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Research on Model Calibration Method of Chiller Plants Based on Error Reverse Correction with Limited Data

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Abstract: Model-based optimization is an important means by which to analyze the energy-saving potential of chiller plants. To obtain reliable energy-saving results, model calibration is essential, which strongly depends on operating data. However, sufficient data cannot always be satisfied in reality. To improve the prediction accuracy of the model with limited data, a model calibration method based on error reverse correction was investigated. A traditional optimization-based calibration method was first used for preliminary model calibration to obtain simulation data and simulation errors. Then, the sources of the simulation errors were analyzed to determine the distribution characteristics of the corresponding operating conditions of the model. Finally, the performance of the model was reversely corrected by adding a correction term to the original model. The proposed calibration method was tested on a chiller plant in Xiamen, China. The results showed that the proposed calibration method improved prediction accuracy by 2.61% (the coefficient of variation of the root mean square error (CV (RMSE)) was reduced from 3.96% to 1.35%) compared to the traditional method. The maximum mean bias error (MBE) for monthly chiller energy consumption was 2.66% with the proposed calibration method, while it was 10.42% with the traditional method. Overall, in scenarios with limited data, the proposed calibration method can effectively improve the accuracy of simulation results.

Keywords: model calibration; limited data; Modelica; chiller plant

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1. Introduction

Heating, ventilation, and air conditioning (HVAC) systems account for 40–60% of energy consumption in buildings [1]. As an important link in the central air conditioning system, chiller plant energy consumption occupies a major part of the total energy consumption [2,3]. Therefore, reducing the operating energy consumed by chiller plant equipment has become an important way to save energy [4]. In the analysis of chiller plant energy efficiency, simulation has been widely used, and a number of simulation software have been developed, including EnergyPlus [5], TRNSYS [6], and Modelica [7], etc. Simulation models can be used to evaluate system performance, identify operational problems, propose improvement solutions, and verify the effectiveness of energy saving measures [8–10].

In order to improve the reliability of simulation results, we need to establish a baseline model that can accurately predict the operating conditions and energy consumption of the system. Calibration is one of the most important steps [11]. ASHRAE Guidelines 14-2014 define calibration as the: "process of reducing the uncertainty of a model by comparing the predicted output of the model under a specific set of conditions to the actual measured data for the same set of conditions" [12]. The calibration process aims at closing, or at least reducing, the performance gap. It consists of tuning the different unknown input parameters within a defined range in order to match the simulated and measured values [13]. Tüysüz et al. [14] divided the calibration process into four main

stages: modeling, measuring the calibration data, making improvements for calibration, and acquiring results. In the preliminary stage, the model input data required for calibration and the calibration target data are collected. Then, under the condition that the model inputs match the actual inputs, the selected calibration parameters are then tuned so that the simulated outputs match the observed outputs. Therefore, high quality data is an important basis for calibration. When collecting data for calibration, two dimensions must be considered: the attribute dimension (i.e., the parameters used for calibration, such as temperature, flow rate, and power) and the time dimension (i.e., the time resolution for monitoring various data, such as daily, monthly, hourly, etc.).

The time dimension of the data required for calibration depends on the size of the study population and the use of the simulation. The calibration process can be performed based on yearly, monthly, daily, or hourly data. Adrian et al. [15] observed a clear trend in increasing temporal data resolution as researchers moved from urban scale to building to component/system energy simulations. The calibration process is typically based on hourly data in simulation studies aimed at system energy optimization. Raftery et al. [16] detailed the calibration of a whole building energy model of the target building using hourly measured data. As a result of this study, the coefficient of variation of root-mean-squared error ((CV(RMSE)) for HVAC power consumption was 7.8%, and the final model was used to investigate Energy Conservation Measures (ECMs) for feasibility. Kim et al. [17] proposed a method to calibrate the building energy model using hourly measured data, which was well verified in an office building and two campus buildings. Lee et al. [18] proposed a simulation-optimization approach for the energy efficiency of a chilled water system, and the accuracy of the simulation system was verified using hourly data. Similarly, Li et al. [19] used simulations to find the optimal operation strategy for a data center cooling system with a water-side economizer by selecting practical weather data, cooling load, and equipment control signals as inputs. Simulation results were compared with hourly measured data to verify the accuracy of the model predictions. Given the hourly variability in energy consumption and equipment operating conditions, many researchers have agreed that chiller plant equipment models should be calibrated based on hourly or even smaller time scales data [20].

In the above, we discussed the requirements for the time dimension of the data for chiller plant model calibration, and we will now introduce the characteristics of the attribute dimension. The type of measured data required for model calibration is related to the model characteristics. Martin et al. [21] used the airflow rate and the mixed air temperature to calibrate a variable air volume fan model in EnergyPlus to accurately predict the fan power and supply air temperature. Huang et al. [22] developed a simulation model for the primary loop of the studied chiller plant and calibrated the chiller models using one week of measured data. The temperatures of the condenser and chilled water entering the chillers were selected as input variables during the calibration process. As a result, the relative error in chiller power was less than 5% by adjusting the chiller performance curves. Yin et al. [23] selected the chiller, cooling tower, and fan power as target variables for the calibration of HVAC systems. Meanwhile, an automated model calibration procedure was proposed to link the model with a real-time data monitoring system so that the model could be updated at any time. In summary, model calibration for HVAC equipment places more emphasis on the identification of performance values/curves. In addition, the type of data used for calibration needs to match the characteristics of the simulation model, and there are differences in the type of data required by different simulation models. Monfet et al. [24] calibrated the EnergyPlus model of a central cooling plant and analyzed the differences in model inputs and performance values/curves of key equipment models in EnergyPlus and TRNSYS. Fu et al. [11] modeled the cooling and control systems of an actual data center using Modelica and detailed the model inputs, calibration parameters, and calibration targets when calibrating critical equipment, such as chillers and cooling towers. The popularity of simulation software has brought great convenience to energy-

saving renovation work for existing chiller plants, but, at the same time, has limited the characteristics of the simulation model and the requirements for the type of measured data.

Table 1 shows a summary of the literature reviewed. In order to obtain a baseline model that can accurately predict the actual operating condition of the system, most current studies often select the operating power, medium temperature, and other state parameters as calibration targets and perform hourly calibration. At the same time, almost all calibration studies are based on a complete type of hourly measured data, but this is not always the case.

Table 1. Overview of studies on model calibration of chiller plant systems.

