SIMULATION ASSISTED CONTROL IN BUILDING ENERGY MANAGEMENT SYSTEMS

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ABSTRACT

Technological advances in real-time data collection, data transfer and ever-increasing computational power are bringing simulation assisted control and on-line fault detection and diagnosis closer to reality than was imagined when Building Energy Management Systems were introduced in the 1970s. This paper describes the development and testing of a prototype simulation assisted controller, in which a detailed simulation program is embedded in real-time control decision making. Results from an experiment in a full-scale environmental test facility demonstrate the feasibility of predictive control using a physically-based thermal simulation program.

Keywords: Building energy management systems, predictive control, simulation assisted control.

INTRODUCTION

The majority of recent developments in Building Energy Management Systems (BEMS) have followed the advances made in computer technology, telecommunications and information technology. Significant developments have been made in the standardisation of communication protocols [1] and in web-enabled controllers [2]. There has been less focus on the development of new concepts in control, particularly in the built environment. Despite this, some significant advances on the application of new building control techniques have been made. These are outlined below.

The concept of predictive control, which uses a model in addition to measured data in order to forecast the optimum control strategy to be implemented, could assist in the more efficient operation of BEMS. This should result in lower energy consumption and more comfortable buildings. Work has been done on predictive controllers using stochastic models [3], [4], [5]. Both short term (10-20 min) and long term (days) prediction errors lay within acceptable ranges both in terms of temperature and humidity control. Prediction errors were found to be within 1°C and 1.5% relative humidity.

Other developments include the use of fuzzy logic control [6], [7] and the use of neural networks [8], [9]. The basic idea behind fuzzy logic control is to incorporate the experience of a human process operator in the design of the controller: this unfortunately requires good quality experiential knowledge and data about the controlled system's operating characteristics. A neural network is a control mechanism based on the operational principles of the human brain. It can be considered as a set of linked units that connect an input to an output. These units interact with each other by means of weighted connections. The network requires training by giving the related output to a given input, resulting in certain weights being assigned to particular connections. A clear drawback with the use of neural networks in control is the requirement for extensive training data [10].

Controllers incorporating self-learning algorithms in control systems are now quite common, for example in optimum start of heating plant [11]. The aim is to achieve the defined zone conditions at the desired time of arrival (DTOA) of the occupants in the shortest possible time. However, the International Energy Agency (IEA) Annex 17 research work [12] showed that these learning algorithms can initially take days to predict the correct optimum start time and have difficulty dealing with unusual conditions such as long shut-down periods, exceptional weather conditions and changes in building operation. Even the best trained self-learning controller cannot extrapolate beyond its range of experience.

All the previously discussed methods of control have one common feature: they have no underlying physical model of the system and process being controlled. The controlled entity is essentially a non-physical "black-box model". There are inherent limitations in the black box approach to control as the controller has no knowledge of the cause and effect relationships between the elements of the controlled system and external excitations such as climate and occupant interaction. With passive buildings employing natural resources such as daylight and free cooling, control actions become convoluted due to these interactions between the elements of the controlled system (e.g. glare requiring blind repositioning, causing luminaire actuation, leading to increased cooling loads). Such interactions can best be represented in a physically-based model in which all the elements interact. Building simulation programs provide such a model.

SIMULATION ASSISTED CONTROL

At the present time, detailed simulation programs are playing significant roles in two areas:

Emulators: Emulators replace a building and its HVAC systems and use a computer program to simulate their response to the BEMS commands. Emulators can also be used for control product development, training of BEMS operators, tuning of control equipment and imitating fault situations to see how the BEMS would cope [13]. Collaborative research work on emulation was carried out by the IEA under Annex 16 and Annex 17 [12]. Six different emulators were developed: three used HVACSIM+ and three used TRYNSYS. One of the best-known emulators developed within the framework of Annex 17 was 'SIMBAD' (SIMulator for Buildings And Devices), which uses both the TRNSYS and HVACSIM+ simulation software. The early versions of SIMBAD had difficulty simulating dynamic conditions, the creation of HVAC models was tedious and the user interface was not user friendly. In order to address these difficulties CSTB are currently developing a "toolbox" of models of HVAC components and plant for the design and testing of control systems [14]. Johnson Controls and the National Institute of Standards and Technology (NIST) in the US have developed a low cost PC based emulator [15]. The company is now using this for the purpose of testing new control products.

