PERFORMANCE OPTIMIZATION OF BUILDING CONTROL SYSTEMS

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ABSTRACT

This paper presents a case of real-time performance optimization of environmental building systems (temperature, illuminance, luminance, CO2, comfort, etc.). The approach uses a calibrated simulation model and an optimization routine. A 'minimalistic' lumped model predicts the physical response of systems. Based on the simulation model prediction, the optimization routine finds optimal control variables. The optimal control variables minimize a cost function predetermined by occupants. The minimization of the cost function becomes a classical constrained nonlinear optimization problem. This is realized in a local web server that receives sensor data, commands to motorized devices and updates current states to a web-browser. The approach in this paper can be embedded in either building automation systems or Building Energy Management Systems (BEMS).

1. INTRODUCTION

Controlling of building environmental systems have originally related to (1) a simple on/off control strategy or (2) a dimming control strategy. Both on/off and dimming control strategies are not based on optimal control theory which accounts for the dynamic characteristics of a system but based on the 'current status' so it is difficult to attain optimal performance. Recently, many trials have been attempted to adapt optimal control combining optimal theory and mathematical model into the building related systems but they are still remain immature e.g., HVAC systems, chillers, heat storage systems, etc. (Zaheer-Uddin 1992; Knabe and Felsmann 1997; Ren and Wright 1997; Jung et al 1997; Wang and Jin 2000).

However, studies on integration of building environmental systems (cooling + heating + ventilation + artificial lighting + day lighting) have been focused on integration of different simulation models (Eliyahu Ne'eman 1984; Mahdavi 1997; Clarke 2001). Such integrated simulation models require a steep learning curve, significant computation time, (e.g., CFD model and energy simulation model, artificial lighting and day lighting and detailed input data for modelling are not suited to predict and control system performance on-line real-time. In particular, obtaining optimal control variables requires a complex iterative process for simulation models so that it is indispensable to develop simple but fast integration simulation models with optimal algorithms.

The aim of this paper is to develop a lumped simulation model and using the model incorporated with optimal theory to develop on-line real-time performance optimization technique for integrated building environmental systems on the World Wide Web rather than focusing on integrating building simulation models. This study selects five building systems: cooling, heating, ventilation, lighting and daylighting. To accomplish this, it is necessary to have: (1) an underlying mathematical model to describe complicated physical phenomena of building environmental control systems, (2) an optimal algorithm solving for on-line real-time optimal control, (3) development of a platform to integrate the mathematical model and optimal algorithm on WWW, and (4) inclusion of user's preferences. This paper addresses the current development of actual online real time optimal control systems on the World Wide Web.

2. SIMULATION MODEL AND CALIBRATION

For the optimal control of the system it is necessary to develop simulation models to predict the response of a system (Lewis and Syrmos 1995). There are two approaches in developing simulation models: (1) using whole building simulation tools (e.g. EnergyPlus, Esp-r, TRNSYS, IDA ICE, TAS, etc.), (2) using lumped simulation models. The former is easy with simulation modelling but it is difficult to apply it to actual optimal control because the tools are not developed for in-house use of optimal control study. The latter simplifies heat and mass phenomena of the system such as a state-space approach for lumped modelling of the system. This model is simple and suitable to real-time optimal control and performance assessment when it is calibrated to be accurate enough. This study follows the latter approach. The mathematical model can be expressed in a state-space equation as shown in Eq. (1).

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{b} \qquad (1)$$

Where **x** is a state vector, **A** is a state matrix, **b** is a load vector. The lumped model is simple and demands less computation time so that it is more appropriate for on-line real-time control than a 3D full-blown model like Computational Fluid Dynamics (CFD).

Usually, any simulation model involves unknown variables, simplification of reality, and modeling assumptions, which makes model calibration indispensable. In such case, validating of the calibrated model is also of a necessity. Model validation is possible through parameter estimations on-line or off-line. The self-calibration technique, one of the parameter estimation techniques, is the on-line real-time process of calculating unknown parameters for the system which minimizes the deviation difference between the self-calibration model data and the measured data. This can be formulated into minimizing an objective function S over the measurement period as follows (Yoon et al 2011):

$$\min S = \sum_{k=1}^{z} \lambda^{z-k} [\mathbf{Y}_k - \boldsymbol{\psi}_k(\xi_i)]^T [\mathbf{Y}_k - \boldsymbol{\psi}_k(\xi_i)] \qquad (2)$$

Where S is an objective function, λ is a time-varying weighing vector designed to give higher weight to later data values than earlier values, **Y** is a vector of observations, $\boldsymbol{\psi}$ is a vector of predicted observations, ξ is a vector of unknown parameters, and z is a number of observation.

The real-time on-line calibration model developed in this study constantly updates the model which makes the simulation model more accurate and reliable. Finally, the online updating model is integrated to an optimization routine in MATLAB in WWW platform as shown in Fig. 1.

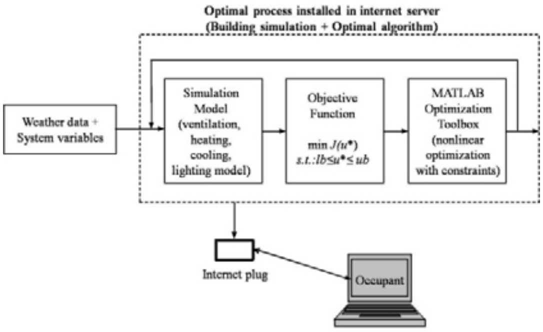

Fig. 1: Simulation-assisted online optimal control in WWW

The lumped simulation model, the on-line parameter estimation, and the validation for the double skin system are reported in previous studies (Park et al 2004; Yoon et al 2011). In addition, an integration study of a room model to the building skin system is reported in (Park and Augenbroe, 2013). The study incorporates the DSF system and room model with a set of differential equations for states such as floor, ceiling, and walls.