References	Time Dimension	Model	Calibration Targets	Simulation Software
[11]	Hourly	AHU Chiller Cooling tower	the outlet temperatures on both air and water side of AHU the chiller power the outlet water temperature	Modelica
[18]	Hourly	Chiller	the chiller power the chilled water supply temperature the cooling water supply temperature	EnergyPlus
[19]	Hourly	Chiller Cooling tower	the chiller power the chilled water supply temperature the tower power the outlet water temperature	EnergyPlus
[21]	Hourly	Fan	the fan power the supply air temperature	EnergyPlus
[22]	Hourly	Chiller	the chiller power the cooling water supply temperature	Modelica
[23]	Hourly	Chiller Cooling tower Fan	the chiller power the tower power the fan power	EnergyPlus
[24]	Hourly	Chiller Cooling tower	the chiller power the chilled water supply temperature the cooling water supply temperature the tower power the outlet water temperature	EnergyPlus and TRNSYS

One of the longstanding challenges of energy and buildings research has been the issue of data access [25]. The available measured data for model calibration varies in quality, quantity, and frequency from one chiller plant to another [21]. In reality, the lack of time dimension of data collection for chiller plant operation is objective, and there are a variety of limited data scenarios; e.g., the lack of hourly measured data for equipment power consumption available only as a monthly cumulative value [26] and the lack of itemized equipment power consumption [27], etc. This chiller plant is often in operation for a long period of time, so the need for energy saving renovation is more urgent. However, little attention has been paid to model calibration based on limited data. The calibration process encounters difficulties when the measured data conditions do not match the data requirements of the simulation tools commonly used for model calibration. This study focuses on the calibration method of chiller plants based on limited data. The main contents of this study are as follows:

1. Proposing a model calibration method based on error reverse correction with limited data.
2. Choosing chillers as the case study object and creating the model calibration system using Modelica. The monthly chiller energy consumption is selected as the calibration target.

3. The advantages of the proposed calibration method under limited data conditions are analyzed by setting up three calibration schemes.

The reminder of this paper is organized as follows. Section 1 introduces the current status of and research gaps on the model calibration method of chiller plants. Section 2 describes the research object and the proposed calibration method. Section 3 presents the case study. Section 4 summarizes the results and discussion, and Section 5 considers the conclusions.

2. Methodology

2.1. Research Object

Figure 1 depicts the system diagram of a water-cooled chiller system, which is used to supply chilled water to the air conditioning system. The chiller system consists of nine chillers, nine condenser pumps, nine chilled pumps, and eleven cooling towers distributed in two separate loops (Loop A and Loop B). The monitoring of system operating data is uniformly performed for both loops. When calibrating the chiller plant simulation system, it is common practice to individually calibrate the equipment in the system. As the main components of the chiller plant, the chillers consume about 35–40% of the energy consumption of the air conditioning system [28,29]. Therefore, the chillers are selected as the study object to introduce the calibration method.

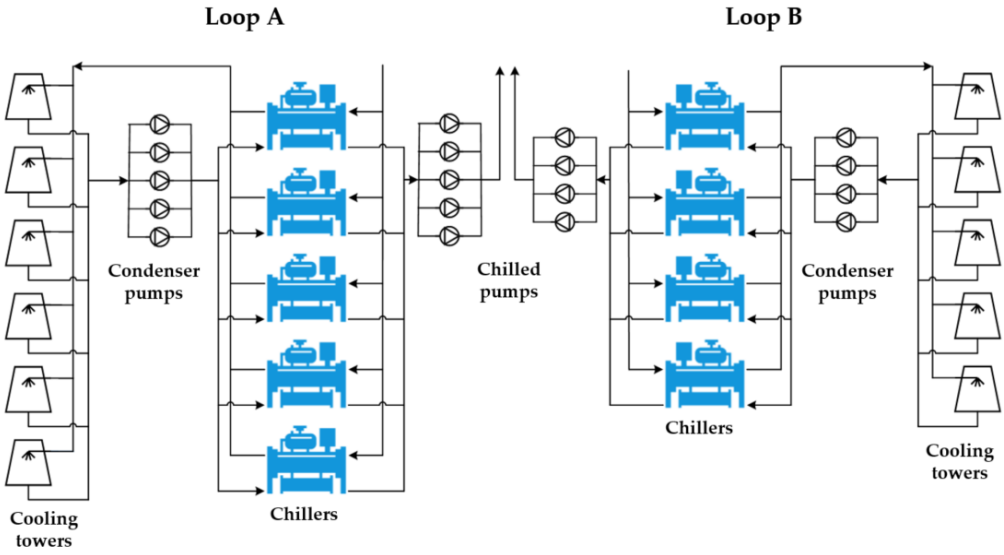


Figure 1. The schematic diagram of a water-cooled chiller system.

The DOE-2 model [30] is the most commonly used chiller model. The calibration methods of the DOE-2 chiller model have been demonstrated in many field studies. Some studies employed standard least-squares linear regression techniques to calibrate chiller models [30,31]. Other key studies proposed an optimization-based calibration approach [11,22]. We summarize the ideal data conditions required to calibrate the DOE-2 chiller model based on the above studies. Table 2 shows both the ideal dataset and the limited dataset dealt with in this paper. It can be seen that there is no measured data for the cooling water supply temperature in the limited dataset. Furthermore, only monthly statistics for equipment energy consumption are available. It is impossible to evaluate the hourly accuracy of chiller performance under the limited data conditions. To improve the prediction accuracy of the model with limited data, this paper proposes a model calibration method based on error reverse correction.

Table 2. Available data in the idea dataset and the limited dataset.

Idea Dataset		Limited Dataset	
Attribute Dimension	**Time Dimension**	**Attribute Dimension**	**Time Dimension**
the chilled water supply temperature	Hourly	√	√
the chilled water return temperature	Hourly	√	√
the cooling water supply temperature	Hourly	-	-
the cooling water return temperature	Hourly	√	√
the chiller water flow rate	Hourly	√	√
the cooling water flow rate	Hourly	√	√
the chiller on/off state	Hourly	√	√
the chiller power	Hourly	√	Monthly
the chiller capacity	Hourly	-	-

2.2. Calibration Method with Limited Data

The methodology for the calibration process proposed is divided into four main stages: modeling, optimization-based calibration, error-based reverse correction, and acquiring results. To start, the information of available measured data is determined, and a calibration system is created. Then, the calibration parameters are adjusted to match the simulation results with the observed outputs. Further, the sources of simulation errors in the second stage are analyzed to determine the characteristics of the distribution of model operation conditions that lead to errors. The model is improved by adding correction terms to the original simulation model to realize the reverse correction of performance. Finally, when the results meet the calibration criteria, the calibration is completed and the model can be used for analysis in subsequent research.

2.2.1. Modeling

The chillers are modeled using the Modelica language. Modelica is an equation-based and object-oriented language that can couple thermal, hydraulic, and control systems with variable step size [7]. The Modelica Buildings library contains components for HVAC system modeling, equipment performance libraries, etc., that can be directly used for modeling or improved based on existing models [32]. We chose to use an improved DOE-2 electrical chiller model, and the model path in the Building library was "Building. Fluid. Chillers. ElectricReformulatedEIR".