Simulation models play a similar role in the development of fault-detection and diagnosis (FDD), a technique which aims to detect and locate faults or predict the presence of faults in energy management systems [16]. FDD uses a model of the correctly operating system to supplement the conventional feedback loop, the model acting as a reference for correct behaviour of the controlled system. Test results [17] on an air handling unit serving a dual duct air conditioning system show that the use of FDD improved the control performance and achieved good results in detecting leakage of a control valve on a cooling coil and the sticking of a return air damper.

Evaluators: In this role, simulation programs can be used to test the efficacy of possible control strategies. In this case a detailed model of the building/HVAC system is established, and various control strategies are evaluated in terms of comfort acceptability and energy efficiency (e.g. [12], [18]).

The objective of this research was to investigate a possible third use for simulation programs: their encapsulation within the BEMS system in order to provide simulation assisted control. The research, undertaken in collaboration with Honeywell Control Systems, involved executing the simulation program as part of the control task in order to evaluate several possible control scenarios and make a selection in terms of some relevant criteria. Although this possibility had been suggested previously, it was dismissed at the time as being "beyond the capabilities of the detailed simulation programs" [19]. The premise of the present study is that simulation program capabilities and BEMS flexibility are now sufficiently advanced for simulation assisted control to be feasible.

Although there are potential difficulties associated with simulation assisted control (e.g. the need to make and calibrate a model of the system, particularly when dynamic variations due to airflow and solar radiation are important; the difficulty of parsing from complex result-sets to simple actions), physically-based models offer the following benefits over "black-box" models:

- they are able to address cause and effect scenarios such as outlined previously;
- they can adapt to the impact of changing building use or operation (provided that the change is incorporated into the model);

- they potentially offer better control through calculation of interactions and can identify the factors that result in particular building performance; and

- they provide the possibility of comparing options for different control strategies by testing them on the building model.

Simulation assisted control is likely to be of most use in the following circumstances:

- when significant look-ahead times are involved (hours, rather than minutes);

- for high-level supervisory control, e.g. load shedding, where several alternatives and their implications for environmental conditions (particularly occupant comfort) may need to be evaluated;

- where interaction is high, e.g. blinds/lighting/cooling; and

- where the building use varies or changes (e.g. large variations in occupancy) and where this variation is known in advance.

Table 1 lists those plant systems that have been identified as presenting opportunities for simulation assisted control (extracted in part from the comprehensive library of BEMS control strategies in [11]). In addition, where integrated control is emphasised, a BEMS system would likely benefit from explicit simulation of the interactions within the building.

The primary objective of this pilot project was therefore to investigate the possibility of integrating simulation within real-time BEMS operation to provide a prototype control decision-making capability. The envisaged system is depicted in Figure 1. This shows the usual BEMS control structure—inputs are obtained from climate and building state sensors, and an internal control algorithm decides on the appropriate control action for switching heating, cooling etc. The new elements are the simulator, which models the building/HVAC using sensed data as boundary conditions, and an evaluator, which scans the simulation results to suggest an appropriate control action to the main simulation assisted controller.

The study investigated whether real-time simulation could be introduced as shown in Figure 1. In view of the many practical interface issues that would be inherent in using a BEMS system directly, as demonstrated in the development of the SIMBAD emulator [14], it was decided to use LabVIEW as a BEMS replacement and the dynamic simulation program ESP-r [20] for control scenario appraisal. LabVIEW is used widely in industry for SCADA (Supervisory Control and Data Acquisition) applications, and for prototype development it offered the necessary flexibility without being tied to a particular BEMS protocol. The ESP-r system was used as it is a detailed simulation program with explicit representation of all heat and mass transfer processes and includes an extensive array of control capabilities.

