

MODEL BASED OPTIMAL CONTROL FOR INTEGRATED BUILDING SYSTEMS

A. Yahiaoui¹, J. Hensen¹, L. Soethout², D. van Paassen³

¹Center for Building & Systems TNO-TU/e, 5600MB Eindhoven, Netherlands

²TNO Built Environment and Geosciences, 2600AA Delft, Netherlands

³Department of Mechanical Engineering, TU Delft, 2628CD Delft, Netherlands

E-mail: a.yahiaoui@bwk.tue.nl

ABSTRACT: Building performance simulation has traditionally concentrated on the use of basic and conventional control methods, which are of limited use since they cannot solve all the challenges encountered. With this regard, there is a great interest in the concept of modern control strategies for integrated building systems. To explore this potential, the paper focuses mainly on the application of model-based optimal control to buildings. In this case, a performance criterion minimized by linear programming is proposed in order to maintain the temperature of indoor environment comfortable while minimizing energy consumption. Particularly, this paper is concerned with the relevance and reliability of integrating control and building performance simulation environments by run-time coupling, over TCP/IP protocol suite. In addition, this paper involves a case-study with two important steps; the first step consists of experiments obtained in a test-cell that demonstrate the potential ability of advanced control strategies in buildings, and then simulation results are obtained with the use of distributed control and building performance simulation software by run-time coupling.

Keywords – Building performance simulation, run-time coupling, model-based optimal control, and energy consumption.

1. INTRODUCTION

Modern control theory is an emergent discipline that has been mainly applied to large-scale projects and complex systems, used broadly in aeronautic, automobile and space industry since early sixties. For the building domain, there is still a need for developing optimal control strategies for rapid response of HVAC (Heating, Ventilation and Air-Conditioning) and lighting systems of buildings to achieve the desired comfort (including its effect on satisfaction and productivity) while minimizing energy consumption and cost. Especially the advent of computer-based Building Automation Systems (BAS) has fueled the investigation of building equipment and components, in order to attain optimal control and management of their functions in an efficient and rational way while reducing fossil fuel consumption and green house gas emissions (see e.g. IEA, 2002). Modern control methods are in fact an efficient way for handling emergency issues in buildings, as a central computer of a BAS can in turn devise an optimal control strategy for specific urgent situations. As an example, Lute J. P. (et al., 1995) attended to find a cost-effective optimum to supply heat to the building using a predictor for the indoor temperature, while maintaining a comfortable temperature in the building within a certain range of variation. Furthermore, the control of the temperature in heating or cooling mode is kept between two predefined limits, instead of maintaining a process variable, as long as possible, constant at its set-point.

As mentioned by e.g. Galata (et al., 1996), multivariable control systems are an efficient and consistent way to control building energy services as a whole, with a potential of energy savings around 18% for the HVAC systems over the year, and around 52% for lighting. Integrated control strategies for heating, cooling and artificial/natural lighting are regulated simultaneously by one multi-controller rather than individually by various control strategies. Besides this important potential, many additional perspectives may exist, like stability of comfort aspects in buildings and steady-state concepts used generally as a basis for

multivariable systems. Most building components (e.g. valves) are basically characterized with saturations constraints. This limited factor must be prioritized by means of state space methods, which are not only useful in analysis and design of linear systems, but are also an important starting point for advanced optimal and nonlinear control in buildings.

However, these previous studies do not take into account all building material and construction properties plus system components and performance aspects including requirements imposed by occupants and environmental conditions. In most cases, this necessitates appropriate methods to control comfort and energetic aspects involving one or more limited factors (like for instance, the measured variable must rendezvous with the set-point before the required time is accumulated). To tackle these problems, an approach to distributed control and building performance simulation environments by run-time coupling has been developed and implemented. The run-time coupling uses Internet sockets in order to exchange data to each other during simulation. In this approach, the building model and the control system, separated in different environments, work together through run-time coupling. The models can be located on different kinds of hosts where performance simulation is much faster than using a single computer.