The chiller model consists of three performance curves: CAPFT—a curve that represents available cooling capacity as a function of condenser leaving and evaporator leaving fluid temperature; EIRFT—a curve that represents the full load efficiency as a function of condenser leaving and evaporator leaving fluid temperature; and EIRFPLR—a curve that represents the efficiency as a function of evaporator leaving fluid temperature and the part-load ratio. Detailed curves are described in Equations (1)–(3), and the chiller power calculation method is described in Equation (4).

$$\mathrm{CAPFT} = a_1 + T_{chw,out}(a_2 + a_3 T_{chw,out}) + T_{cw,out}(a_4 + a_5 T_{cw,out}) + a_6 T_{chw,out} T_{cw,out} \quad (1)$$

$$\mathrm{EIRFT} = b_1 + T_{chw,out}(b_2 + b_3 T_{chw,out}) + T_{cw,out}(b_4 + b_5 T_{cw,out}) + b_6 T_{chw,out} T_{cw,out} \quad (2)$$

$$\mathrm{EIRFPLR} = c_1 + T_{cw,out}(c_2 + c_3 T_{cw,out}) + \mathrm{PLR}\left(c_4 + c_5 \mathrm{PLR} + c_6 \mathrm{PLR}^2\right) + c_7 T_{cw,out} \mathrm{PLR} \quad (3)$$

$$P_{chiller} = P_{ref} \cdot \mathrm{CAPFT} \cdot \mathrm{EIRFT} \cdot \mathrm{EIRFPLR} \quad (4)$$

where $T_{chw,out}$ is the chilled water supply temperature, °C; $T_{cw,out}$ is the cooling water supply temperature, °C; PLR is the part load ratio; P_{ref} is the nominal power of the chiller, kW; P is the power of the chiller, kW; and a, b, c are the coefficients of the performance curve.

2.2.2. Optimization-Based Calibration

Figure 2 describes a general procedure of optimization-based calibration, which was adapted from Fu et al. [11]. This stage aims to match the simulation results with the observed outputs by adjusting the calibration parameters. We used the GenOpt [33] optimization engine and employed particle swarm optimization (PSO) to complete the calibration parameters update. Normalized mean bias error (NMBE) can be used as an indicator of all biases in the simulation predictions, which can be expressed by Equation (5). However, NMBE suffers from cancellation between positive and negative bias, which can lead to misleading interpretations of predictive performance [34]. To avoid this problem, we improved the calculation method of NMBE, recorded as NMBE' (Equation (6)).

$$\mathrm{NMBE}(\%) = \frac{1}{\overline{m}} \frac{\sum_{i=1}^{n}(m_i - s_i)}{n-p} \times 100 \quad (5)$$

$$\mathrm{NMBE}'(\%) = \frac{1}{\overline{m}} \frac{\sum_{i=1}^{n}|m_i - s_i|}{n-p} \times 100 \quad (6)$$

where m_i and s_i are the measured and simulated values, respectively; $\overline{m}$ is the mean of the measured values; n is the number of data points ($n_{monthly}$ = 12, n_{daily} = 365, n_{hourly} = 8760); and p is the number of adjustable model parameters. The number of adjustable model parameters p is suggested to be set to zero for calibration procedures [35].

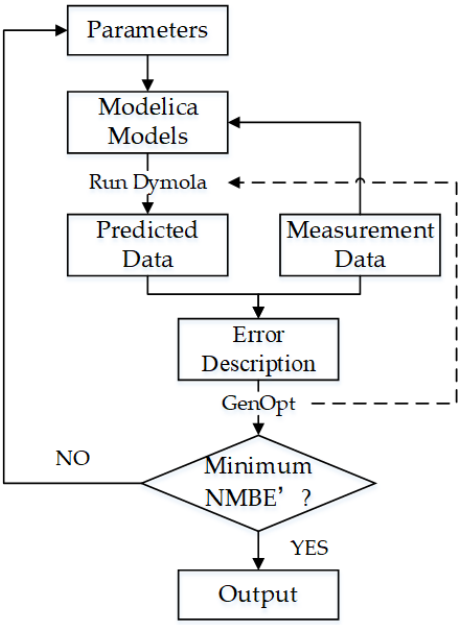


Figure 2. The procedure of optimization-based calibration.

2.2.3. Error-Based Reverse Correction

The performance of the chiller depends on the operating conditions of the unit, and this is also true for the simulation model. After determining the performance curve coefficients, the power of the DOE-2 chiller model is directly related to $T_{chw,out}$, $T_{cw,out}$, and PLR. This paper defined the state parameter that affects the model performance as the performance-related state parameter. By mining the relationship between simulation errors and the distribution of the performance-related state parameters, it is possible to determine the range of model operating condition distributions that cause errors. Based on this, model performance can be corrected within the determined range of the operating condition to effectively improve model accuracy.

In Figure 3, the flow chart of error-based reverse correction is presented in an easy-to-understand manner. After completing the optimization-based calibration based on the

monthly measured data of chillers energy consumption, the hourly simulated data of performance-related state parameters and the monthly simulated data of chillers energy consumption can be obtained. The mean bias error (MBE) was used to calculate the error between the simulation and reality, determining the degree of proximity for each month. The formula is as follows:

$$\mathrm{MBE} = \frac{m_i - s_i}{m_i} \tag{7}$$

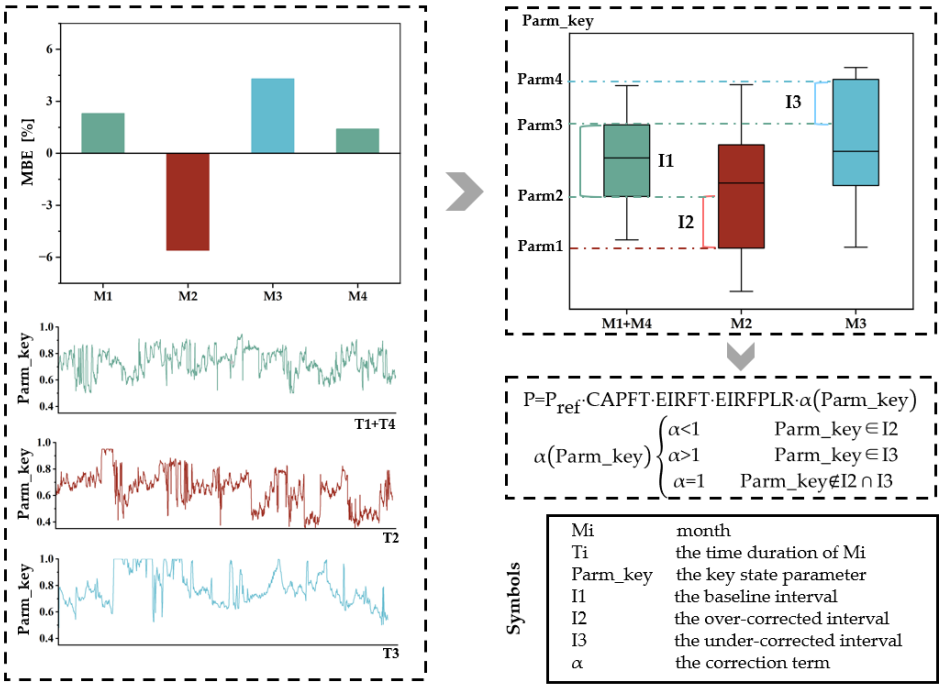


Figure 3. Schematic illustrating the process of error-based reverse correction.