The research had the following elements.

a) The identification of control functions of current BEMS that might benefit from simulation assistance.

b) The creation of LabVIEW routines for data acquisition and control actuation.

c) The development of the real-time linking of these routines to ESP-r to permit scenario appraisal, selection and enactment.

d) A testing of this linked system in realistic scale experiments.

CONTROL CAPABILITIES OF ESP-r

For simulation to be of use in the present context, it must be possible to represent the building/HVAC system and the imposed control as an integrated system. Within ESP-r a control system is implemented as a set of closed or open control loops acting jointly or individually. Each loop comprises a sensor linked to an actuator via an algorithm; in certain cases loops may be cascaded. ESP-r offers an extensive library of sensors, actuators and algorithms representing both idealised and realistic components, ranging from basic "ideal" control, through PID

control to global sequence control [21].

As part of a design evaluation, the usual practice is to firstly employ idealised components to constrain system states (required temperatures, available heating capacity, mechanical ventilation rates etc) in order to facilitate the intercomparison of control options. Later, in support of detailed design, these idealised components may be substituted by more realistic counterparts to facilitate the study of control system stability and efficacy. By arranging that different sets of control loops can be activated over different periods, it is possible to implement any conceivable control regime (even conceptual regimes for which no actual hardware is available).

IMPLEMENTATION

The implementation of a prototype simulation assisted controller required the following elements:

i) A calibrated model of the building and HVAC system.

ii) Sensors to measure all critical boundary conditions (external temperature, solar radiation etc) and internal conditions (temperature, humidity etc); the data must be collated in the BEMS (i.e. within LabVIEW).

(iii) A mechanism for transferring data to the simulator.

(iv) A routine within the BEMS for initiating the simulation(s) against a predefined control strategy.

(v) A simulator to predict internal conditions and ascertain parameters (start time, plant output etc) to meet some user-defined criterion.

(vi) A controller to make decisions based on modelling outputs.

(vii) A mechanism for transferring control data back to the BEMS (LabVIEW).

(viii) Actuators controlled by the BEMS to initiate the control action.

(ix) A structure to allow iteration and updating of control actions.

An independent software module was developed that, together with LabVIEW and ESP-r, forms the prototype simulation assisted controller. The software module combines several of the elements outlined above. The three programs operate as shown in Figure 2. The function of these three programs, and the developments required in each case are summarized in the following paragraphs.

ESP-r

The main use of the ESP-r system is for design decision support. Several changes were required to cope with the novel aspects of real-time simulation. The most important of these were the transfer of acquired data into ESP-r databases, and the subsequent use of this measured data to maintain the correct model state until the current time, after which the specified predictive controller was invoked.

LabVIEW

In its role as a surrogate BEMS, LabVIEW is the controlling entity. Programs were therefore written in LabVIEW's in-built G programming language to collect sensor data, to display and store this data in a format suitable for import to ESP-r's databases, to commission simulations, to receive the suggested control action and to initiate that action.

BEMS to ESP-r link

This new interface module operates on the basis of a control definition file containing the following information:

- the type of control simulation to be conducted (e.g. winter:heating, summer:cooling);
- designated controlled spaces;

- control action type(s) to be investigated (e.g. optimum start/stop, night ventilation);
- available plant capacity for each space;
- control strategy end time;
- target set-point for each space;
- target time at which set-point is to be attained.

The interface module is controlled by the BEMS system (LabVIEW), and is passed a file containing LabVIEW's monitored climate and internal temperature data. The module then performs the following tasks:

(i) *Simulation Synchronisation*: The required start and stop dates for the simulation are determined, based on the time-stamped data contained within the file provided by LabVIEW. The program also calculates a simulation frequency (time step) based on the sampling rate of the monitored data.

(ii) *Climate Prediction*: The LabVIEW data file is read and its climate information used to predict weather conditions for the next 24 to 48 hours. At this stage, only a structure for short-term climate prediction has been implemented with a simple algorithm: further work will be required to develop this function.

