Co-simulation Setup for Online Model-assisted Control Design

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Abstract

For reduction of energy intensity of the building sector, effective and parsimonious use of energy resources and climate control systems is a prerequisite. Intelligent Building Energy Management Systems (BEMS) can be key ingredients towards achieving this goal; the incorporation of forecast data into the decision process can help achieve improved performance compared to existing state-of-the-art approaches. In the present paper, the potential of model-based supervisory control design algorithms for automatically designing BEMS is evaluated by performing experiments in a real building. A co-simulation setup is implemented where the thermal simulation model of the building is warmed up using past sensed data and then, given weather and occupancy forecasts, a controller is designed by solving a constrained minimization problem. A stochastic optimization algorithm is used to intelligently search the controller parameter space and identify a controller that minimizes an energy-related cost function, subject to thermal comfort constraints. A middleware solution is deployed in the building to facilitate two-way communication between the building (sensing and actuation) layer and the algorithmic layer.

Keywords – Co-simulation; BEMS design;BMS; Model-assisted control

1. Introduction

The building sector contributes significantly to global energy consumption. Building Energy Management Systems (BEMS) can be an effective way to improve energy performance by more effective utilization of actuating components. Towards providing effective building operation, significant effort has been consumed with the goal of defining “intelligent” BEMS. In current practice, it is quite common that BEMS comprise a set of rules, implemented in the buildings’ Programmable Logic Controllers (PLCs). These rules can range from the very simple to the extremely intricate, and given sensor – system state awareness – measurements, produce control decisions, that are in turn applied to the building. A significant research effort has been expanded towards designing such good rule-based control strategies – and, in many cases this is an effective approach. In modern buildings, the plethora of energy systems installed, often times make the design of a proper rule-based BEMS system a formidable challenge, while rule-based strategies offer no guaranties of performance. Recent research efforts focused on Model-Predictive Control (MPC) techniques [2], in which weather and occupancy predictions along with a linear state-space model capable of capturing thermal behavior of the building, are used to design elaborate control strategies [12], [14]. The simulation models can be developed using first principle approaches [11], [14], but for larger buildings their construction is impractical, due to the increased complexity [16]. Data-driven models, produced by system identification methods [10], [17], can be viable alternatives, but still it is very often that the identification process fails when applied on real, occupied buildings, due to under-excitation of system dynamics [17]. In more recent approaches [16] a detailed thermal simulation model of the building is used for the identification phase, which remains a difficult process. Despite the fact that MPC approaches in BEMS design are intuitive, their dependence on purpose-built state-space models is a challenging task that can hinder their application.

To avoid the above caveats, detailed zonal-type thermal simulation models developed during the design phase of the building, can be used as black-box models by model-assisted control design approaches. Within the FP7 PEBBLE project [15], a co-simulated controller fine-tuning procedure, using a stochastic optimization algorithm [7], [8], along with a detailed thermal simulation model of the building and weather and occupancy forecasts, is used to automatically generate effective control strategies, while preserving user thermal comfort levels. In the present work, a detailed description of the co-simulation setup, including all necessary sensing and actuating modalities is provided, along with the required components for application in a real building. In Section 2, the methodology is presented; in Section 3 the experimental setup is described; and, in Section 4 concluding remarks are presented.

2. Methodology

In the work presented here, the proposed approach is applied and evaluated on the Maintenance support building of the Technical University of Crete, located in Chania, Greece [5]. It is a two-floor building with a North-North-West orientation and large openings, including a large horizontal semicircular opening on the rooftop (Fig. 1).

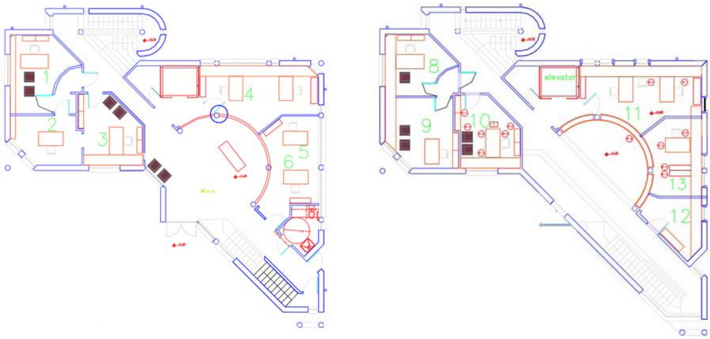

Fig. 1 The demonstration building - Ground floor (left) and first floor (right) plan views

The use of model-assisted control techniques for the BEMS design presupposes two processes running in parallel; one on the “simulation world”, designing a new controller in predefined intervals and one on the “real world”, applying the controllers to the real building, named *Control Design* and *Control Application* respectively (see Fig. 2).

