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CALIBRATION OF BUILDING MODELS FOR SUPERVISORY CONTROL OF COMMERCIAL BUILDINGS

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ABSTRACT

Past research of predictive optimal control of active and passive building thermal storage inventory has confirmed the importance of accuracy in the employed building model. In a subsequent investigation of model-free learning control for the same application, a hybrid model-based/model-free control scheme based on simulated reinforcement learning has been proposed. Experimentation validated this approach, yet the experiment data analysis also revealed that the accuracy of the training model for the learning controller can significantly affect the knowledge base of the controller and its resultant performance. As a result, procedures of model calibration to improve the model accuracy are needed to improve the control quality in both model-based predictive optimal control and hybrid control schemes. This paper describes a methodology for model calibration that is based on system identification and has been successfully applied in both approaches. A numerical analysis demonstrates that by carrying out the model calibration the performance of the controllers has been improved.

INTRODUCTION

BACKGROUND

The advantage of shifting building cooling loads by using active and passive thermal storage capacity has been recognized for a long time. Properly utilizing thermal storage may offer substantial cost savings and potentially increase plant efficiency. By definition, the *active* building thermal capacity refers to the thermal energy storage (TES) system, which is either a chilled water or ice based system; the *passive* building thermal storage capacity refers to the building envelope, structural systems, internal construction and furniture, which affect the building cooling load.

The motivation for the current study stems from a research project that investigated model-based predictive optimal control of active and passive building thermal storage inventory. In this study, a model-based predictive optimal control approach was developed in order to evaluate the merits of controlling active and passive thermal storage optimally in a continuous closed-loop fashion. Simulation study and experimental analysis were carried out to investigate the combined usage of both active and passive building thermal storage inventory by (Henze, Felsmann & Knabe 2004) and (Henze, Kalz, Liu & Felsmann 2005). The analysis showed that when an optimal controller for combined utilization of active *and* passive storage is given perfect weather forecasts and when the building model used in the model-based predictive control perfectly matches the actual building, the utility cost savings are significantly greater than for *either* active *or* passive storage, but less than the sum of the individual savings and the cooling-on-peak electrical demand can be drastically reduced.

Further research by (Henze, Kalz, Felsmann & Knabe 2004) demonstrates that prediction uncertainty in the required short-term weather forecasts will affect the controller's cost saving performance. (Liu & Henze 2004a) investigated the impact of five categories of building modeling mismatch on the performance of model-based predictive optimal control of combined thermal storage assuming perfect prediction. The results showed that a simplification or mismatch of the building geometry and zoning only marginally affects the optimization strategy. However, the mismatch of internal heat gain, building construction, and energy system efficiency can lead to significant deviations in the optimal control strategy. The model needs to be calibrated before it is implemented into a real application. Moreover, the utilization of the real building such as occupancy schedule and internal heat gain density may also change over time, thus the model also needs to be updated correspondingly in order to ensure that the quality of the supervisory controller is maintained.

To overcome the shortcomings of model dependency and mismatch that are associated with the model-based approach, a reinforcement learning approach has been investigated in a follow-up research study. The reinforcement learning approach does not require a building model but instead learns the optimal control policy only through direct interaction with the environment. (Liu & Henze 2004b) and (Liu & Henze 2005) demonstrate that the reinforcement learning approach can find the optimal or near-optimal control policy without prior knowledge about the environment, but it takes an unacceptably long time and the performance of the controller is sensitive to many factors including the selection of the state-action space and learning parameters. Implementation of such a controller with no prior domain knowledge would not be a practical solution in any real building control application. As a result, a hybrid control scheme was proposed to combine the merits of model-based approach and model-free learning approach. The hybrid approach is based on a variation of the classic reinforcement learning approach and called simulated reinforcement learning. Instead of interacting with the environment directly, a simulator is used in the early training period of the learning controller. The simulator is developed to imitate the physical environment. It was found that the accuracy of the training model significantly affects the performance of the learning controller in the subsequent experiment of hybrid control in an actual building. However, the experimental data collected provides an opportunity to calibrate the training model, and consequently the performance of the learning controller can be improved.

