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DESIGN OF MODEL BASED LQG CONTROL FOR INTEGRATED BUILDING SYSTEMS

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ABSTRACT
The automation of the operation of integrated building systems requires using modern control techniques to enhance the quality of the building indoor environments. This paper describes the theatrical base and practical application of an optimal dynamic regulator using model-based Linear Quadratic Gaussian (LQG) control design for integrated building systems. This LQG regulator consists of an optimal state-feedback controller and an optimal state estimator. In this case, a performance criterion is minimized in order to maintain the indoor temperature of the building comfortable within a minimum energy consumption. Besides this regulation performance, a Kalman filter (KF) is used to minimize the asymptotic covariance of the estimation error when those building systems are encountered with disturbances. 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.

KEY WORDS
Model-based LQG control, run-time coupling, building performance simulation, regulation performance, Kalman filter, and energy consumption

1. Introduction

Control strategies have been recognized as an efficient way to improve building process automation. But, still there is 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. [6]). 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, [7] 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 in [4], 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, like for example 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 its control system, separated and built 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.
Linear optimal control theory provides a systematic approach to design active controllers for integrated building systems [13] and has been demonstrated with success in various applications such as automobile (see e.g. [9]). Although to deal with a controller that regulates indoor temperature under constraints to avoid undesirable operation regimes, a model-based LQG (Linear Quadratic Gaussian) control is used to optimize the regulation performance of a building heating system and to reduce the sensor noise along with the environmental disturbance. This LQG regulator consists of an optimal state-feedback controller and an optimal state estimator. Furthermore, a Kalman filter is used as a common tool to calculate an optimal estimation of a system state, that the controller considers when this system is encountered with disturbances. In this paper, a performance criterion minimized by linear programming is proposed in order to optimize the response of the control system within the minimum use of energy cost. This model-based LQG controller is applied for a building heating system, 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 proprieties and climate data used for experimental design.
The first part of this paper presents a brief description of distributed control and building performance simulation. The next part elaborates a mathematical modeling that is developed for heating mode in buildings. Then, a model based LQG optimal control design is described by minimizing a performance index in order to optimize the comfort and energetic aspects. The fourth section consists of the synthesis relevant to the LQG control feedback structure for integrated building systems. The last essential part of this paper elaborates an application for a building case-study model resulting on a balance between theoretical aspects and practical issues.

2. Distributed Control Modeling & Building Performance Simulation Environments

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), which is usually relatively basic in terms of control modeling and simulation capabilities (e.g. ESP-r, TRNSYS). On the other hand, there exists domain for control modeling environments (CME), which is 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 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 [10] and [12]), 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, as illustrated in figure 1.. This approach has been implemented to perform distributed simulation by a network protocol in order to exchange data between building model and its controller, as it almost 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.

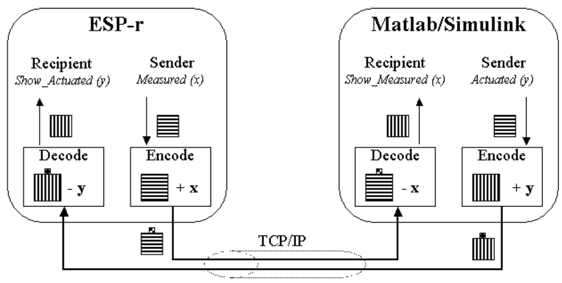

Figure 1 Distributed control modeling and building performance simulation environments

During 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 followed in this case, as shown on figure 1.
In the current implemented approach of run-time coupling between ESP-r and Matlab/Simulink, 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 ([10], [11] and [12]).

3. Mathematical Modeling

This section is devoted to the mathematical modelling of a building heating system, considering particularly a heating plant used for TU Delft test-cell as schematically shown in figure 2. A simple mathematical model of this building 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:

$$mc\frac{d}{dt}(T_{in}-T_{out}) = Q_{in} - Q_{loss} \qquad (1)$$

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 inside and outside air temperatures (^oC).