The *Control Design* process consists of a *Warming-up* and a *Forecast Phase*. During the *Warming-up Phase*, a detailed thermal simulation model of the building is used – combined with historical in-building sensor measurements and weather data – to estimate the actual thermal state of the building at the beginning of the *Forecast Phase* (Fig. 2). Subsequently, when the *Warming-up Phase* finishes, the *Forecast Phas*e initiates. Here, a stochastic optimization algorithm is used to solve a constraint optimization problem that requires minimization of the energy consumption, while preserving user thermal comfort levels [8]. The optimization algorithm, starting from a provided initial controller constructs series of candidate controllers, which are evaluated using the “warmed-up” simulation model of the building along with weather and occupancy forecasts, to design a new controller. A closer look on the functionality of the algorithm makes obvious that application of the dynamical actuation schedules defined by the candidate controllers, as well as their performance evaluation through the model should be possible. The *Control Design* process is repeated every two hours.

The outcome of the *Control Design* process (the Optimized Controller in Fig. 2) is forwarded to the *Control Application* process. Here, at regular time intervals (every 10 minutes in our case), a control application service implemented at the *Middleware* layer is invoked to calculate new control actions using real sensor measurements, which are then sent to the *Real Building*. Of course, the efficiency of the applied control strategy depends on the quality of the controller provided by *the Control Design* process.

The thermal model of the building plays a central role in the *Control Design* process and is required to interact with the control design algorithm.

This is achieved through the co-simulation setup, which: a) incorporates into the simulation historical weather and in-building sensor data; b) injects weather and occupancy forecasts in the simulation model; and c) facilitates simulation scenarios using dynamical actuating schedules, thus allowing the evaluation of the candidate controllers. Since performance evaluation of the candidate controllers is performed on the basis of energy consumption and user discomfort levels, the use of detailed building thermal simulation models through co-simulation, allows incorporating more elaborate thermal comfort indices, such as the Fanger index [9]. This way, the model can be used to evaluate user comfort levels using historical sensor measurements from the building and to predict future ones, using forecasts and the simulation model.

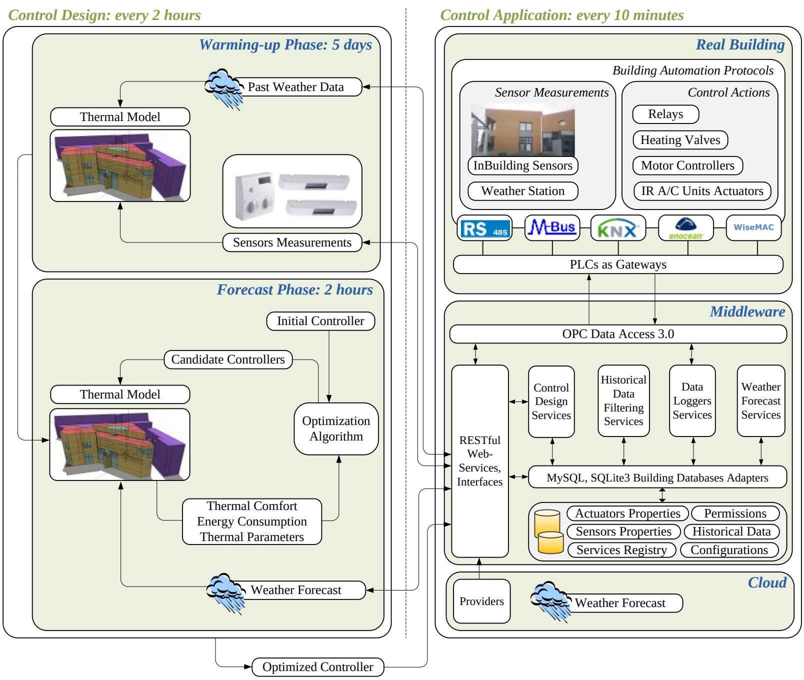

Fig. 2 The Methodological Approach

A. Simulation Thermal Model

Having in mind the functionality required by the simulation model, an accurate thermal model of the building is developed in EnergyPlus [4]. EnergyPlus is a thermal simulation engine released by the U.S. Department of Energy, which follows the zonal thermal models paradigm, where the building is divided into spaces (thermal zones), each with constant internal conditions. The energy and mass conservation differential equations on each zone are used to evaluate the evolution in time of the zonal thermal parameters. For more information on the simulated building, please refer to [6].