In summary, the necessity to ascertain the accuracy of the building model has been revealed in the analysis of both model-based predictive optimal control and hybrid reinforcement learning control of building thermal storage inventory. Efforts have been made to develop a model calibration procedure to achieve this goal. This paper introduces the methodology used in the calibration procedure. Cases studies in both model-based optimal control application and hybrid reinforcement learning control approach demonstrate that the model accuracy can be improved by using the proposed approach, and consequently the performance of the controller can be enhanced.

LITERATURE SURVEY

The importance of model calibration has been discussed in several research studies on building energy analysis. Procedures have been proposed that meet the specific requirements of different applications. (Clarke, Strachan & Pernot 1993) introduced an approach to calibrate a passive solar building model that entails first using simulation to obtain model predictions and parameter sensitivities, then acquiring high-quality measured data, and finally quantifying residuals and explaining their causes. (Carroll & Hitchcock 1993) developed a tuning method to systematically adjust the parameters of an explicit analytical building model in order to match the simulated building energy performance to the consumption of the corresponding actual building. More recently, (Yoon & Lee 1999) proposed a step-by-step procedure to calibrate a commercial building model in the DOE-2.1 (LBL 1982) simulation environment starting with base case modeling and analysis, mid-season calibration, site interview and confirmation, heating and cooling season calibration, and final validation. (Pedrini & Lamberts 2001) describes a methodology using building visits and field measurements to improve the model quality. Common to these methods is that they employ statistic metrics, e.g. root-mean-square error *RMSE* and mean bias error *MBE*, as the calibration performance index, and the input parameters of simulation model are adjusted manually. A fundamentally different approach is described in ASHRAE-sponsored research project RP-1050 Inverse Model Toolkit ((Haberl, Sreshthaputra, Claridge & Kissock 2003)). Inverse models use rich sets of measured data to identify the parameters of either physical (e.g., thermal resistance-capacitance network models) or regression models.

The model calibration approach proposed in this study also uses error metrics to compare simulated with actual data. However, instead of manually adjusting the identified tuning parameters, optimization tools are applied. Besides, the model that has been investigated is a full-scale building simulation model and not a regression or analytical building model. Therefore, algorithms such as linear or non-linear regression cannot be applied here. Instead, an optimization environment was developed that integrates the global optimization algorithm with the building simulation program, which offers a convenient approach to improve the model quality.

METHODOLOGY

Fundamentally, the calibration is divided into two steps: 1.) First, all those parameters affecting the building cooling load profile are identified. Next, a pre-processing step attempts to ascertain initial values for these parameters. The remaining model parameters are then found using an error minimization scheme described below. 2.) Once the building cooling load is accurately modeled, the capacities, efficiencies, and part-load performance of the building energy system are assigned initial values. Subsequently, a similar error minimization process will find those energy system parameters that lead to the best fit of the predicted electricity or other end-use consumption compared to the measured data from the building automation system.

The proposed methodology for building model calibration can be categorized as a system identification technique, which is widely applied in many applications. System identification can be deemed as an investigation process generating a mathematical model of a given system based on experimental data, measurements, and observations. Figure 1 shows the system identification loop (modified from (Ljung 1987)).

System identification problems can be formulated as follows: At time t we have observed m inputs $\vec{u}_t$ and n outputs $\vec{y}_t$ from a dynamic system:

$$\vec{u}_t = [u(1), u(2), \ldots, u(m)] \tag{1}$$

$$\vec{y}_t = [y(1), y(2), \ldots, y(n)]. \tag{2}$$

We are looking for a relationship between past observations $[\vec{u}_{t-1}, \vec{y}_{t-1}]$ and future outputs $\vec{y}_t$:

$$\vec{y}_t = g\left(\vec{u}_{t-1}, \vec{y}_{t-1}\right) + \vec{v}_t \tag{3}$$

The additive term $\vec{v}_t$ arises from the fact that the next output $\vec{y}_t$ cannot be an exact function of past data.