To deal with the indoor temperature controller under constraints that avoid undesirable operation regimes, a model is developed using the notion of the block diagram representation of the temperature control process of a space, modeled by a continuous-time transfer function of different elements forming the feedback control system. This paper describes a model-based optimal control strategy that suitably regulates the indoor temperature in a building. In this case, a performance criterion minimized by linear programming is proposed in order to optimize the comfort aspects within the minimum use of energy cost. This model-based optimal control is in terms of a reduced steady state form, derived from experimental studies within a test-cell, located at Delft Technical University (TU Delft). Then, through a run-time coupling between domain independent building environments and domain specific building performance simulation software, the same proposed model is used to obtain simulation results with respect to the same material properties and climate data used for experiments.

The first part of this paper presents a brief description of distributed control and building performance simulation. The next part elaborates the concept behind our idea concerning the integrated performance assessment by identifying the overall effect of innovative control strategies for integrated building systems. Then, a mathematical formulation for heating mode is described that proposes a performance index for the optimization of the comfort and energetic aspects. The fourth section consists of the synthesis relevant to the control feedback structure for integrated building systems. The last essential part of this paper is a case study resulting on a balance between theoretical aspects and practical applications.

2. DISTRIBUTED CONTROL AND BUILDING PERFORMANCE SIMULATION

One key of the issues facing us when we want to simulate a building modeling plus environmental control systems is that frequently certain system components and/or control features can be modeled in one simulation environment while models for other components and/or control features are only available in other simulation software. In other words, there is domain specific software for building performance simulation (BPS) is usually relatively basic in terms of control modeling and simulation capabilities (e.g. ESP-r, TRNSYS). On the other hand, there exists domain dependent control modeling environments (CME), which are very advanced in control modeling and simulation features (e.g. Matlab/Simulink). To alleviate the restricted issue mentioned above, it is essential to reason behind our hypothesis that marrying the two approaches by run-time coupling would potentially enable integrated

performance assessment by predicting the overall effect of innovative control strategies for integrated building systems.

Previous (in Yahiaoui et al., 2003 and Yahiaoui et al., 2005), it has been described that a promising approach to run-time coupling between ESP-r and Matlab/simulink is an IPC (Inter-process Communication) using Internet sockets. This approach performs distributed simulation by a network protocol in order to exchange data between building model and its controller, as it relatively happens in a real situation. Both building model and its controller which are separated and work together through run-time coupling can be located on different kinds of hosts in which the performance simulation is much faster than using a single computer. Consequently, the development of this new advent would potentially enable new flexible functionalities of building control strategies that are not yet possible.

During the simulation, commands and data are transmitted between ESP-r and Matlab/Simulink. If for instance the building model (i.e. ESP-r) has to send its current measured process to its controller (i.e. Matlab/ Simulink) with TCP/IP-stream, a method called encodes them and transmits them with a defined control sequence via TCP/IP to a method received. This then receives the control sequence, decodes data from TCP/IP-stream format and sends data to the recipient (Matlab/ Simulink). When the controller has to send back the actuated process to its building model via TCP/IP, the same procedure is in this fact repeated, as shown on figure 1.