The simulation dataset is divided into the baseline dataset (data in M1 and M4) and the required-corrected dataset (data in M2 and M3) according to the simulation error level. The required-corrected dataset include the under-corrected dataset (data in M2), with a large negative bias, and the over-corrected dataset (data in M3), with a large positive bias.

Then, the performance-related state parameter that can reflect the difference in the distribution of the device operating conditions under the baseline dataset and the required-corrected dataset is selected as the key state parameter (Parm_key). The interval in which the key state parameter is centrally distributed in the baseline dataset is defined as the baseline interval (I1). In the under-corrected dataset, the part of the key state parameter that is centrally distributed and different from the baseline interval is defined as the under-corrected interval (I2). Similarly, in the over-corrected dataset, the part of the key state parameter that is centrally distributed and different from the baseline interval is defined as the over-corrected interval (I3).

Finally, the model performance is reversely corrected by adding a correction term α to the original model. The correction term α is a piecewise function with the key state parameter as the independent variable, which is assigned a value greater than 1 in the under-correction interval to amplify the model performance, and a value less than 1 in the over-correction interval to retrace the model performance, and 1 in the other intervals to maintain the original level of performance correction. In addition, the value of the correction term can be determined by optimization. The objective of the optimization is to minimize the difference between the model output and the corresponding measurement.

The difference is defined by NMBE′. The formulation of the optimization problem is shown in Equation (8).

$$\min(\mathrm{NMBE}') = \min\left(\frac{1}{\overline{m}}\frac{\sum_{i=1}^{n}|m_i - s_i|}{n-p}\right) \quad (8)$$

2.2.4. Calibration Results Evaluation

Some criteria are selected to evaluate the calibrated model. NMBE and CV(RMSE) are the most commonly used [35]. NMBE can be calculated by Equation (5), and CV(RMSE) can be calculated by Equation (9).

$$\mathrm{CV(RMSE)} = \frac{1}{\overline{m}}\sqrt{\frac{\sum_{i}^{n}(m_i - s_i)^2}{n-p}} \times 100 \quad (9)$$

Furthermore, the acceptable criteria defined by ASHRAE [12], IPMVP [36], and FEMP [37] are shown in Table 3. The calibrated model is then approaching reality and can be used to evaluate the effectiveness of various energy conservation measures before applying them to an actual chiller plant.

Table 3. Acceptance criteria for the calibration process.

Standard/Guideline	Monthly		Hourly	
	NMBE	CV(RMSE)	NMBE	CV(RMSE)
ASHRAE Guideline 14 [12]	±5%	15%	±10%	30%
IPMVP [36]	±20%	-	±5%	20%
FEMP Criteria [37]	±5%	15%	±10%	30%

3. Case Study

3.1. Case Description

In this case, a chiller plant located in Xiamen City, Fujian Province, China, was chosen as the research object. The configuration of the chiller plant is shown in Figure 1. The chiller plant is responsible for the cooling service of the entire campus and has two separate cooling loops (Loop A and Loop B). Due to the high energy consumption, we focused on the model calibration for the chillers. The nominal data for the chillers are listed in Table 4. There are five identical chillers in Loop A and four in Loop B. Therefore, two models need to be calibrated; denoted as Chiller_A and Chiller_B, respectively. We determined the number of units, the connection type, and the value of the nominal parameters in combination with the design information.

Table 4. Technical parameters of the chillers in the cooling system.

Equipment	Number of Units	Parameter	Units	Design Value
Chiller_A	5	Cooling capacity	kW	7032
		Power	kW	1321
		COP	-	5.32
Chiller_B	4	Cooling capacity	kW	6950
		Power	kW	1134.1
		COP	-	6.13

The operating data of the chillers in 2021 were monitored, as shown in Table 5. The input data required for chiller simulation, such as the return temperature and the flow rate of chilled water, the return temperature and the flow rate of cooling water, etc., are monitored each hour. However, only monthly monitoring data is available for the energy consumption of the chillers.

Table 5. Monitoring data in the chiller plant used to calibrate chiller model.

Date	Units	Date	Recording Frequency	Data Set Size
the chilled water supply temperature	°C	1 January to 31 December 2021	1 h	8760 × 11
the chilled water return temperature	°C			
the cooling water return temperature	°C			
the chiller water flow rate	m^3/s			
the cooling water flow rate	m^3/s			
the chiller on/off state	-			
the chiller energy consumption	kWh		1 month	12

3.2. Calibration Scheme

In order to compare the effectiveness of the calibration method proposed in this study, we created three calibration schemes:

- Init: Calibrating the chiller model using the optimization-based calibration method;
- Manual: On the basis of Init, calibrating the chiller model based on error reverse correction, and the value of the correction terms are manually determined.
- Opt: On the basis of Init, calibrating the chiller model based on error reverse correction, and the value of the correction terms are determined by optimization.

3.2.1. Init: Optimization-Based Calibration

In Init, we performed only the traditional optimization-based calibration. Figure 4 shows the chiller calibration system model in Modelica. The measured data of chilled water supply temperature were selected as the set point in the simulation. The calibration target was the total energy consumption of the chiller. When calibrating two types of chillers (Chiller_A and Chiller_B), the number of correction coefficients to be optimized is significant, and it is difficult to determine a suitable range for finding the optimum. Therefore, we applied an exhaustive optimization method to select the best performance coefficients from the reference samples of chillers provided by the Building library. The chiller energy consumption $NMBE'_{monthly}$ was used as a screening index. Finally, the nominal COP of Chiller_A and Chiller_B were calibrated considering the possible performance degradation of the chillers. $\mathrm{Min}\left(NMBE'_{monthly}\right)$ was chosen as the optimization objective, and the optimization process was completed using GenOpt with PSO.