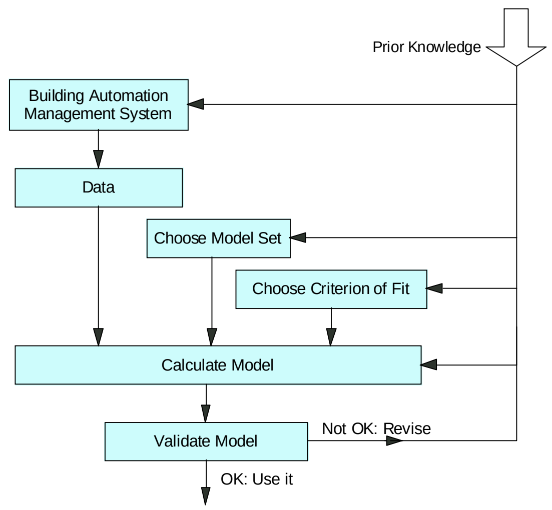

Figure 1: System Identification Loop

A modern building automation system provides a wealth of information available either directly from measured data or indirectly generated by post-processing measured data. In the following description, we assume that the total building cooling load is monitored by the building automation system. At time t a set of data with T past samples is recorded which represents the hourly cooling load profile.

$$Rl_t = [Rl_1, Rl_2, \ldots, Rl_T] \tag{4}$$

Each element of the vector represents the hourly building cooling load, t is the index of the time series, and T is the number of hours of the monitoring period, which is equal to the total calibration hours. On the other hand, the predicted hourly cooling load profile is generated by the simulation program.

$$Sl_t = [Sl_1, Sl_2, \ldots, Sl_T] \tag{5}$$

Then a set of error data is generated:

$$\begin{aligned} Er_t &= [Rl_1 - Sl_1, Rl_2 - Sl_2, \ldots, Rl_T - Sl_T] \quad (6) \\ &= [Er_1, Er_2, \ldots, Er_T] \end{aligned}$$

Then the root-mean-square error $RMSE$ can be defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T} Er_i^2}{T-1}} \tag{7}$$

In our system identification process, we are trying to calibrate the parameters of the building simulation model to minimize the root-mean-square error *RMSE*.

A variety of factors affects the simulation model, which are summarized in Table 1. It is impossible to take all of them into consideration. An information collection procedure must precede the setup of the simulation model for a building. Some of the parameters in Table 1 can be obtained with sufficient accuracy during this procedure. For example, the geometry and scale of the building, fenestration area, and the layout of zones can be attained

Table 1: Calibration categories

Category	Parameters
Building Construction	Geometry and scale of the building; Layout of zones; Thermal properties of construction materials (conductance, specific heat, etc.)
Internal Heat Gain	Schedules for occupancy, light, and equipment; Lighting and equipment power densities; Number of occupant
Energy System	Capacity of energy system components; Part-load performance of the HVAC systems (COP, PLR, etc)

from architectural drawings of the building. A checklist is proposed to make this procedure as accurate as possible. This checklist can be considered a pre-processing step in the calibration of the building simulation model. Table 2 provides a sample of the checklist; the detailed list of items depends on the conditions of the specific building we are trying to control.

Table 2: Checklist of pre-processing and calibration information

Pre-Processing Information	
Building Construction	Building orientation
	Building dimensions Layout of the zones
	Fenestration
	Construction dimensions
Internal heat gain	Schedule for occupancy
	Schedule for lighting
	Schedule for equipment
Energy system	System configuration Capacity of system component
Calibrated Information	
Building Construction	Material properties
	✓Thermal conductivity ✓Specific heat ✓Density
Internal heat gain	Lighting power density (LPD)
	Equipment power density (EPD)
Energy system	Operating parameters Coefficient-of-performance (COP) Part-load performance

Techniques of system identification can be applied to find the optimal value of the parameters of interest. Numerous algorithms have been developed for different applications. Detailed discussions can be found in (Ljung 1987) and (Crassidis & Junkins 2004). Due to the complexity and nonlinearity of building simulation models, an analytical expression of the cost function cannot be found and the optimal estimation of model parameters is tackled as an optimization problem without reliance on function gradients and Hessians. Such black-box optimization problems occur in many disciplines, and algorithms to solve such problems are well developed (Horst & Pardalos 1995). In the proposed application to building model calibration, direct search methods such as the Nelder-Mead and Hooke-Jeeves algorithms as well as gradient-based Quasi-Newton methods have been applied.

ANALYSIS

The proposed model calibration procedure has been applied in the analysis of optimal control of building active and passive thermal storage inventory. Two case studies are presented in this section. The first one is a simulation based analysis for model-based optimal control, in which two models were developed: one represent the actual building; and the other was tuned by using the developed calibration techniques. The second case is taken from the experimental study of hybrid learning control. The developed training model was calibrated to approximate the measured data. Both cases demonstrate the advantages of improving the model quality by applying the calibration procedure.