(iii) *Control Strategy Preparation*: Based on the control action type specified in the control definition file, the interface module develops a suitable control strategy for use in the ESP-r simulation.

Firstly, the controlled space temperatures are held to those contained in the monitored data passed by LabVIEW until time t_c, the last monitored time in the file, after which the simulation evolves freely (with predicted climate data) until time t_p.

Secondly, the module determines the plant action start time: this is either advanced or retarded based on the progress of the predictive simulation. Plant action is made according to a defined plant control strategy until time t_e, the specified shut down time.

(iv) *Simulation Commissioning*: Based on the calculated simulation start and stop dates, simulation frequency and user defined control strategy, the interface module commissions n simulations (where $n = (t_{stop} - t_{start}) \times 1/\text{frequency}$). In each of these simulations a control parameter (e.g. plant start time) is changed by a fixed increment. The parameters for the simulation are passed to the simulator in the form of a control definition file and a simulation parameter file (defining the period over which the simulation is to be run and the time step of the simulation).

(v) Results Interpretation : At each iteration, the interface module examines the simulation output and compares the value of the controlled space variable reached at the target time with that specified in the control definition file. If the controlled value is not acceptable then another simulation is commissioned with the plant action time t_p advanced or retarded by one time increment depending on the type of simulation being conducted. If the controlled value is within bounds then the sequence of simulations is stopped and the time and/or value which meets the control criteria reported back to LabVIEW.

As a result of these developments, it is possible to implement the functions listed in Table 1. For the purposes of this project, one commonly used function was tested—optimum start control. The following sections describes experiments that were set up to test the real-time simulation link - the first is a simple laboratory rig, the second a full size test room environment.

PRELIMINARY EXPERIMENT

This experimental configuration was designed to test the practicality and effectiveness of the simulation assisted controller and to demonstrate real-time use of simulation for control purposes. A simple test rig was used, comprising an opaque box, a 150W bulb as a heat source, internal and external mechanically aspirated temperature sensors and a computer running the BEMS configured LabVIEW programs, the specially extended version of ESP-r and the new interface module (Figure 3).

Several experiments were conducted based on optimum start control. In these, LabVIEW commissioned a series of ESP-r simulations with the aim of determining at what time, the heat source inside the box would need to be switched on so that the internal air temperature would reach the set-point temperature. Prediction of switch-on time was generally found to be reasonable. The experiments demonstrated the practicality of the controller, and the accuracy of the results, for a roughly calibrated model, were encouraging. Figure 4 shows the results for one of the experiments conducted.

TEST CELL EXPERIMENT

A more realistic scale test was conducted in the environmental test facility at Honeywell's Newhouse site in Scotland. This facility consists of two realistically dimensioned rooms surrounded by temperature controlled voids (Figure 5). The constructions used in the test rooms are as would be found in a real UK dwelling (insulated cavity walls, with double glazed windows). Each room is heated by a central boiler; there are also two low-temperature hot water radiators in each room. Two dedicated PCs running LabVIEW monitor heating system temperatures, room air temperatures and void temperatures.

An ESP-r model of the test rooms was developed (Figure 6) using geometrical and construction data supplied by Honeywell. This model, along with ESP-r itself, was installed on the PC monitoring test room 1. The LabVIEW programs described previously were modified and linked to the existing test room data acquisition program.

The ESP-r model was firstly calibrated using data from a heating sequence conducted on test room 1: the room was heated at full power (using one radiator) for two hours and allowed to cool for 3 hours. This sequence was repeated twice. The same heating sequence was simulated with the ESP-r model and predicted room temperature were deemed to be sufficiently close to that of the real room for the purposes of the experiment.

The main experiment involved using simulation assisted control to predict the optimum start time for the test room 1 heating system. Data collection was at 1 minute intervals. At the start of the experiment, the test rooms were left in a free-floating state for 24 hours. The surrounding voids remained unconditioned throughout the experiment, while the adjacent test room (being used for another experiment) was maintained at 24°C. The simulation controller was set to determine the switch-on time required to bring the room to a temperature of 25°C with a nominal 1200W heat input. Figure 7 shows the results of the experiment, with the actual collected temperature data superimposed upon the simulated values.