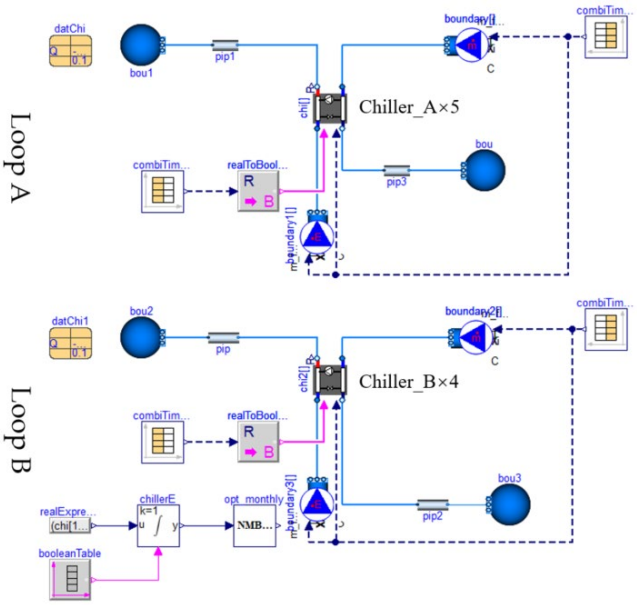


Figure 4. Chiller calibration system model in Modelica.

3.2.2. Manual and Opt: Error-Based Reverse Correction

Manual and Opt were performed based on Init, including the complete stages presented in Section 2.2. Since the performance-related state parameters of the chiller are $T_{chw,out}$, $T_{cw,out}$, and PLR, it was first necessary to filter out the appropriate key state parameter. Then, the ranges of over-correction intervals and under-correction intervals were determined based on the distribution characteristics of the key state parameter. Finally, the values of the correction terms for the different over-correction intervals and under-correction intervals were determined. Manual and Opt were set according to the different methods used to determine the correction terms. Manual: the values of the correction terms were manually determined according to the energy consumption simulation error level. Opt: GenOpt was used to determine the values of correction terms. In the proposed approach, the particle swarm optimization was selected.

4. Results and Discussion

4.1. Init: Optimization-Based Calibration

Table 6 shows the optimization results of the calibration parameters in Init. As can be seen from Table 6, the nominal COP of Chiller_A fell from 5.32 to 5.21. Therefore, it is necessary to consider the performance degradation that occurs during the operation of the equipment.

Table 6. Optimization results of calibration parameters in Init.

Model	Adjusted Parameters	Results
Chiller_A and Chiller_B	$[a_1, a_2, \ldots, a_6]$	$[8.850533 \times 10^{-1}, 2.837149 \times 10^{-2}, -5.511387 \times 10^{-3}, 8.194635 \times 10^{-3}, -6.603948 \times 10^{-4}, 2.956238 \times 10^{-3}]$
	$[b_1, b_2, \ldots, b_6]$	$[7.658820 \times 10^{-1}, 1.245831 \times 10^{-2}, -4.811737 \times 10^{-3}, -2.449180 \times 10^{-3}, 1.633990 \times 10^{-4}, 1.270390 \times 10^{-3}]$
	$[c_1, c_2, \ldots, c_7]$	$[-4.774361 \times 10^{-1}, 5.162751 \times 10^{-2}, -5.614109 \times 10^{-5}, -2.035828 \times 10^{-1}, 1.353495 \times 10^{0}, -4.892949 \times 10^{-2}, 2.956492 \times 10^{-1}]$
Chiller_A	the nominal COP	5.21 *
Chiller_B	the nominal COP	6.13

* The optimized value is smaller than the sample value.

Figure 5 shows the monthly measured and simulated chiller energy consumption. After completing the optimization-based calibration, the accuracy of chiller energy consumption significantly varied from month to month. The monthly MBE reached −8.14% in April and 10.42% in December. The prediction accuracy of the calibrated model was not satisfactory.

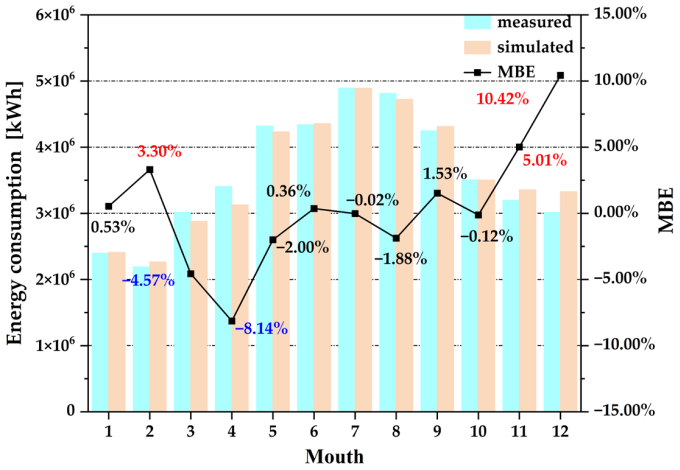


Figure 5. Energy consumption of the chiller.

4.2. Manual and Opt: Error-Based Reverse Correction

Table 7 shows the classification results of the baselined dataset, over-corrected dataset, and under-corrected dataset. The monthly MBE within the range of −3% to 3% was considered to be an acceptable error level, and the measured data were divided into three groups according to the calibration results of Init. The data in March and April belonged to the over-corrected dataset. The data in February, November, and December belonged to the under-corrected dataset. The data in the remaining months belonged to the baseline dataset.

Table 7. The classification results of the baselined dataset, over-corrected dataset, and under-corrected dataset.

Dataset Name	Month	Features
Baseline dataset	January, May, June, July, August, and September	$-3\% < \text{MBE} < 3\%$
Over-corrected dataset	March and April	$\text{MBE} \leq -3\%$
Under-corrected dataset	February, November, and December	$\text{MBE} \geq 3\%$

Figure 6 shows the simulation results of the performance-related state parameters of Chiller_A and Chiller_B. The performance-related state parameters of the chiller model are $T_{chw,out}$, $T_{cw,out}$, and PLR. It can be seen from Figure 6a that PLR better reflects the operating condition distribution characteristics of Chiller_A than $T_{chw,out}$ and $T_{cw,out}$. Specifically, in the over-corrected dataset, the concentrated distribution interval of PLR was higher than that of the baseline dataset. The opposite characteristic was shown in the under-corrected dataset. As can be seen from Figure 6b, there was no significant difference between the concentrated distribution interval of the performance-related state parameters in different months. In particular, $T_{chw,out}$ distributed in a higher range in the over-corrected dataset (May and April). Selecting a single performance-related state parameter could not accurately reflect the equipment operating characteristics. Therefore, we chose PLR together with $T_{chw,out}$ as key state parameters.