MODEL-BASED OPTIMAL CONTROL

Model-based predictive optimal control integrates the building model with an optimization engine as well as a short-term weather predictor. In each time step, e.g., an hour, the controller will first make a weather prediction over the planning time horizon, usually the next 24-hours; the building model will then be able to project the cooling load and operating cost based on the weather prediction; and finally the optimizer can search the optimal control strategy iteratively calling the building model until the objective function reaches the minimum. As shown by previous studies, the accuracy of the building model is essential to the controller and affects the optimal controller performance drastically. Based on the methodology described above, a calibration environment has been developed to find the optimal values of the parameters which are hard to obtain by manual trial-and-error. Two approaches have been investigated to meet this task: One is to use the generic optimization framework for building simulation, called GenOpt (Wetter 2005), to co-operate with *EnergyPlus* (EnergyPlus 1.2.1 2005); the other approach is to use optimization routines from the IMSL Math Library (The IMSL Fortran Numerical Library v5.0 2005) or other optimization tools integrated within *EnergyPlus* modules. This section presents a case study, which follows the first approach using the generic optimizer GenOpt.

The case study presented here considers a three-zone building as an example. Due to the lack of actual information coming from a building automation system, the results from a base case run is selected and assumed to be the actual building information as fed back from the building automation system. The specific heat of the materials, lighting power density, and equipment power density of each zone are selected as the calibration parameters. Construction is simplified to one layer to reduce the dimensionality of the optimization problem. Table 3 gives the settings of the base case and selected calibration cases.

Table 3: Parameter settings for base and optimization cases

Calibration Parameters	Specific heat [kJ/(kgK)]		Lighting Power [kW]			Equipment Power [kW]		
Component	Wall	Roof	Zone					
			I	II	III	I	II	III
Base case	1.75	1.35	1.5	2.5	1.5	3.0	1.5	3.0
Initial value	1.75	1.35	1.5	2.5	1.5	3.0	1.5	3.0
Opt. case 1	✓	✓						
Opt. case 2			✓	✓	✓	✓	✓	✓
Opt. case 3	✓		✓	✓	✓			
Opt. case 4	✓					✓	✓	✓
Opt. case 5	✓	✓	✓	✓	✓	✓	✓	✓

The results revealed that in all five calibration cases, the minimization routine can find optimal parameter values which lead to a thermal response that is very close to the actual response of the base case. Table 4 shows the RMSE of each case after calibration. It can be seen that the RMSE in all five optimal cases are small, sufficient for building energy system simulation. However, when more calibration parameters are involved, the value of RMSE increases in general because the optimization problem becomes more complex as the dimensionality of the optimization problem increases. Figure 2 compares

Table 4: RMSE of calibration cases

Opt. case	case 1	case 2	case 3	case 4	case 5
RMSE	0.009	0.0001	0.007	0.014	0.027

the cooling load profile of the base case which represents the measured values from the building automation system, with the initial profile and the profile associated with the optimal values found by the optimizer.

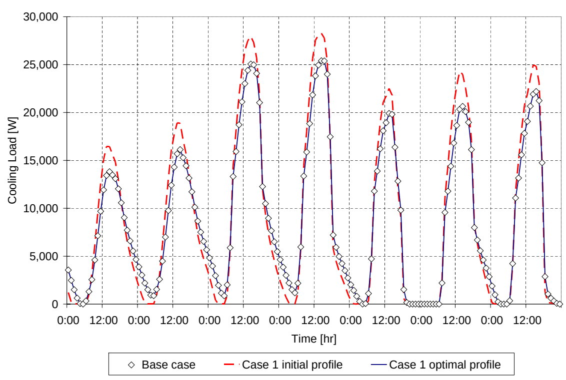

Figure 2: Cooling load profiles of base case and case 1 with initial and optimal values

The results of the simulation study above demonstrate that the method of calibration can be expected to satisfy the demands of supervisory control of commercial buildings. This process is not only supposed to be carried out before the supervisory building control procedure begins, but also to be repeated periodically (e.g., once a month) to ascertain that the building simulation models adequately represent the real building.