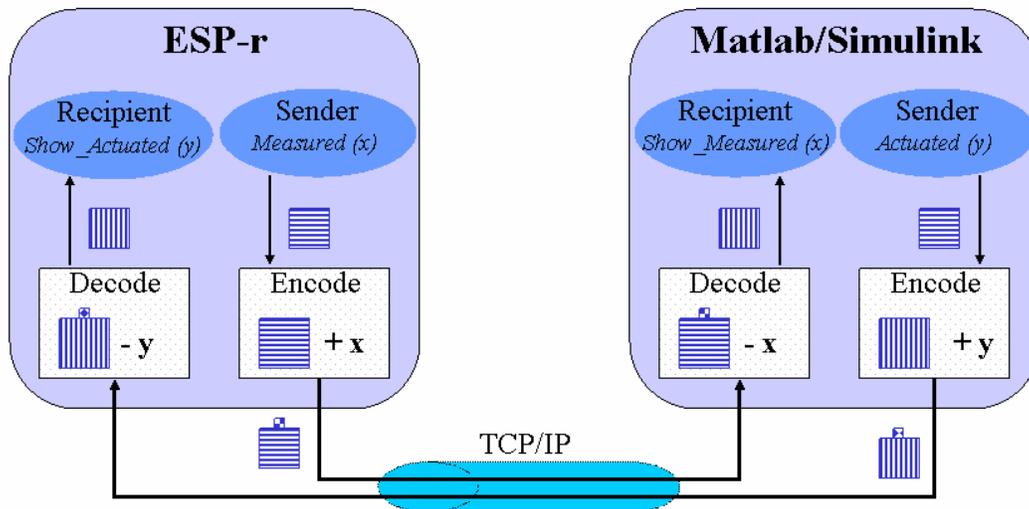


Fig. 1. Distributed control and building performance simulation environments

In the current implemented approach of run-time coupling between ESP-r and Matlab, it is ESP-r which starts simulation. Indeed, Matlab is launched at every ESP-r time-step as a separate process. If the connection between ESP-r and Matlab breaks down the data to be exchanged cannot be transferred until the communication between them is reconnected. More detail about distributed building domain specific and domain independent software tools by run-time coupling can be found in (Yahiaoui et al., 2004 and Yahiaoui et al., 2005).

3. OPTIMAL CONTROL CONCEPTS FOR INTEGRATED BUILDING SYSTEMS

The design process of optimal control uses a sequence of high-level steps similar to those of pole placement design. In optimal control, it necessitates first to develop optimality criterion for the controller gain. Then, mathematical algorithms compute this gain to produce a compensation factor that satisfies the proposed criterion.

Integrated building systems involve all the physical elements and user requirements that affect the design of buildings, including structural systems like mechanical, electrical and so on. Those elements can consist of HVAC (Heating, Ventilation and Air-Conditioning), lighting, power and energy, fire and safety, and water supply systems. Besides, most process control problems in buildings are related to the control of flow, pressure, temperature, and level (e.g. light, daylight, etc), in which it is not suitable to use traditional or conventional control methods. Optimal control theory is the powerful tool to solve closed set constrained variation problems. Although in design of such control systems, it is sometimes necessary to design controllers that are not only effectively regulate the behavior of a system, but also minimize or maximize some user defined criteria such as energy or time conservation, or obey other physical or time constraints imposed by the environment. Hence, the advantage of using this technique consists of finding a feasible control law (model) so as the system starting from the given initial condition transfers its state to the objective set, and minimizes a performance criterion.

3.1 Optimization for Modern Control

The main purpose of the automatic control systems can be formulated as multi-objective optimization tasks (Andersson, 2000 and Coello et al., 2002), in which a building system must focus more on numerous distinct goals:

- Optimization of comfort aspects (thermal and visual);
- Safety of occupants;
- Satisfying occupants' wishes; and
- Minimization of energy consumption.

Each of these objectives may conflict with others- for instance, attempting to maximize conflicting thermal comfort requirements of different occupants can be expected to result in increased energy consumption if not well optimized at the system level. Nevertheless in the literature, several methods have been proposed to address multi-objective optimization tasks (e.g. Lute et al., 1995). In fact, optimization is a very useful technique for conducting realistic studies when the cause and effect relationship between objectives and outcomes can be specified mathematically or through simulation. Optimization seeks to mathematically minimize (or maximize) an objective functional of many parameters in the presence of one or more constraint functions. Although, the optimal control of building processes and plants under dynamics conditions, i.e. the concerned variables are changing with respect to time and this time is involved in system description that needs dynamic optimization techniques to be solved, differential equations are used as good means to describe their processes and plants.

3.2 State Space Based Modeling Procedure

The traditional and conventional control theory and methods (for instance root-locus) that have been used in buildings so far are based on simple-input and simple-output description (SISO) of building plants, usually expressed as a transfer function. These methods do not use any knowledge of the interior structure of the building equipment and components, in which it means that those methods do not capture all building dynamics and disturbances that affect its components. In fact, those methods allow only limited control of the closed loop behavior when the feedback path is used.

Modern control techniques, for instance optimal control theory, can solve such limitations by using a much "richer" description of the building plant dynamics (such as valve actuators).

The so-called, the state-space representation provide the dynamics as a set of coupled first-order differential equations in a set of internal variables known as state variables, together with a set of algebraic equations that combine that state variables into physical output variables. With this description, the Multi-input Multi-output (MIMO) plants are formed through a complete building model.