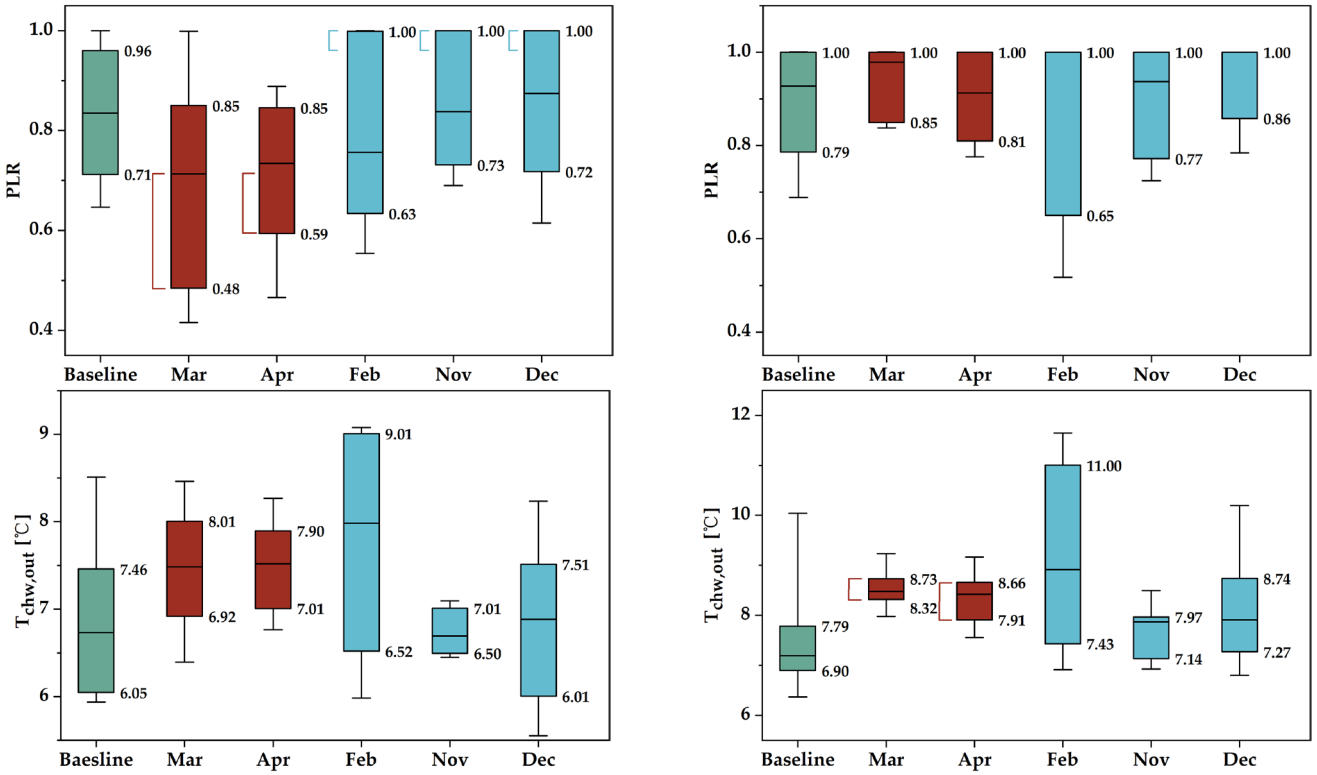


Figure 6. *Cont.*

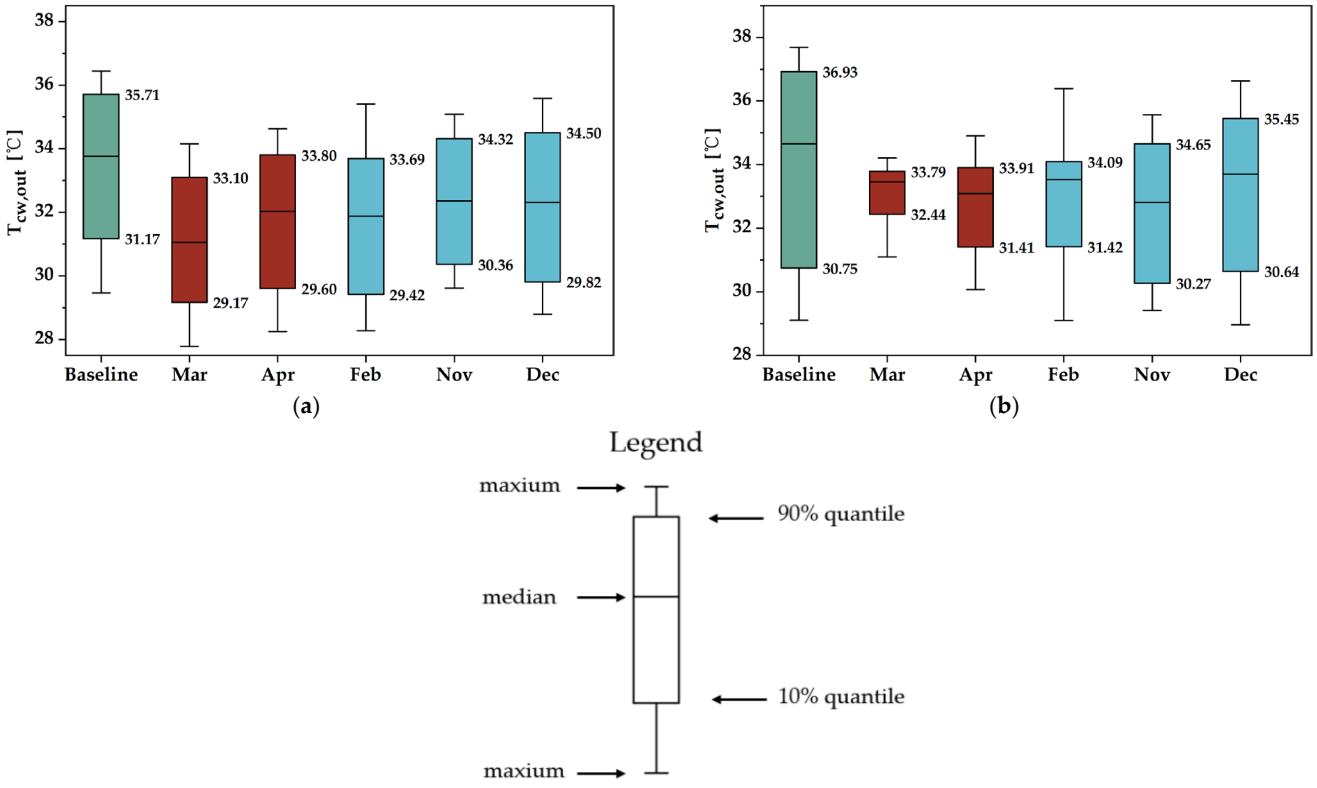


Figure 6. (**a**) Box plot of performance-related state parameters of Chiller_A; (**b**) box plot of performance-related state parameters of Chiller_B.