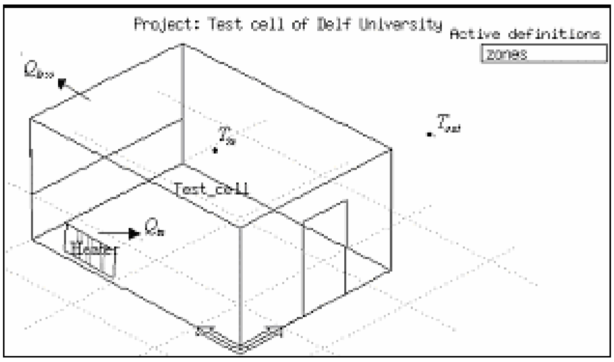

Figure 2. TU Delft test-cell case study

When the outside temperature T_{out} is constant (or very slowly varying), the relation given by equation *(1)* can become, $mc\frac{d}{dt}(T_{in}) = {V_h^2}/{R} - Q_{loss}$ *(2)*

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, as follow: $Q_{loss} = U_0(T_{in} - T_{out})$ *(3)*

where U_0 is a heat loss coefficient (W/K)
Submitting from equation *(3)* into equation *(2)* gives a relation in the form of the state-space representation, as follow:

$$\frac{d}{dt}T_{in} = -\frac{U_0}{m.c}T_{in} + \frac{1}{m.c}Q_{in} + \frac{U_0}{m.c}T_{out} \qquad (4)$$

where the $\frac{U_0}{m.c}T_{out}$ factor is the effect of the disturbance input, which is proportional to the air temperature outside the building. Consequently, this temperature disturbance can be estimated through the measurement of the outside air temperature.
The value of c for this example consisted of using common proprieties for air temperature in which it is taken from a table with respect to the average temperature of the building in wintertime, as mentioned in [4]. 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.

4. Optimal Controller Design

The objective of the modern state-space techniques based on design of optimal regulators is to suppress and to reduce resonant modes of integrated building systems by filtering disturbances appeared in their nominal responses. Although we have the freedom to place the closed-loop poles desired, the task involved can be greatly simplified by the selection of the state-space model used for the design/analysis.
The LQG regulator consists of an optimal state-feedback controller and a Kalman state estimator. This enables to specify and define the trade off between regulation performance and control effort and to take into account both disturbance proprieties of the plant and measurement noise ([3] and [8]). The design of model-based LQG controller which is used to optimize the regulation performance of a building heating system and to reduce both sensor noise and environmental disturbance consists of two steps. The first design step is to seek a state-feedback control gain that minimizes the cost function of regulation performance, which is measured by a quadratic performance criterion with tuning weighting matrices [1]. The next design step is to derive a state estimator using a Kalman filter because the optimal state-feedback controller cannot be implemented without reducing disturbances that perturb the system. Although a Kalman filter is used as a common tool to calculate an optimal estimation that is required to cancel a disturbance when this disturbance perturbs the state response of a system, this estimator minimizes the asymptotic covariance of the estimation error, which is denoted e.

The state-space equation *(4)* describes the linear –time-invariant (LTI) system, which is similar to

$$\dot{x}(t) = Ax(t) + Bu(t) + \Gamma w_d, \quad x(0) \qquad (5)$$

where $x(t)$ represents the inside air temperature T_{in}, $u(t)$ represents the heat flux Q_{in} supplied by the heater and w_d denotes a temperature disturbance.

The input to the state-feedback controller is the output of the system y, which is generally expressed in the form of $y(t) = Cx(t) + v$, where v is a measurement noise.

For controller design, it is assumed that all states are calculated and measured exactly. Optimal control theory provides mathematical tools for solving problems, either analytically or through computer iterative methods, by formulating the user criteria into a cost function (e.g. [2]). This control theory consists then of finding a control law 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 $J(U)$. The performance index J penalizes the sate variables and the inputs, thus it has the general form of:

$$\min_{u \in U} J(U) = \lim_{T \to 0} E\left\{ \int_0^T (zQz' + uRu')dt \right\} \qquad (6)$$
$$with \quad Q \geq 0, \qquad R > 0,$$

where $z = N \cdot x$ is some linear combination of the states, 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.

To obtain a solution for the optimal controller introduced by equation (4), the LTI system must be stable. This condition can be verified when the unstable modes are controllable. Therefore the case being considered in this paper is that the optimal solution is assured for a building system with no unstable mode.

Linear quadratic control theory provides the solution of the equation *(6)*, in which the optimal controller gain K is computed by $K = R^{-1}B'P$ *(7)*

where P is evaluated being the solution of the Algebraic Riccati Equation, given by

$$AP + A'P - PBR^{-1}B'P + Q = 0 \qquad (8)$$

The optimal solution for equation *(6)* and *(8)* representing the optimal solution and its final performance of the closed loop system respectively are directly related to the initial values of weighting matrices Q and R.