In the preceding 24 hours the room temperature floated at around 21°C. Given a 25°C set-point and target of 11:00, ESP-r predicted a heating system switch on time of 10:20. Note that the room temperature was not at exactly 25°C at this time as the simulated temperature was compared to the set-point with a tolerance of ±0.5°C. When the test room heating was switched on, the room reached 25°C at 11:06. The room temperature coincided with the ESP-r room temperature prediction at 11:02. From Figure 7, it is clear that ESP-r slightly overpredicts the response of the test room to heating, with the prediction leading the actual room temperature. However, given the rudimentary calibration of the model, the predictive performance of the simulation assisted control tool was encouraging. Measured and simulated temperatures coincided with a temporal error of 5%, maximum error in temperature prediction was around 1°C and the actual set-point was reached 6 minutes later than predicted but within the time interval of one simulation time increment (10 minutes).

Subsequent alterations to the model, including a more accurate representation of the radiator which heats the test room, gave results which gave a closer match to the measured data. Figure 8 shows the performance of the re-calibrated model compared to the same test data. Note the improvement in the simulated room dynamics during the heating phase.

CONCLUSIONS

This research was conducted to test the feasibility of using simulation to enhance the control capabilities of BEMS. Building and plant control functions amenable to simulation assisted control were identified.

Modifications to the ESP-r system were undertaken to allow real-time simulation (i.e. simulation using data as it is gathered and which returns control actions for real-time implementation). This paper described an experiment undertaken with the prototype control system in full scale rooms within Honeywell's test facility, demonstrating how such a system could be used to generate optimum start times. On a realistic scale experiment, it was shown

that it is feasible to include simulation in control decision making. Typically, the simulation time (for a total of about 6 different simulations of the Honeywell test facility) was about 1 to 2 minutes on a low-end Pentium PC. Although only optimum start was demonstrated, the structure is in place for other applications.

Further research is necessary to develop the idea further. This should focus on testing on a full scale building subject to external climate variation, integrating improved short-term climate prediction algorithms into the simulator, testing different control strategies, replacing LabVIEW with a modern BEMS system, developing the link to ESP-r (and/or other simulators) with BEMS standard protocols and developing calibration strategies.

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Table 1: Applications suitable for simulation assisted control.

Application	Controlled Component	Output to be optimised
Optimum start/stop	Heating/ cooling system	Start/stop time
Night-time cooling	Fans	Hours of operation
Optimum set-back temperature	Heating system	Set-back temperature
Boiler sequencing	Boilers	Heating system efficiency
Load shedding	Heating system	Priority for heating
Combined heat and power	CHP engine	Hours of operation
District heating	Heating system	Forecasting of heat demand
Underfloor heating	Heating system	Hours of operation
Mixed mode ventilation systems	Fans	Start/stop time
Charging of ice storage	Refrigeration	Hours of operation
Night operated ground water source heat pumps	Water pump/compressor	Start time
Optimum control mode	Various	Control mode selection

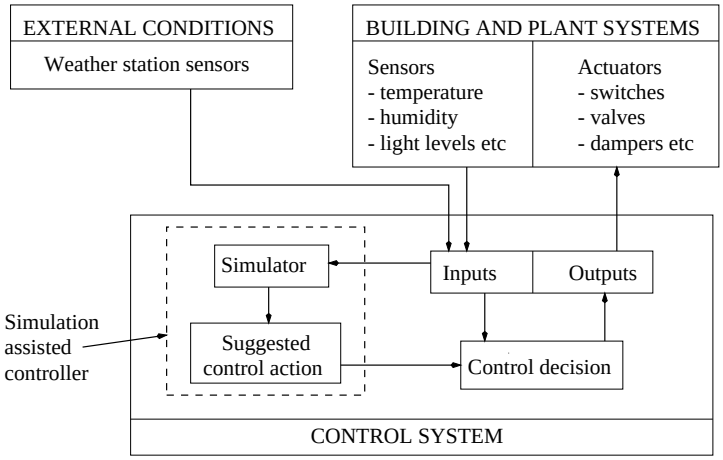

Figure 1: Simulation assisted control in BEMS.