Figure 7 shows the distribution of key state parameters for the chillers in Loop A in the baseline dataset and in April. In the dot-density map, the darker the color, the more chiller operating points are distributed. It is obvious that the two were different, and the operating conditions of the chillers in April were concentrated in the blue rectangle:

$$\mathrm{PLR} \in (0.56, 0.83) \text{ and } T_{chw,out} \in (7.4, 7.7) \quad (10)$$

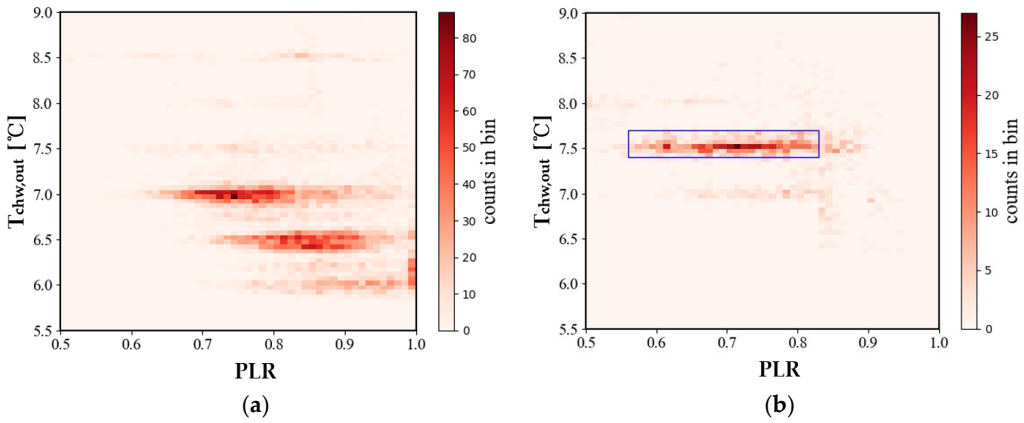


Figure 7. (**a**) Dot-density map of $T_{chw,out}$ versus PLR in the baseline dataset for chillers in Loop A; (**b**) dot-density map of $T_{chw,out}$ versus PLR in April for chillers in Loop A.

By the same method, the distribution ranges of over-corrected intervals and under-corrected intervals for the two loop chillers were determined. Table 8 shows the results of the determined interval ranges, where $\alpha_{A,i}$, $\alpha_{B,i}$ are the correction term set for Chiller_A and

Chiller_B, respectively. On this basis, the values of the correction terms were determined in next step.

Table 8. The distribution ranges of over-corrected intervals and under-corrected intervals.

Model	Dataset Types		Interval Ranges	Correction Term
Chiller_A	Over-corrected dataset	March	PLR $\in (0.50, 0.56)$ and $T_{chw,out}$ $(6.90, 8.10)$ PLR $\in (0.56, 0.77)$ and $T_{chw,out}$ $(7.75, 8.10)$	$\alpha_{A,1}$
		April	PLR $\in (0.56, 0.83)$ and $T_{chw,out}$ $(7.40, 7.70)$	$\alpha_{A,2}$
	Under-corrected dataset	February	PLR $\in (0.62, 0.75)$ and $T_{chw,out}$ $(8.90, 9.00)$ PLR $\in (0.77, 0.80)$ and $T_{chw,out}$ $(7.95, 8.05)$	$\alpha_{A,3}$
		November	PLR $\in (0.73, 0.82)$ and $T_{chw,out}$ $(6.65, 6.75)$ PLR $\in (0.99, 1.00)$ and $T_{chw,out}$ $(6.45, 6.80)$	$\alpha_{A,4}$
		December	PLR $\in (0.99, 1.00)$ and $T_{chw,out}$ $(4.50, 6.00)$ PLR $\in (0.99, 1.00)$ and $T_{chw,out}$ $(6.30, 6.40)$	$\alpha_{A,5}$
Chiller_B	Over-corrected dataset	March	PLR $\in (0.93, 0.99)$ and $T_{chw,out}$ $(8.40, 8.60)$	$\alpha_{B,1}$
		April	PLR $\in (0.75, 0.92)$ and $T_{chw,out}$ $(8.40, 9.50)$	$\alpha_{B,2}$
	Under-corrected dataset	February, November, and December	PLR $\in (0.78, 0.99)$ and $T_{chw,out}$ $(7.90, 8.00)$ PLR $\in (0.99, 1.00)$ and $T_{chw,out}$ $(7.60, 8.20)$ PLR $\in (0.99, 1.00)$ and $T_{chw,out}$ $(8.90, 9.80)$	$\alpha_{B,3}$

Table 9 shows the values of the correction terms in Manual and Opt. Figure 8 shows the monthly measured and simulated chiller energy consumption in Manual and Opt. The range of MBE was −2.36% to 3.37% in Manual and −2.40% to 2.66% in Opt.

Table 9. The values of the correction terms.

Correction Term	Value	
	Manual	Opt
$\alpha_{A,1}$	1.2	1.22
$\alpha_{A,2}$	1.1	1.09
$\alpha_{A,3}$	0.8	0.78
$\alpha_{A,4}$	0.85	0.84
$\alpha_{A,5}$	0.9	0.94
$\alpha_{B,1}$	1.2	1.3
$\alpha_{B,2}$	1.1	1.04
$\alpha_{B,3}$	0.8	0.78

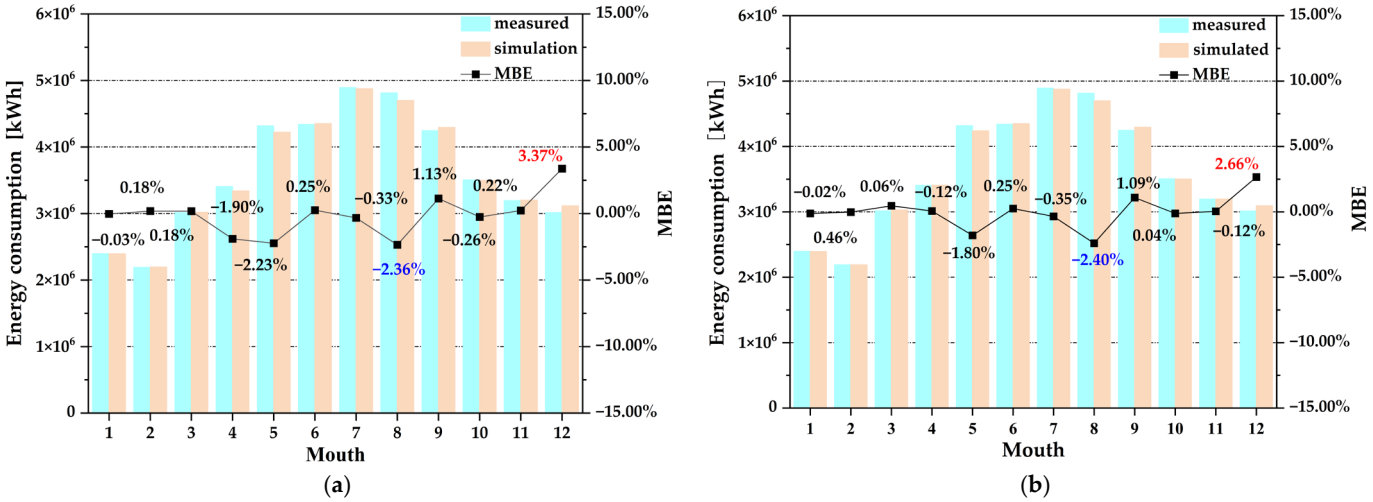


Figure 8. (**a**) Energy consumption of the chiller in Manual; (**b**) energy consumption of the chiller in Opt.