HYBRID LEARNING CONTROL

The incentive to develop a hybrid control scheme was to eliminate the need for a building model and forecasting tools. The hybrid learning control applies the fundamental structure of classic reinforcement learning, but divides the learning procedure of the supervisory controller into two phases, which are called simulated and implemented learning phases. A training model needs to be developed in advance and will be applied to train the learning controller first in a simulation environment. With the pre-trained knowledge, the controller then will be implemented in the real application and tuned further by directly interacting with the environment.

An experiment was carried out in September 2004 in the Energy Resource Station of the Iowa Energy Center in Ankeny, Iowa to validate the proposed hybrid control approach. The experiment generally confirmed that the supervisory controller had learned the optimal control action pattern, but still could not reach the true optimum given limited experiment time and improper learning parameter settings. A detailed analysis of the experiment will be presented in a forthcoming publication. Quite obviously, the deviation of the measured data and simulated data revealed the mismatch between the training model and actual HVAC plant under control. It was observed that the measured cooling load profiles were in good agreement with simulated data, but the state-of-charge of the thermal storage system (TES) showed substantial deviations between the measured and simulated data due to 1) the heat loss through the piping system and poor insulation of the TES ice tank and 2) the low efficiency of the dedicated ice-making chiller when the plant is switching between ice-making mode and chilled-water mode frequently.

The simulated learning phase serves the role of a school teacher who is responsible to offer the student, which in our case is the learning controller, the fundamental process knowledge before it is exposed to the actual environment. An obvious question is how the mismatch of training model affects this knowledge, and if the controller will be able to correct this incongruence in the implemented learning phase through direct interaction with the actual environment. In order to answer this question, the training model needs to be calibrated, and the simulated learning phase will be repeated using the refined model. A second objective to calibrate the training model is that the model will be used to evaluate the performance of the leaning controller by comparing it with other control strategies. It is not possible to carry out the comparison of these control strategies in the actual facility due to a lack of available testing time and because the exact weather condition is not repeatable. To this end, the training model should be calibrated as close as possible to the actual HVAC plant. The training model was developed in the Matlab/Simulink environment; Figure 3 depicts the overall structure of the simulation environment. The building thermal dynamics and energy consumption are modeled by four major groups of modules. The first one consists of the external and internal heat gain models for weather data, solar radiation, and building internal heat gain. The second group of modules describes the building envelope. Using state space modeling, the transient heat transfer through each construction element of the building is calculated using a R3C2 second-order lumped capacitance model with two capacitors and three resistors. The third group contains HVAC components modules, which includes a VAV terminal box with reheat coil, an air-handling unit including an economizer, a cooling coil, and a circulation fan, and finally a simple plant module including an electrical chiller, a cooling tower and a chilled water pump. All secondary system modules are developed based on models from the *AHSRAE Secondary Toolkit* (Brandemuehl 1993), and the plant model applied simple polynomial model based on (King & Potter 1998). The three groups of modules are linked together by a sensible and latent energy balance function. The active thermal energy storage system is modeled as an ideal thermal battery and dynamics of this ideal TES model (without considering losses due to heat transfer) can be expressed by:

$$x_{k+1} = x_k + u_k \frac{\Delta t}{SCAP} \tag{8}$$

where x_k is the state-of-charge of the TES, and $SCAP$ is the TES capacity.

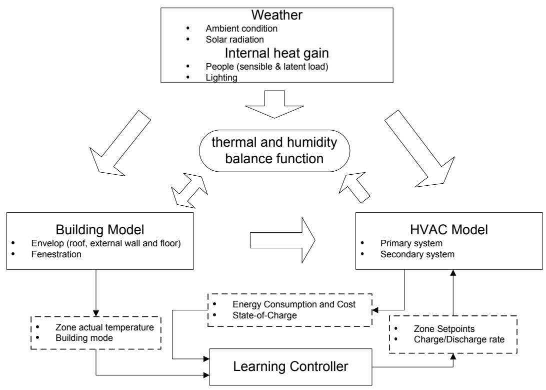

Figure 3: Schematic of the simulation environment

Two calibration procedures were carried out consecutively. The first one aimed at minimizing the deviation of the state-of-charge profiles between the simulated value and measured data. Two correction factors are introduced to reflect these factors contributing to the loss of state-of-charge. One is a discount factor $F_1 \in (0, 1]$ that is applied in the charging process. In the experiment of model-based predictive optimal control (Henze et al. 2005), it was estimated that about 12% charging load was lost due to heat losses, which implies $F_1 = 0.88$. This value was used as the initial value in our calibration procedure. The second one is an amplification parameter $F_2 > 1$, which is applied in the discharging process. It is not necessarily the reciprocal of F_1 because other factors may contribute to the ineffectiveness of heat transfer as explained in last section. The second calibration is to improve the match of HVAC plant power profiles, and the calibrated parameters are the equipment efficiencies for pumps, fans, and chillers. Table 5 lists the initial and calibrated parameter values for the calibration procedures.