For time invariant systems, mathematical model for building plants are based on physical laws normally results in a state space model of the following form:

$$\begin{cases} \dot{x} = f(x, u) \\ y = h(x, u) \end{cases} \quad (1)$$

where $f(\cdot)$ and $h(\cdot)$ are nonlinear functions of their arguments: $x(t)$ is the internal state vector, $u(t)$ is the control input vector, $y(t)$ is the measured output vector and $\dot{x}(t)$ represents the differentiation with respect to the time t . The first equation, called the state equation, is used to capture the physical dynamics of the system and has memory inherent in the n integrators. The second equation, called the output, or the measurement equation, is used to represent the way on how the measurements of system variables are performed, in which the results depend on the type of sensors used.

3.3 Linear Quadratic Regulator Design

The purpose of linear quadratic regulator (LQR) design is to realize a building system with practical components that will provide the desired operating performance. The desired performance can be readily stated in terms of time-domain indices. In this steady state and transient periods, the performance indices are normally specified in time domain and therefore it is obvious to enlighten some of those practical aspects, which should be considered when designing controllers for real applications.

Optimal control theory provides the mathematical tools for solving problems, either analytically or through computer iterative methods, by formulating the user criteria into a cost function (e.g. Burns, 2001). This control theory consists then of finding a control function u , either in an open-loop form $u(t)$ or a feedback (a closed-loop) form $u(x, t)$, which can drive a system from the state x_1 at the time t_1 to the state x_2 at the time t_2 in such a way to minimize or maximize the performance index $J(U)$, as follow:

$$\min_{u \in U} J(U) = \int_{t_1}^{t_2} (xQx' + uRu') dt, \quad Q \geq 0, \quad R > 0, \quad (2)$$

where Q is a state weight matrix in which its choice may lead to a control system that requires the state x larger than desired and R is a control weight matrix in which its choice may lead to the controller gain k such that the feedback control law is:

$$u(t) = x_{ref} - K.x(t) \quad (3)$$

where x_{ref} is the desired state, called set-point.

3.4 Indoor Thermal Comfort

Previous research reported in (Bloomfield et al., 1977) has described that intermittent conditioning can save the energy used in buildings. Then (lute et al. 1995) mentioned that it is also possible to save energy by a certain variation from the temperature set-point. But neither of those studies tried to minimize energy by keeping the indoor temperature as long as around the set-point. In the current case, a mathematical performance criterion is proposed in order to

minimize the energy consumption so that the temperature of building stays as close as possible to the set-point. The control is designed to maintain an indoor temperature within the adaptive optimum comfort temperature used in winter for buildings with natural ventilation, in which it can be deduced from the ASHRAE 55 standard (see e.g. Hensen et al., 2001).

For the period of non-occupied of an office building, the indoor temperature can float and sometimes it cannot be in certain safe boundaries. Though the energy is saved, i.e. the heater is completely switched-down; the performance of controller can be tested to see how long the controller takes to get the indoor temperature to the set-point. During the occupied period of an office building, the controller is designed in order to minimize the energy consumption and to optimize the indoor temperature together with the Predicted Mean Vote (PMV) by choosing an appropriate weighting state matrix of the controller. In addition, PMV is a measure used to predict a comfortable situation in buildings.

4. MATHEMATICAL STATEMENT OF THE PROBLEM

As a heating system for Delft test-cell is sealed up a building model shown schematically in figure 2. A simple model of its plant is represented as the rate change of the temperature difference in the heat flow Q_{in} supplied by the heater, and the heat rate Q_{loss} lost through the wall insulation, related by the following equation:

$$mc \frac{d}{dt}(T_{in} - T_{out}) = Q_{in} - Q_{loss} \quad (4)$$

where m is the building mass (Kg), c is the average specific heat ($J/Kg.K$), Q_{loss} and Q_{in} are heat flow rates (J/s or W), and T_{in} and T_{out} are temperatures ($^{\circ}C$).