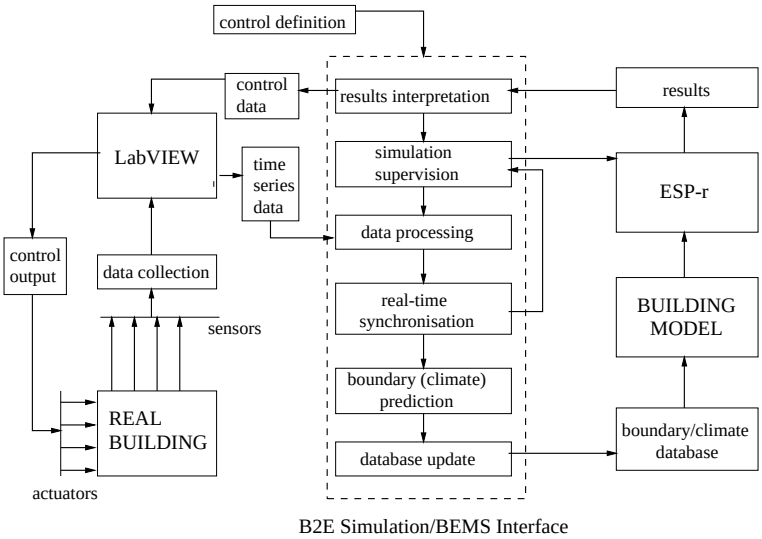

Figure 2: Overview of the interface structure.

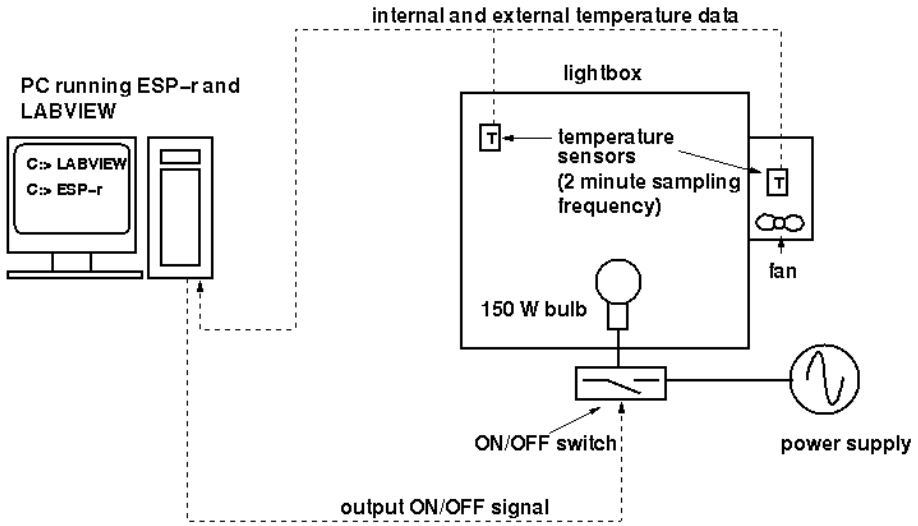

Figure 3: Preliminary experimental configuration.