Table 5: Calibration of training model

Calibration of state-of-charge (SOC)					
Parameters	F_1		F_2		
Initial value	1.00		1.00		
Calibrated value	0.62		1.28		
Calibration of power data					
Parameters	η_{fan}	η_{pump}	COP_{chw}	COP_{pre}	COP_{ice}
Initial	0.85	0.85	2.1	3.4	2.4
Calibrated	0.65	0.8	2.4	2.9	2.8

In Table 4, η_{fan} and η_{pump} stand for the motor efficiency of the circulation fans and pumps; COP_{chw} and COP_{ice} indicate the COP for the main chiller in chilled water making mode and ice making mode; COP_{pre} is the efficiency of the additional precooling chiller that is responsible for the precooling load when the main chiller is not available. Figure 4 and 5 present the profiles of state-of-charge and power consumption of the plant with the calibrated model.

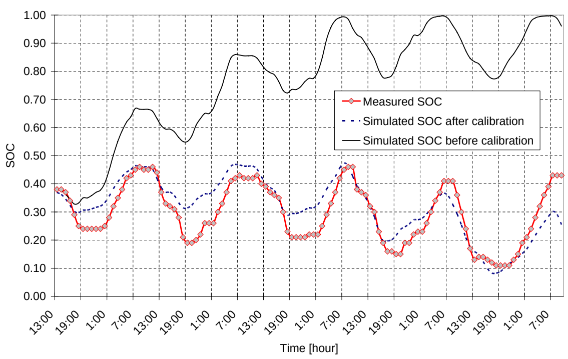

Figure 4: State-of-charge profiles of calibrated model

It can be seen from both Figure 4 and 5 that better agreement between the measured and simulated data was achieved through the calibration process. The discount factor F_1 is lower than the value calculated in the experiment of the model-based predictive optimal control approach. The power data deviation is mainly attributed to the incorrect initial efficiency values for fans and pumps,

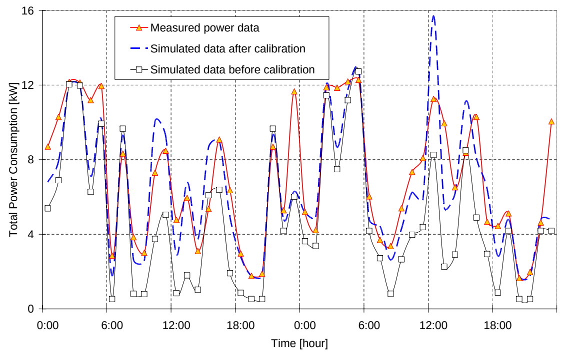

Figure 5: Power profiles of calibrated model

which are higher than the calibrated values. The COP value of the new chiller is lower than previously assumed, and the calibration confirmed the idiosyncratic fact that the main chiller operation in the ice-making mode was more energy efficient than in the chilled-water mode, which had been revealed in previous experimental study in (Henze et al. 2005).