B. *Co-Simulation*

With the simulation model of the building at hand, the dynamic interaction between the model and the control design algorithm has to be defined using co-simulation, which enables the use of different software for run-time coupling. In our case, the dynamic connection between EnergyPlus, where the model of the building has been developed, and Matlab, where the control logic has been implemented has to be effectively utilized. Such a connection can be achieved using EnergyPlus with External Interfaces and especially with the Building Controls Virtual Test Bed (BCVTB) [18]. The BCVTB is a software environment, developed by Lawrence Berkeley National Laboratory which enables the coupling of different software codes for distributed simulation, by allowing simulation of the building envelope and HVAC system in EnergyPlus and implementation of the control logic in Matlab (or other general purpose programming languages), facilitating dynamic data exchange between the two programs at each time step of the simulation.

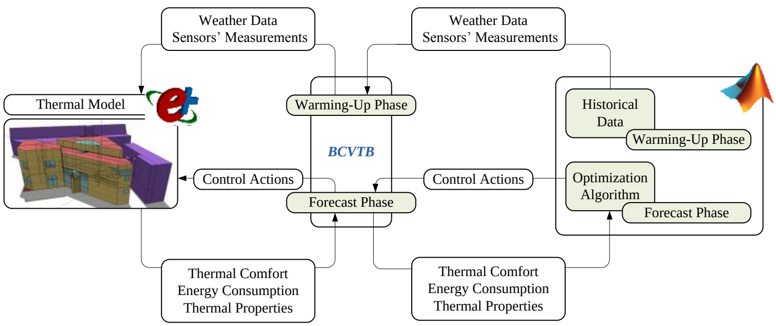

Fig. 3 Architecture of the connection between EnergyPlus and the BCVTB and the connection between MATLAB and BCVTB during *Control Design*.

Fig. 3 shows the system architecture and the data exchange paths that establish BCVTB as the central communication node in EnergyPlus-Matlab connection. During the *Warming-up Phase*, a Matlab script requests historical weather and in-building sensor data from the real building, which forwards them to the EnergyPlus simulation model through BCVTB, thus using the one-way data exchange path, shown in the upper part of Fig. 3. Consecutively, during the *Forecast Phase* a set of candidate controllers produced by the optimization algorithm are evaluated on the simulation model. Here, these controllers are implemented in Matlab and require information on specific building states, in order to produce control decisions in each simulation time-step. So, in every time-step of the simulation, a vector of building states (e.g. room temperature, outside humidity, etc.) is transmitted from the EnergyPlus model to the control logic in Matlab, through BCVTB. Subsequently, the new control decisions are communicated from Matlab back to EnergyPlus using the BCVTB (Fig. 2). When the simulation ends, the performance of the control strategy, in terms of energy consumption and user comfort levels, is acquired by the optimization algorithm, again using the BCVTB (Fig. 3).

C. Middleware

Once the *Control Design* process concludes to a control strategy for the building the *Control Application* process requests the updated controller to be applied to the building. Here, the available controller is used to produce control decisions in predefined time interval using sensor measurements from the real building (and not from the simulator, as in the *Forecast Phase*). Within this context, the Middleware is responsible for acquiring real-time sensor measurements from the building, executing the control logic and communicating the control decisions back to the building actuating components through the Building Management System (BMS).

With respect to the BMS, five different communication protocols are available and used to supply sensor measurements to the PLCs or transmit control actions from the PLCs to the components of the building. So, EnOcean and WiseMAC wireless protocols are used to retrieve in-building sensor measurements, such as temperature, humidity and illumination levels, as well as information of window opening through contact sensors. RS-485 wired protocol is used to acquire weather station measurements, while KNX/EIB wired protocol is used to communicate the desired settings to the A/C systems. Once the real-time data are available on the PLCs, the OLE for Process Control (OPC) interface – which is the only real-time interface between the middleware and the BMS – is used to forward them to the middleware-residing services that have requested them, though the Data Access (DA) specification.

The Control Application process requests the real-time values of specific sensors using a restful client. Here, the middleware service responsible for applying the controller to the building uses HTTP requests to retrieve the sensor data from the building PLCs through web services. Once the data are retrieved, the control application service communicates the new control actions back to the building with the same way.

In addition, the middleware is not only responsible for applying the control strategies produced, but also supports with historical data and weather predictions the functionality of the Control Design process. Thus, first of all multithreading OPC clients called Data Loggers (DLs) are used to record and store sensor data by managing the data logging process for different data logging groups. DLs support customizable properties such as time delay between successive records, database location, authentications parameters etc. Weather Forecast on the other hand, is the only middleware service allowed to communicate to the Internet. This service provides access to an external cloud-based forecast system and in predefined intervals acquires the predicted data and stores them to a database, making them available for other services through the use of proper database software adapters.