3. PERFORMANCE OPTIMIZATION

The simulation model presented in the previous section can be used for simulation-assisted optimal control. The optimal control attempts to find control variables which minimize the cost function over a certain period of time. The performance of the system can be categorized into the following: energy use in heating, cooling, and lighting, visual and thermal comfort, etc. Such cost elements can be formulated in the cost function as follows:

$$J = w_1 j_h + w_2 j_c + w_3 j_l + w_4 j_{DGI} + w_5 j_{PPD} \quad (3)$$

where j_h is heating energy, j_c is cooling energy, j_l is lighting energy, j_{DGI} is visual comfort in Daylighting Glare Index (DGI), j_{PPD} is thermal comfort in Predicted Percentage of Dissatisfied (PPD, %) and w_1,w_2, w_3, w_4, w_5 are weighting factors.

Eq. (3) can be solved analytically or numerically. The analytical approach includes: Pontryagin's minimum principle, Hamilton-Jacobi-Bellman equation, and Riccati equation according to the types of problems (Lewis and Syrmos1995). The numerical approach is classified as follows: gradient method, exhaustive search, evolutionary search, simulated annealing, etc. Gradient method can be used when the cost function is differentiable. It is defective in that it sometimes converges to a local minimum, but it finds optimal control variables quickly and so it is more appropriate than other methods for the real-time optimal control problem.

Eq. (3) is a constrained nonlinear optimization problem and is difficult to solve analytically. FMINCON, one of the optimization routines in MATLAB optimization toolbox is used because it is specially designed to solve this kind of problems and to expeditiously generate a reliable estimate of the solution.

The aforementioned self-calibration technique constantly updates the model based on information from sensors. The self-calibration experiment was done on December 5th-8th. The simulation results are good enough in terms or the difference in temperature between the measured and simulation prediction. The average difference in temperature proved to be 0.49(˚C).

Real-time optimal control simulation runs were conducted during separate winter days, totally for 50hours or 4 days. A sampling time of 15 minute was used. The optimal louver slat angle was maintained in accordance with outdoor weather conditions. The optimal slat angle keeps track of the solar altitude so that it can absorb direct solar radiation during daytime. At night-time, the louver closes such that it can reduce heat loss by long wave radiation between the interior glazing and the colder exterior glazing.

4. E-SIMULATION

This study presents the control system which collects the sensor data installed in/out of the test unit in real time. The data logging computer is a local machine which acts as an internet server for the system. The server computer consists of hardware (Input/output Data Card) and software (NI LabVIEW 8.2) for data acquisition. The VI of LabVIEW 8.2 with ActiveX, DDE (dynamic data exchange), and SQL (structured query language) realize data acquisition on the control panel of the server computer. The server computer controls building environmental control systems (diffusers, supply air temperature, outdoor air volume, natural lighting, and illuminance) in real-time depending on the weather change and outdoor conditions or user preference control modes.

The data logging computer is posting collected data from sensors and the user can monitor current status (energy flow and use, indoor temperature, outdoor luminance and humidity, indoor micro-climate information, etc.) located remotely on their desktop/laptop computers on the web.

Users can choose one of control modes (energy saving, visual comfort, thermal comfort, and autonomous, etc.) or sets manually based on user preferable conditions (e.g., set point temperature as in 24°C, illuminance in 600 Lux, PPD within 10%, CO2 concentration below 1,000 ppm meeting all those conditions simultaneously is difficult, users enters weighting factors on the subjects preferable by adjusting a slide bar of the web browser).

The building environmental control technique presented in this paper have several features: (1) it allows the use of e- simulation, (2) it makes the best use of modern optimal control theory to determine control variables in real time that minimizes a the cost function, (3) it allows occupants' access for better environmental control via the World Wide Web. In comparison to classical building control, it provides several advantages as follows:

- User-oriented easy-to-use control and data-acquisition: The user can control his/her environment using any standard web browser. Real-time update and posting of the current status of building systems is provided for better comfort and satisfaction.

- User's cognitive adaptation and learning for building environment: The user is allowed to access environmental information through the web browser, and controls his/her indoor environmental devices. This is helpful for the user in terms of cognitive adaptation and learning. The user can monitor real-time energy use and the energy cost. The occupant's behavior in controlling indoor environment may be affected by informed rational decision making. In addition, more energy saving and comfort level will be achieved.

- Energy saving, productivity, and satisfaction: With the use of the aforementioned approach, each user will have better understanding of building energy and environment, will act as intelligent energy saving agents, and will achieve higher level of productivity and satisfaction. The cost for occupants is most expensive compared to maintenance and operation costs. This approach will give higher ROI to building stakeholders.

- Changes in AEC industry: The new trend of building environmental control systems using e-simulation, World Wide Web, and optimal control theory will influence relevant industry sectors such as architectural design and construction, design of control systems, building operation schemes, etc.

5. CONCLUSION

Over last several decades, studies in area of building simulation have been focused on the analysis of physical phenomena in buildings, interoperability, and code sharing, etc. One of the new challenges is to integrate building simulation and optimal control theory to ubiquitous smart devices. With this in mind, this paper presents how to optimize building environmental control systems augmented by simulation-assisted optimal control via WWW. The simulation model is incorporated with the optimization routine and WWW network. The control system is optimized in terms of energy, daylighting, ventilation, etc. In addition, occupants can have better satisfaction and comfort (visual, thermal, etc.). The further in-situ experiment will be reported elsewhere.

6. ACKNOWLEDGMENT

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