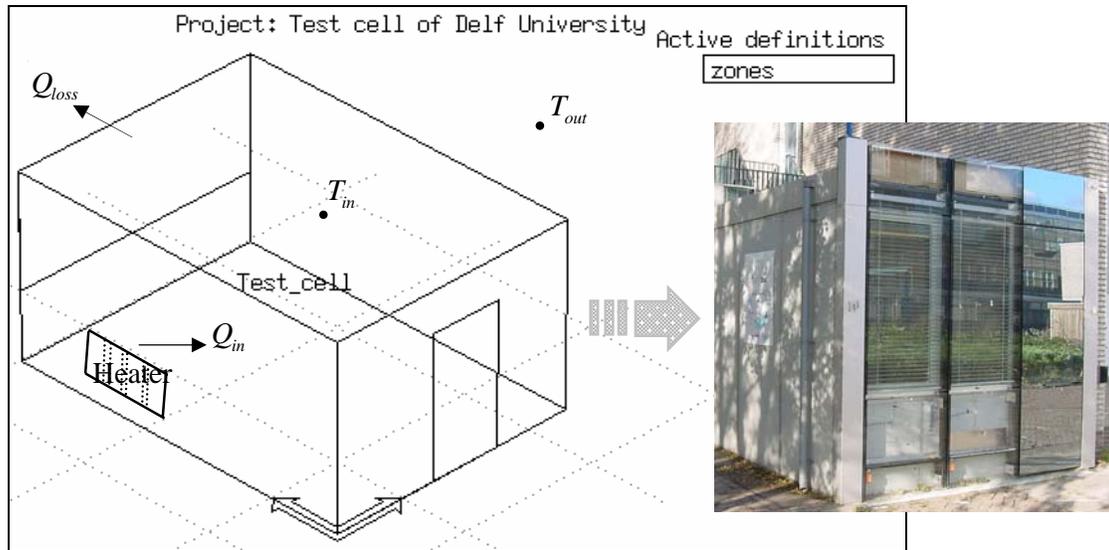


Fig. 2. TU Delft test-cell case study

When the outside temperature T_{out} is constant (or very slowly varying), the relation given by equation (4) can become, $mc \frac{d}{dt}(T_{in}) = \frac{V_h^2}{R} - Q_{loss}$ (5)

where V_h is the heater voltage, and R is the electric resistance of the heater.

The rate of heat Q_{loss} lost through the wall insulation is proportional to the temperature difference across the insulation, in which it is given by $Q_i = U_0(T_{in} - T_{out})$ (6)

where U_0 is a heat loss coefficient (W/K)

Submitting from equation (6) into equation (5) gives a relation in form of the state-space representation, which is as follow:

$$\frac{d}{dt}T_{in} = -\frac{U_0}{m.c}T_{in} + \frac{1}{m.c}Q_{in} + \frac{U_0}{r.c}T_{out} \quad (7)$$

where the $\frac{U_0}{r.c}T_{out}$ factor is the effect of the disturbance input.

According to state-space form represented in (1), the notation of the equation (7), used in this paper becomes, $\dot{x} = -\frac{U_0}{m.c}x + \frac{1}{m.c}u + \frac{U_0}{r.c}\xi$ (8)

The value of c for this example consisted of using common proprieties for air temperature in which it is taken from table with respect to the average temperature of the building in winter time, as mentioned in (ETB, 2005). On the basis of this table, c is something like $1.005(k.J / Kg.K)$. The value of m is also calculated with respect to density ρ , which is in the order of $1.205(Kg/m^3)$. The heat loss coefficient U_0 is calculated in relation of U-value defined by each area in relation with all areas of the room model.

Sensors are installed more or less all over different places in the room to provide timely detection of potential temperature changes where the indoor temperature is the average of all measures collected by those sensors. An optimal controller strategy needs to be designed in order to optimize the thermal comfort in the room and to minimize the energy consumption within the cost function that satisfies the requirements imposed by occupants.

The answer to that issue depends on the satisfaction of thermal environment in an office building and the energy saving. The mathematical formulation is proposed as follows:

- Performance index, minimize the total expression over time period t_1 to t_2 :

$$\min_{u \in U} J(U) = \int_{t_1}^{t_2} (q_1 x^2 + R.u^2 + q_2.(100PMV)^2)dt, \quad \text{with } Q = \begin{bmatrix} q_1 & 0 \\ 0 & q_2 \end{bmatrix} \quad (9)$$

- Constraints on energy $u(t)$ and on comfort PMV are:

$$\left. \begin{array}{l} u_{\min}(t) \leq u(t) \leq u_{\max}(t) \\ PMV_{\min} \leq PMV \leq PMV_{\max} \end{array} \right\} \quad (10)$$

In the performance index defined by the relation (9) three terms contribute to the integrated cost of control: the quadratic form xq_1x' which represents a penalty on the deviation of the state x from the initial (which is the desired state), the term uRu' which represents the performance of the controller and the last term $q_2.(100PMV)^2$ signifies the optimum comfort temperature in the room.