3. Experiment

In this section, a series of experiments on the real building are presented, highlighting the necessity of the co-simulation setup within the model-assisted control design context.

The first experiment indicates the significance of the *Warming-up Phase* for the simulation model accuracy. Here, the simulation model is provided with historical weather and in-building sensor data for 13 days (from December 10^{th} to December 30^{th}) and exploits them to assimilate the thermal state of the building at the beginning of the 14^{th} day. After that, and for about 4 days, the real building is unoccupied and allowed to free-float (i.e. no actuating components are operated), while the simulated model is required to accurately predict the zone temperature values (model validation). Note here that during the warm-up the sensed air temperature of each office room is set as the thermostat temperature setpoint of the room. As Fig. 4 depicts for zone O11 (see Fig. 1), during the warming-up period simulated and measured temperature trends are (almost) identical, thus the historical sensor values provided to the simulation model through the middleware, using the co-simulation setup, enhance the accuracy of the model. As for the validation phase (days 14-17), the results on Fig. 4 show that the maximum temperature difference between the simulated and real temperature schedules is 0.61˚C, while the mean absolute error 0.25˚C, indicating high model accuracy.

The second experiment presents the quality of the controllers produced by applying the overall methodology to the real building. Here, for a hot summer weekend where the outside temperature rises up to 27°C during the day and drops as low as 20°C during the night, a new controller is designed using the Control Design process every 2 hours, while the produced controllers are applied to the real building every 10 minutes. The final control strategy applied to zone O11 is shown in Fig. 5 along with the predicted room temperature values, while in Fig. 6 the actual room conditions are presented. A closer look on the results reveals the intelligent behavior of the control strategy generated by the proposed approach. To start, the use of occupancy information by the control application middleware service allows identifying unoccupied periods, thus shutting-down the cooling system. Moreover, the algorithm identifies that during the morning less cooling power is required and follows a conservative cooling policy, while during noon lowers the setpoint to maintain acceptable comfort levels in more demanding conditions. This behavior stems from the enhanced model accuracy, due to the incorporation of historical and forecasted data through co-simulation. This enhances the evaluation accuracy of candidate controllers tested by the optimization algorithm, thus assisting towards better control design. In addition, utilization of feedback from the building at each control application cycle by the respective middleware service, allows recovering from unpredicted events, like user absence.

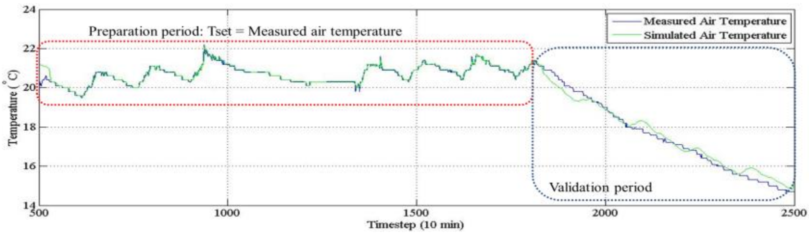

Fig. 4 Warming up and validation period: comparison of simulated and measured room temperatures for zone 11

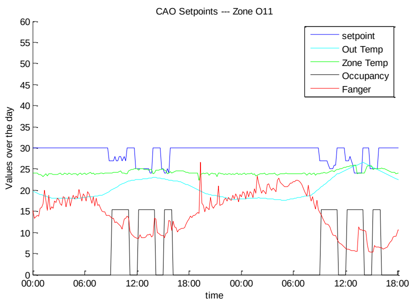

Fig. 5 Control setpoints for zone O11

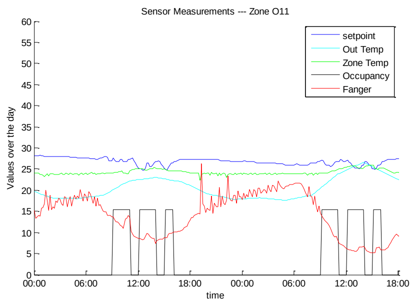

Fig. 6 Actual zone O11 conditions

4. Conclusions

In the present work, the significance of a co-simulation setup on the application of a model-assisted BEMS design technique is presented. The use of detailed thermal simulation models that act as surrogate to the real building require the definition of the Control Design and the Control Application processes. The first produces efficient control strategies supported by the incorporation of real data into the simulation model, thus enhancing its accuracy, while the second utilizes the middleware of the building in order to adapt the provided control strategies to any unpredicted events. The efficiency of the overall approach is supported by the results of two experiments conducted on a real demonstration office building, located in Chania, Greece.

5. Acknowledgment

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