For estimator design [13], it is assumed that the estimate $\hat{x}$ is constructed by replacing the process dynamics as in

$$\dot{\hat{x}} = A\hat{x} + Bu \qquad (9)$$

where $\hat{x}$ is an optimal estimate of the state x, in which the state estimation error $e := x - \hat{x}$ is minimized. This means that when the matrix A is asymptotically stable the error e converges to zero for any input u which means in turn that $\hat{x}$ eventually converges to x as $t \to \infty$. However, when A is not stable the error e is unbounded and $\hat{x}$ grow further and further apart from x as $t \to \infty$. To avoid this case, the correction structure is given in term of ,

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - \hat{y})$$
$$with \quad \hat{y} = C\hat{x} \qquad (10)$$

where $\hat{y}$ is an estimate of the output y and L is the optimal estimator gain (or also called Kalman-Bucy filter), which produces an LQG optimal estimate $\hat{x}$. Accordingly, the Kalman filter gain is evaluated and given by $L = P_e C' V^{-1}$ *(11)*

where P_e is the unique positive-definite solution to the Algebraic Riccati Equation, given by

$$AP_e + A'P_e - P_e BV^{-1}B'P_e + W = 0 \qquad (12)$$

where $W = E(w_d w_d')$ and $V = E(vv')$ are covariance matrices for the plant disturbance and measurement noise respectively. The solution to equation *(6)* and LQG control system that estimates the state of its process is generated by the following state feedback control law:

$$u(t) = x_{ref} - K.\hat{x}(t) \qquad (13)$$

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

A crucial property of this optimal controller here is that $(A - L \cdot C)$ is asymptotically stable as long as both conditions are established: equation *(5)* is observable and equation *(5)* is controllable when a disturbance w_d is considered as an input of the system. Consequently, the controller is designed to compensate for this disturbance based on the information on the outside air temperature.

Now, for experimental and simulation purposes the system is the augmented model with combining optimal state-feedback controller equation *(5)* with optimal estimate state equation *(10)*. Adjusting the various covariance and cost-weighting matrices which appear in LQG controller is based on a separated tuning: W and V are attuned so that the system state is well reconstructed and Q and R are weighted to have an optimal state-feedback. However, the choice of weighting the different parts of a criterion performance to minimize (the command signal and the state) is equivalent to adjusting the trade off between this between regulation performance and control cost of the closed-loop transfer function for integrated building system. The use LQG control method for building heating system guarantees actually the internal stability of the heating in order to achieve the smooth control law.

5. LQG Controller Synthesis

Both Linear Quadratic Regulator (LQR) and Kalman filter (KF) provide practical solutions to the full-state feedback and state estimation problems, respectively [2]. Since the disturbance of the plant (or building heating plant) is well-known, the LQG controller synthesis is an approach of designing a proper regulator by combining the LQR and KF into an output feedback compensator.

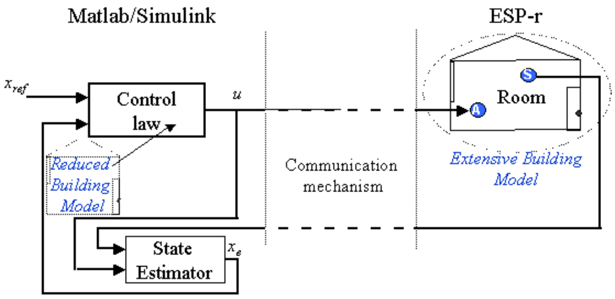

Figure 3. Control feedback structure for integrated building model

The purpose of LQG optimal control theory is to give a systematic method to synthesize a control laws with proprieties specified to optimize a performance index and to cancel the unwanted disturbances that perturb the system as well. 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 and to estimate the state of a system with uncertain dynamics. 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.

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 for better design.

6.1 Experimental Design

A test cell of dimensions (3.15*3.85*2.6 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. 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 the data acquisition/control unit (*HP 3852A*). 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 obtained experimental results are presented in figure 4.