5. CONTROLLER SYNTHESIS

The purpose of optimal control theory is to give a systematic method to synthesize control laws with proprieties specified to optimize a performance index (or criterion) or a cost function. The remaining problem is to obtain the control gain K . In consequence to do so, the control feedback structure for an integrated building model, shown in figure 3 is performed in order to assign the control system with the parameters required for optimization. But to obtain the simulated results, the controller realized for experiments is the same carried-out in Matlab side and the extensive building model is entirely implemented in ESP-r side.

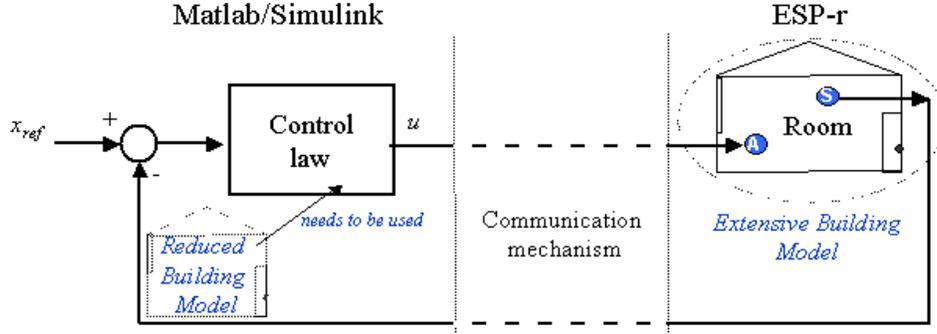


Fig. 3. Control feedback structure for integrated building model

5. 1 Solving Control Problem

Solving the control problem with equality constraints is computationally not complex since it does lead to boundary values. A controller is defined to minimize the performance index:

$$\min_{u \in U} J(U) = \int_{t_1}^{t_2} (q_1 x^2 + R u^2 + q_2 \cdot (100PMV)^2) dt, \text{ with } x(t_1) = x_1, \quad x(t_2) = x_2 \quad (11)$$

subject to the dynamic system $\dot{x} = -\frac{U_0}{m.c} x + \frac{1}{m.c} u, \quad x(t_1) = x_1 \quad (12)$

The Hamiltonian for (11) and (12), is

$$H(x, u, \frac{\partial V}{\partial x}) = (q_1 x^2 + R u^2 + q_2 \cdot (100PMV)^2) + (\frac{\partial V}{\partial x})' (-\frac{U_0}{m.c} x + \frac{1}{m.c} u), \quad (13)$$

The first-order necessary conditions for optimality (a J minimum) is

$$\dot{p}(t) = \frac{\partial H(x, u, \frac{\partial V}{\partial x})}{\partial u}, \quad p(t_1) = p(t_2) \quad (14)$$

The derivative of the Hamiltonian exists, and control function $u(t)$ is found by (14). In particular when x gets to a set-point, we have $\frac{\partial H}{\partial u} = 0 \quad (15)$

and we find the following optimal control $u = -R^{-1} \cdot (\frac{1}{m.c}) \cdot \frac{\partial V}{\partial x} \quad (16)$

From (15) and (16), the minimization of J leads to the following nonlinear differential equation (the so-called Riccati equation) in order to find the unknown (symmetric matrix) p :

$$-\dot{p}(t) = R - 2 \cdot \frac{U_0}{m.c} \cdot p(t) - Q \cdot (\frac{1}{m.c})^2 \cdot p^2(t), \quad p(t_f) = 0 \quad (17)$$

Solving (17), the control law is then obtained with (16) in the form of time-varying. When $t_f = \infty$, the optimal controller becomes time-invariant.

6. BUILDING TEST CELL: -CASE STUDY

The current case study is illustrated to investigate an application with two objectives. The first consists of comparing between experiments and simulation results obtained by using the same building model and the same model-based optimal control within the same time step of 1mn/hour. The second qualifies the importance of the run-time coupling approach when it involves the integration of advanced control applications in building performance simulation.