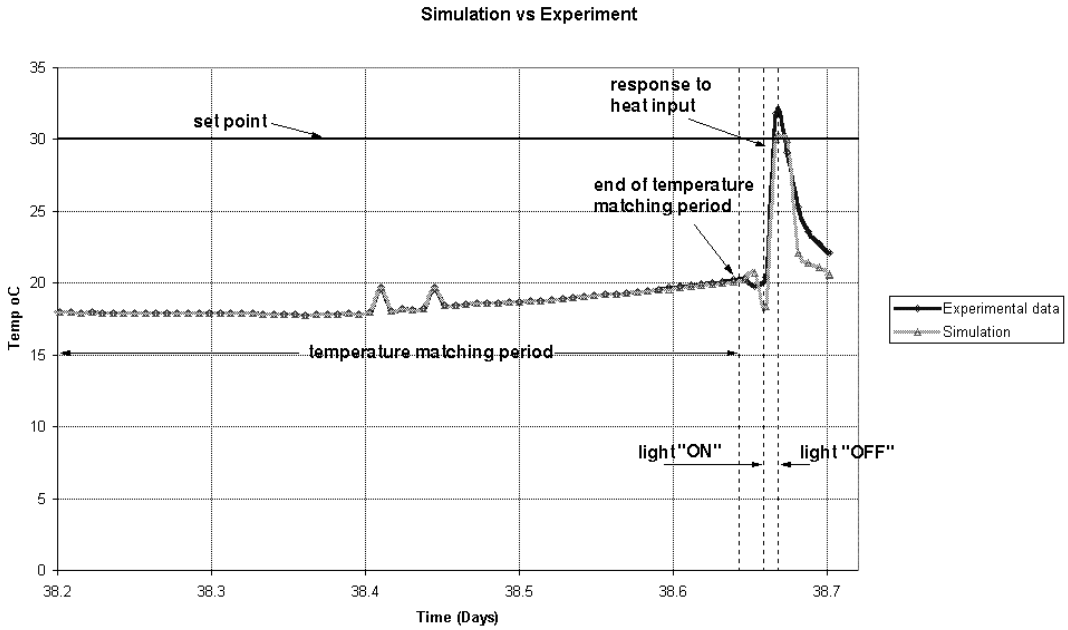

Figure 4: Preliminary experimental results.

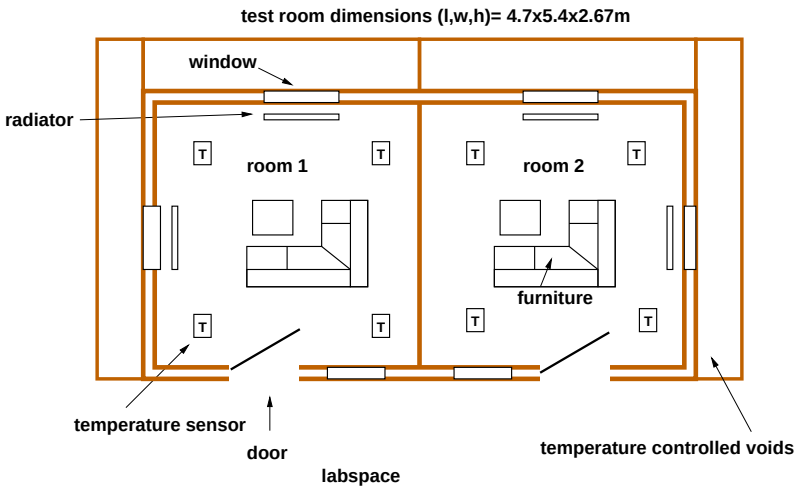

Figure 5: Plan view of the test rooms and voids.

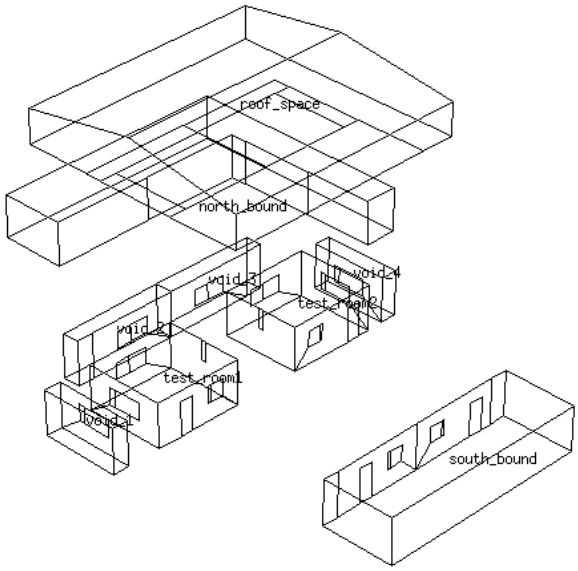

Figure 6: Exploded view of the ESP-r model.

