and the system level are briefly discussed after the corresponding calibrations were completed. This section summarizes and analyzes the validation results.

First, for the validation error of the VAV supply air condition, based on the recommendations of ASHRAE and IPMVP, a flow RMSE of 0.059 kg/s, a temperature RMSE of 0.56 °C (1 °F), and a humidity RMSE of 4.5×10^{-4} $kg_{water}/kg_{dry-air}$ are selected as the air loop validation criteria. The impact on indoor occupant comfort is acceptable at these error levels. In terms of system power, CV(RMSE) = 5% average power is chosen as the validation criterion, which is used for the validation of individual equipment and the whole AHU-VAV system. For the water loop validation, a temperature RMSE of 0.56 °C (1 °F) and a flow rate RMSE of 0.063 kg/s are selected as the validation criteria. Note that in the final system-level validation, the manager or occupant would typically care more about the indoor environment and system energy consumption rather than the details of the water distribution and air distribution within the system. Therefore, only the VAV supply air condition and system power are checked in the system-level validation. Based on the results of the component-level, subsystem-level, and system-level validation as described above, all validation results meet the set validation criteria.

In addition, the consistency of the errors was observed under different levels of validation. For example, in the air loop resistance subsystem-level validation, the VAV1 and VAV2 supply air mass flow rate mean errors in validation are 0.018 and 0.03 kg/s, respectively, while in the system-level validation, these two metrics are 0.022 and 0.026 kg/s, respectively. The difference is not significant. As another example, in the chiller 1 component-level validation, the power mean error over the validation sets is 141W, while in the system-level validation, the mean error is 181 W. Again, the difference is not significant. This indicates that the same metric is consistent across different levels of validation. It also further illustrates the validity of the proposed calibration framework, which is based on decoupling the system.

Supplement of calibrating a comprehensive HVAC model in Modelica

This paper describes a framework for the calibration and validation of Modelica models of HVAC systems, which is applicable to the calibration of the parameters of the equipment in the system. A complete air loop involves heat exchange in the zone other than with the HVAC system. In addition, local control of the HVAC system is necessary for the operation of the HVAC system. These two considerations are not included in the calibration and validation framework presented in this paper. A high-level look at how to model real-life zones and local controllers of HVAC systems in Modelica is presented in this section.

The methods for modeling thermal zones in Modelica include:

- The thermal zone template provided in the Modelica Buildings Library. A typical thermal zone model consists of thermophysical elements such as walls, floors, ceilings, windows, and so on. The room Modelica model is completed by setting the thermal parameters of several objects. The method is summarized in detail by Wetter (2011).
- If a corresponding EnergyPlus model is already available, Spawn-of-EnergyPlus (SOEP) can be used to realize the interaction between EnergyPlus and Modelica models. SOEP converts an EnergyPlus input definition file into an FMU that can be used in Modelica (Spawn-of-EnergyPlus 2014).

The methods for modeling HVAC system local controllers in Modelica include:

- In Modelica, the reproduction of local controllers of the HVAC system, such as proportional–integral–derivative (PID) controllers, can be realized using the controls module provided in the Modelica Buildings Library (Wetter, Zuo, and Nouidui 2011). By setting the same parameters as the real controller, it reproduces the control strategy of each piece of equipment in the HVAC system to adjust the temperature, humidity, or flow rate.
- Modelica external functions, such as C or Fortran functions, can be called to implement the desired controls

by creating new Modelica classes and packages (Olsson and Dynasim 2005; Casella and Richter 2008). This allows the integration of specialized control algorithms and complex computations beyond Modelica's capability, thus increasing the model's functionality.

Recommendations for future work

In this case study, based on the literature (Ruiz, and C, and Bandera 2017), CV(RMSE) was used in the objective function in the air loop and water loop subsystem-level calibrations. This metric is not applicable when the magnitude of the components of the objective equation differ substantially. Applying the CV(RMSE) to evaluate the error may result in an overrate or underrate of part of the objective equation. Therefore, using mean or maximum values, CV(RMSE) or RMSE in the objective function needs to be carefully considered based on the situation.

In the air loop and water loop subsystem-level calibrations, a multivariate global optimization was used to calibrate the performance parameters in the Modelica model. This paper focuses on introducing an optimization process and does not explore which optimizer to use or how quickly the optimization can be achieved. Taking the air loop subsystem-level calibration as an example, using the MATLAB GA optimizer (GA) in a computer configured for Intel(R) Xeon(R) CPU E5-2699 v4 @ 2.20 GHz 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. Integrating the optimization method into the proposed calibration framework using the Modelica Optimization Library can also be explored. In addition, the optimization time has been reduced by strategically narrowing the parameter optimization range (current optimization range for each performance parameter set is 0 to twice the default value) based on expert knowledge of system operating data and system device parameters.

Conclusion

This paper presents a systematic framework for calibrating and validating HVAC system models in Modelica. The framework consists of a decoupling strategy for a complex system and calibration/validation approaches for each decoupled 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 Modelica model is presented. The calibration of the AHU-VAV system was divided into air loop, water loop, and thermal subsystem-level calibrations, where each subsystem-level calibration was further subdivided into component-level and secondary subsystem-level calibrations. Component-level calibrations typically use a curve-fitting method to obtain the performance parameters of a component. A multivariate optimization method was used in the subsystem-level calibration process. Based on the proposed calibration framework, using system normal operational data and a small amount of experimental data, a total of about 200 parameters in the Modelica model of the whole AHU-VAV system were calibrated. After completing the associated component-level and subsystem-level calibrations in sequence, the whole AHU-VAV system was validated in terms of system power and VAV supply air conditions. The validation results indicate that the calibrated AHU-VAV system Modelica model can accurately mimic the energy consumption and the supply air conditions of the real system, where the CV(RMSE) of the equipment power is less than 5%, and the RMSE of the system supply air temperature, flow rate and humidity ratio are less than 0.56°C (1°F), 170 m^3/hr (100 CFM) and 0.000451 $kg_{water}/kg_{dry-air}$, respectively. The study thus demonstrates the feasibility of using the proposed framework to calibrate and validate a complex HVAC system in Modelica.

Note

1. Certain equipment, instruments, software, or materials, commercial or non-commercial, are identified in this paper in order to specify the experimental procedure adequately. Such identification does not imply recommendation or endorsement of any product or service by NIST, nor does it imply that the materials or equipment identified are necessarily the best available for the purpose.

Acknowledgement

The views and opinions of authors expressed herein do not necessarily state or reflect those of the U.S. Government or any agency thereof.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This study is partially funded by the U.S. Department of Energy via grant EE-0009153.

Data availability statement

The data that support the findings of this study are openly available in NIST public data repository at doi:10.18434/mds2-3058 (Wen et al. 2023).

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