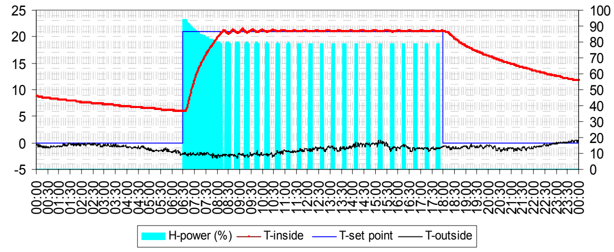

Figure 4. Experimental results

6.2 Simulation Results

A test-cell building model is implemented in ESP-r with new databases created to represent and carry out the same material proprieties that are practically used in the construction of the room, shown in figure 2. The climate measurements are partially integrated as well, but ESP-r considers their values on an hourly basis, in which it uses a certain approximation for the values in between. The simulation results, shown in figure 5 are obtained typically within the same model-based LQG controller realized in the experimental design and implemented on the same (Matlab/Simulink) environments, respectively. Though the run-time coupling approach described above, that is used to exchange data between ESP-r and Matlab, Matlab is synchronously launched at every ESP-r time step as a separate process during the occupied period (from 6:30 to 18 o'clock).

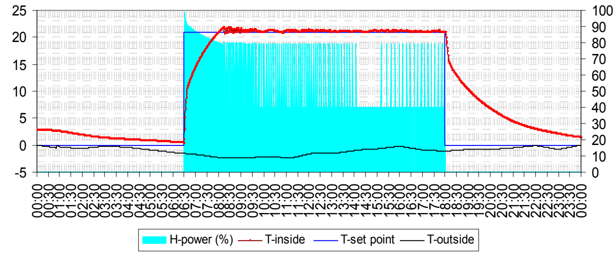

Figure 5. Simulation results

A detailed comparison between experiments and simulation results shows that there are very small changes in both responses of the controller used for the indoor temperature in the test cell. Those small changes are due to the choice of covariance and cost-weighting matrices of the criterion performance minimized. On the anther hand, it is clear that these changes cause a small number of chattering at short intervals of few seconds only. However, the controller designed can be improved by a brief adjustment. In fact, several tentative trials have been performed during experiments and simulation results, but a problem consists on how to choose or to weight the different parts of the performance criterion minimized.

Another point to highlight in comparing experiments and simulation results is that the responded signals (or controlled variables), as shown in both figures (4 and 5) are not very close to each other. This is due to ESP-r, which considers the climate on an hourly base and due probably to theoretical approximations used sometimes to represent closely practical issues. Nevertheless, the controller designed maintains the measured indoor temperature with few variations small and brief around the set-point. Concerning the difference of energy use during experiments and simulation results, as shown in both figures (4 and 5) this is due several factors. One important factor among others is related to infiltration rates, which are needed to be integrated in ESP-r. This step is somehow difficult as it requires finding out the good rates for the infiltration that depends on the real structure of the test cell (i.e. joints, fissures, etc.) without influencing the response properties of the heating system.

7. Conclusion

A model-based Linear Quadratic Gaussian (LQG) control design for integrated building systems has been investigated in this paper using both optimal regulator performance and optimal estimator state. The first consist of the Linear Quadratic Regulator (LQR) by minimizing a performance criterion based on comfort and energetic considerations; and than as a second, a Kalman filter (KF) is used to estimate the state of the system. However, the objective of this paper has been to examine the use of optimal state-feedback controllers in the experimental design for improving the comfort and the stability performance of HVAC (Heating, Ventilation and Air-Conditioning) systems in buildings. For such a reason, distributed control modelling and building performance simulation software by run-time coupling is developed and implemented so that the simulation of a building model and its controller is performed in separate environments, as happened in the real-time situation.

The results of comparison, presented in this paper, lead to the conclusion that the optimal control theory provides a useful mathematical tool to design optimal controllers for integrated building systems. With good knowledge of process proprieties and details, it is possible to design a suitable LQG controller with good robustness proprieties, which it takes integrated performance assessment of the systems into account. But, a problem is on how to choose or to weight the different parts of the criterion to minimize (the command signal and the state). After a several tries without real success, although it is obvious that it requires to use a method more systematic to weight the states. This method can be based on H2 optimal control, in which is based on weighting both performance criterion and Kalman estimator.

Future work includes the development of a model based H2 optimal control, as its tuning method is very simple so it could be very useful for integrated building systems.

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