4.3. Discussion

As can be seen from the above results, the calibration accuracy of the model can be improved by a calibration method based on error reverse correction under limited data conditions. To achieve this goal, we improved the traditional calibration method. By analyzing the causes and characteristics of calibration errors, the chiller models were reverse corrected to improve the calibration accuracy.

Table 10 summarizes the NMBE, NMBE', and CV(RMSE) values for the calibrated model in three schemes. The NMBE value in Init was lower than that of the other schemes. This is because NMBE suffers from cancellation between positive and negative bias, which can lead to misleading interpretations of predictive performance. Moreover, according to the results of NMBE' and CV (RMSE), it could be seen that the accuracy of the model calibration was significantly improved after applying the error-based reverse correction.

Table 10. Monthly NMBE, NMBE', and CVRMSE, values for the calibrated model in three schemes.

	Init	Manual	Opt
NMBE	0.10%	0.29%	0.15%
NMBE'	2.85%	1.10%	0.86%
CV(RMSE)	3.96%	1.59%	1.35%

As can be seen in Figure 9a, the MBE values for the same month belonging to the baseline dataset were almost unchanged in the three schemes. In addition, the MBE values in the over-corrected dataset and the under-corrected dataset were significantly reduced by the error-based reverse correction, as shown in Figure 9b. After optimizing the original model by adding correction terms, this did not affect the prediction accuracy of the model in the baseline dataset. This confirms that the interval classification results shown in Table 8 are accurate.

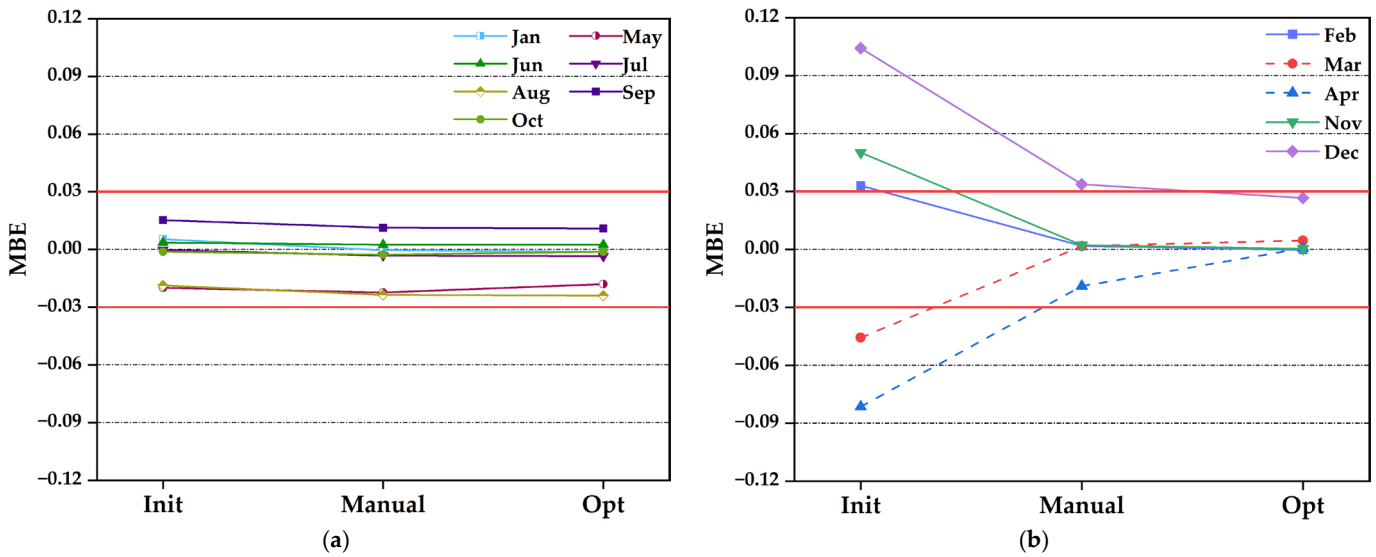


Figure 9. (**a**) The MBE values for the months belonging to the baseline dataset in three schemes; (**b**) the MBE values for the months belonging to the over-corrected dataset and the under-corrected dataset in three schemes.

5. Conclusions

In this study, a model calibration method based on error reverse correction was proposed to improve the model prediction accuracy when only the monthly measured energy consumption data were available. To achieve this goal, a traditional optimization-based calibration method was first used for preliminary model calibration to obtain abundant simulation data and monthly energy simulation errors. Then, the relationship between

simulation errors and equipment operating conditions was analyzed to determine the range of operating conditions that required performance correction. Finally, the performance of the model was reversely corrected by adding a correction term to the original model. The proposed method was tested in a chiller plant in Xiamen, China, via simulation. Based on the results of the test case studies, conclusions could be drawn as follows:

1. When only the monthly measured energy consumption data are available, the calibration results with the optimization-based method can meet the acceptable criteria, but the accuracy of the chiller energy consumption in different months greatly varies. In Init, the $\mathrm{CV(RMSE)}_{\mathrm{monthly}}$ was 3.96%, which met the acceptable criteria. However, the MBE values in July, April, and December were −0.02%, −8.14%, and 10.42%, respectively.
2. Based on the simulation data and the error information obtained from the preliminary calibration, it can be found that there is a relationship between the model simulation accuracy and the model operating conditions. By analyzing the distribution characteristics of the key state parameters in the different months, it is possible to determine the range of operating conditions where errors occur. This is the basis for the reverse correction of model performance. By selecting multiple state parameters, a more accurate range of intervals can be determined.
3. Improving the model by adding correction terms can significantly improve the predictive accuracy of the model. Compared to the manual assignment method, an optimization method to determine the value of the correction term can obtain more accurate simulation results. In Manual and Opt, the $\mathrm{CV(RMSE)}_{\mathrm{monthly}}$ was reduced from 3.96% to 1.59% and 1.35, respectively. The maximum MBE was reduced from 10.42% to 3.37% and 2.66%, respectively.

This study was an initial attempt to calibrate the chiller model with limited data. With the proposed calibration method, accurate simulation results were obtained even under limited data conditions. The calibrated model could be used to support the simulation verification of energy-saving measures. This helps facilitate the use of simulation in engineering cases. However, the calibration effect of other equipment in the chiller plant was not verified. Future work will include more case validation in scenarios with limited data, in addition to examining the best calibration accuracy under different data conditions.

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