6.1 Experiments

A test cell of dimensions ($3.15 \times 3.85 \times 2.6 \text{ m}^3$) is built in TU Delft with light construction materials for the purpose to investigate causes that influence the indoor environment of passive solar buildings. Those causes can include natural ventilation, radiant or solar heat gain and heat loss coefficient. A model-based optimal control for real-time specification is developed and implemented in Matlab/Simulink. This controller actuates the electrical heater of 1750 (W) with proper amount of power needed for the actual situation through a data acquisition located in the room. The obtained experimental results are presented in figure 4.

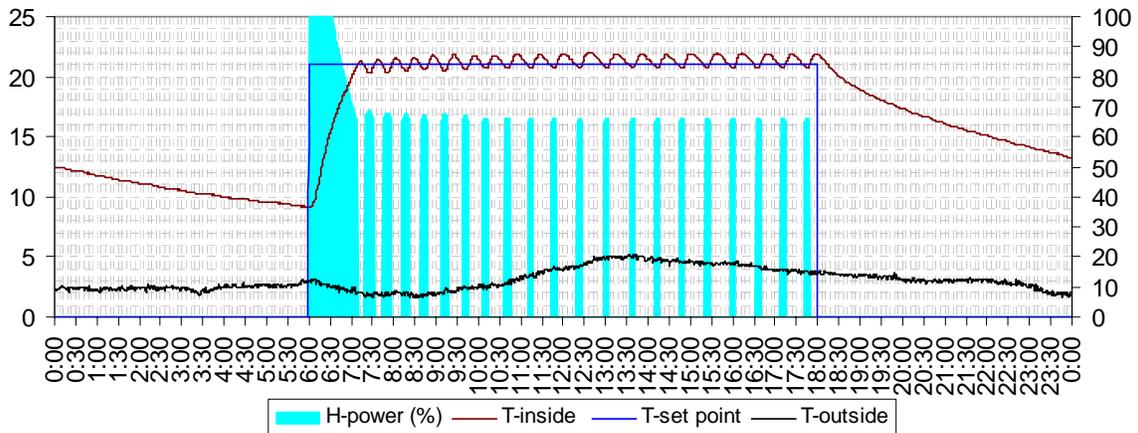


Fig. 4. Experimental results

6.2 Simulation Results

Test-cell building model is implemented in ESP-r with new databases created to carry out the same material properties used practically in the construction, as shown in figure 2. The climate measurements are also partially integrated since ESP-r considers their values on an hourly basis. The simulated results, shown in figure 5 are obtained typically within the same model-based optimal control developed on the same (Matlab/Simulink) environments respectively used for experimental results. Although the run-time coupling approach, described above is used to exchange data between ESP-r and Matlab/Simulink, which is synchronously launched at every ESP-r time step as a separate process during the occupied period, exactly from 6 to 18 o'clock.