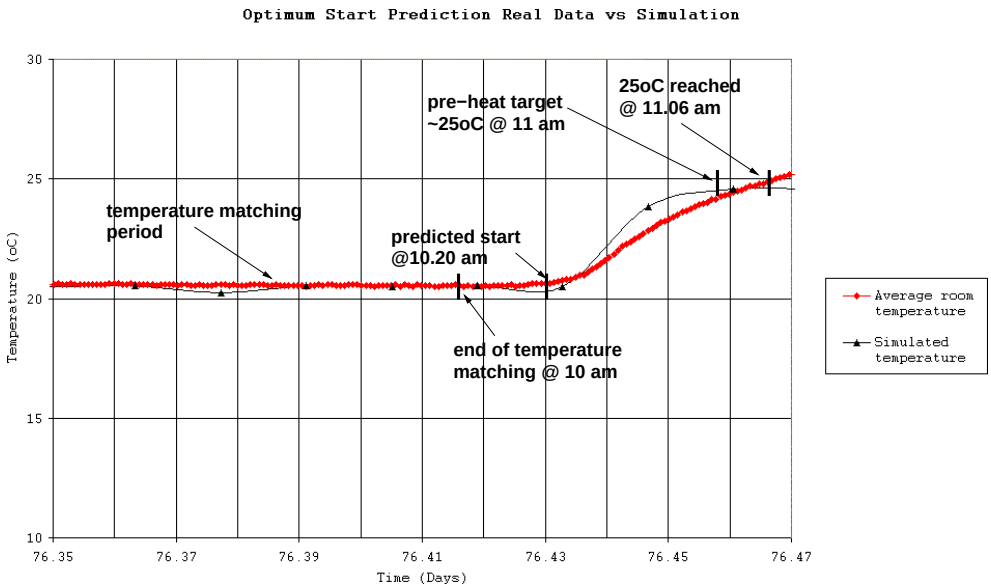

Figure 7: Optimum start experiment - model prediction vs monitored data.

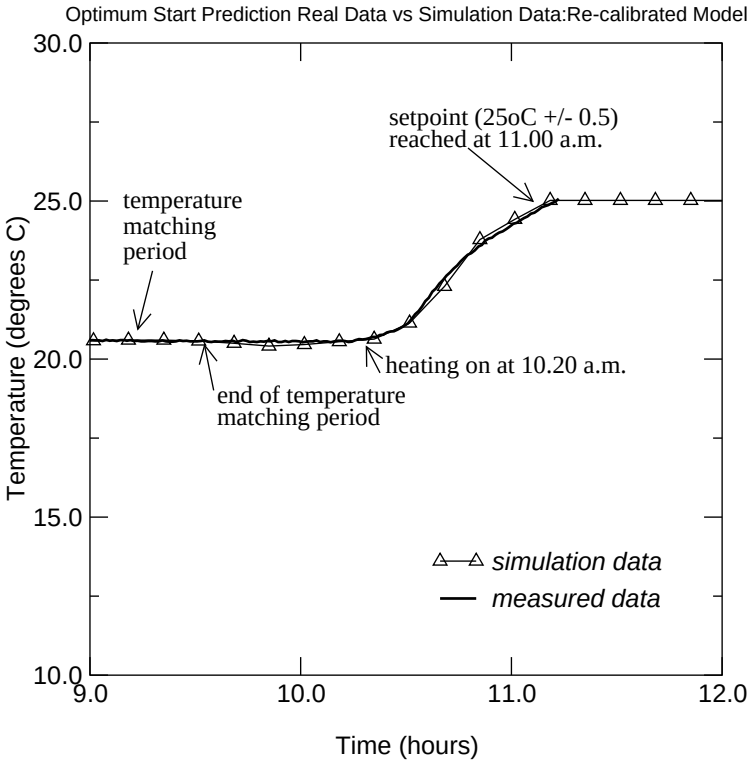

Figure 8: Model prediction vs monitored data after re-calibration.