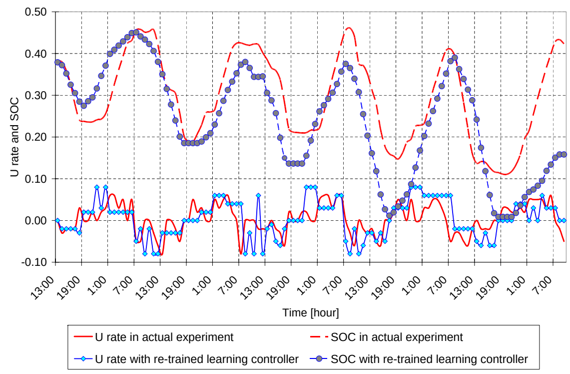

Figure 6: u rate with re-trained learning controller

A simulation study was then carried out using the calibrated model in order to further analyze the hybrid control approach. The simulated learning phase had been repeated to re-train the learning controller with the calibrated training model, and then the controller was implemented in the simulation environment to repeat the experiment for the same weather data as the actual experiment, as well as plant condition, e.g., initial state-of-charge of TES. The objective of the simulation study was to see if the controller performs better or differently than with the uncalibrated training model. Simulation scenarios were carried out with different learning parameters settings. It is interesting to note that in most cases the learning controller indeed behaves differently after using the calibrated model. In general, the learning controller tends to use the active TES system more than the passive thermal storage inventory. Figure 6 compares the control actions (charge/discharge rates and states-of-charge) of the learning controller in the repeated simulation and the actual experiment. In Figure 6, the repeated simulation shows more TES activity had been commanded. Table 6 compares the cumulative TES activity in calibrated simulation study with the measured data and uncalibrated simulation.

Table 6: Comparison of optimization case 1 with experiment

Case	Cumulative Charge rate	Cumulative Disch. rate	Cost [$]	Savings [%]
Actual experiment	1.82	-1.32	93.5	8.3
Simulated experiment	1.93	-1.47	91.9	9.9
Simulated experiment with calibrated model	2.38	-1.85	89.6	12.1

It can be clearly seen that the active TES system is more extensively utilized in terms of cumulative charging/discharging rates. This can be explained as follows. First, through calibration it was found that during charging of the active TES system, only 62% ($F_1 = 0.62$) of the icemaking chiller load lead to a change of state-of-charge. Therefore, for the same change in TES inventory, the charge rate has to be $1/F_1$ times what it would be for a perfect TES system, leading to substantially higher charge rates. Conversely, during discharging for the same contribution to the cooling load, the TES tank has to be discharged by $F_2 = 1.28$ times the value of a perfect TES system, i.e., the tank is depleted 28% faster, and consequently the discharge rates are higher. Secondly, the COP value of the main chiller in ice-making mode COP_{ice} proved to be higher than initially assumed. As a consequence, the learning controller realizes that charging active TES inventory at night is less costly, and thus more TES inventory is used.

On the other hand, however, the utilization of passive thermal storage is not clearly observed in the refined simulation study (results not shown here) compared with the uncalibrated simulation. This is due to the fact that a) the building itself is relatively light-weight and the possible load shifting effect is small. b) Moreover, the learning parameters previously found for the uncalibrated training model are no longer effective in the refined simulation study and revised learning parameters have not been found for the calibrated training model. c) The COP value of the precooling chiller is lower than the initially assumed value. This reduces the potential benefits of precooling and makes it harder to be discovered by the learning controller. Overall, as indicated in Table 6, with the calibrated training model, the learning controller achieves higher savings by utilizing active thermal storage inventory more extensively.

CONCLUSIONS & RECOMMENDATION

The proposed calibration process involves first identifying and tuning those building model parameters that affect the building cooling load profile. In a next step, the capacities, efficiencies, and part-load performance of the building energy system are tuned achieve the best fit of the predicted end-use consumption compared to the measured data from the building automation system.

As the case studies demonstrate, the proposed model calibration procedure can improve the model accuracy and consequently improve the quality of the building supervisory controller, model-based or model-free. The methodology of the calibration procedure is not only suitable for the specific problem at hand but also can be used in all investigations where the quality of a building model is of concern. The calibration process is essentially an optimization application and several commercially available optimization packages may be suitable. Furthermore, the proposed batch process can be transformed into an on-line procedure, which accommodates the application in real-time. In addition to the general calibration process described above, a sequence of specific calibration steps is recommended:

- The pre-processing step will be carried out before the building simulation model is placed into the calibration environment. It is recommended to ensure that all items in the checklist (Table 2) have been accounted for with utmost care.
- It is advisable to calibrate the internal heat gain parameters first when the pre-processing is finished because it is the dominant parameter affecting the building cooling load.
- The number of parameters to be fit should be kept as small as possible in order for the dimensionality of the error minimization task and its associated complexity to be low.
- The material properties are crucial tuning parameters affecting the building thermal response; it is suggested to calibrate these factors when the previous steps have been completed.
- The calibration of the characteristic properties (capacities, efficiencies, and part-load performance) of the building energy system can be performed separately from the other parameters mentioned above, yet the same methodology can be applied.

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