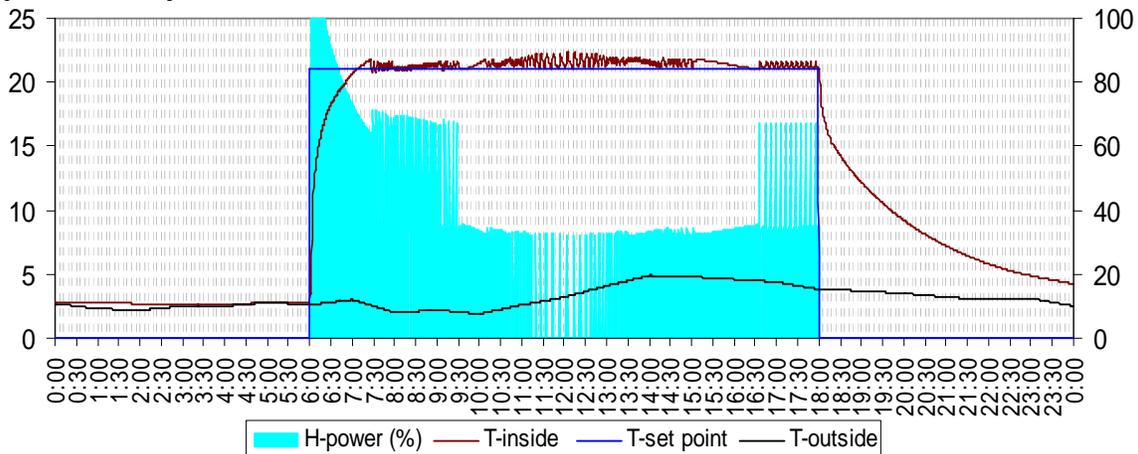


Fig. 5. Simulation results

A detailed comparison between experiments and simulation results shows that there are small changes in both responses of the controller used for the indoor temperature in the test cell. Those changes are due to the climate data that highly influence the temperature inside the test cell. In fact this outside temperature is a disturbance that makes changes over time and the controller designed does not takes action to suppress sensitive input noise, which causes chattering at short intervals of few seconds only. However, the controller designed can filter noises if an estimator is used to operate the actual causes with negative values. Another point in comparison is that the responded signals in both figures (4 and 5) are not very close to each other. This is due to ESP-r, which considers the climate data on an hourly base and probably due to theoretical approximations used sometimes to represent closely practical issues. Nevertheless, the controller designed maintains the indoor temperature controlled within the PMV boundaries of thermal comfort while minimizing energy consumption near optimum.

7. CONCLUSIONS

A mathematical formalism of model-based optimal control for heating mode is proposed by indicating two main factors, of energetic and comfort aspects. These factors are then concerned with improving the indoor environmental quality of buildings. In fact, it may be concluded that corresponding model based control algorithms are possible to be integrated for such purposes. However, the run-time coupling, approach described above can than generates an associated knowledge for wider applicability of advanced control strategies in buildings.

Future work includes a development of LQR control based estimator to filter disturbances.

8. REFERENCES

- Andersson, J (2000) *A Survey of Multiobjective Optimization in Engineering Design*, Technical Report No. LiTH-IKP-R-1097, Depart. of Mech. Eng., Linkping University.
- Burns, R. (2001) *Advanced Control Engineering*, Butter Worth Heinemann, Elsevier, UK
- Brosilow, C.B., Zhao, G.Q. and Rao, K.C. (2001) *A Linear Programming Approach to constrained Multi-Variable Control*, in Proc. American Control Conf, pp. 667-674
- Coello, C.A.C., Van Veldhuizen, D.A. and Lamont, G.B. (2002) *Evolutionary Algorithms for Solving Multi-Objective Problems*, in Proc. Kluwer Acad. Publishers, New York
- ETB, (2005) *The Engineering ToolBox's website*, Inc. <<http://www.engineeringtoolbox.com>>
- Galata, A. Proietto Batturi, F., and Viadana, R. (1996) *A smart control strategy for shading devices to improve the thermal and visual comfort*, in Proc. 4th European Conf.: Solar Energy and Urban Planning, Berlin 1996.
- IEA, (2002) *Control Strategies for Hybrid Ventilation in New and Retrofitted Office Buildings (HYBVENT)*, Annex-35 Report, University of Aalborg, Denmark.
- Hensen, and Centnerova, L. (2001) *Energy simulation of traditional vs. adaptive thermal comfort for two moderate climate regions*, in Proc. Int. Conf. "Moving Thermal Comfort Standards into the 21st Century", Oxford Brookes University, pp. 78-91.
- Lute, P. and Van Passen, D. (1995) *Optimal Indoor Temperature Control Using a Predictor*, in Proc. IEEE Control System Journal, pp.0272-1708
- Yahiaoui, A., Hensen J.L.M. and Soethout L.L. (2003) *Integration of control and building performance simulation software by run-time coupling*, in Proc. "IBPSA Conference and Exhibition 2003", Vol. 3, pp. 1435-1441, Eindhoven, NL.
- Yahiaoui, A., Hensen, J., and Soethout, L. (2004) *Developing CORBA-based distributed control and building performance environments by run-time coupling*, in Proc. 10th ICCCB, Weimar, Germany.
- Yahiaoui, A., Hensen J.L.M., Soethout L.L. and Van Paassen, Dolf (2005) *Interfacing of control and building performance simulation software with sockets*, in Proc. "IBPSA Conference and Exhibition 2005", Montreal, Canada.