MODEL-BASED CONTROL OF RESPONSIVE BUILDING SYSTEMS: A SUMMARY OF ITS POTENTIAL AND CHALLENGES

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ABSTRACT

This paper hopes to aid in the further development of model-based (or 'simulation-based') supervisory control for complex building systems. Model-based control uses simulations to test possible configurations for each controller timestep before chosing the most appropriate one to use in the building system at that point in time. This paper provides a critical review of previous developments of this idea for different systems, and underlines the essential concepts, in hopes of developing a common language for model-based control. It also looks at the major challenges faced in the further development and implementation of this concept, and proposes a generalized tool to facilitate model-based control. A simple example is used to illustrate some of the essential concepts. Possible applications are discussed, including the integrated control of more complex building systems, and the design of new buildings with this control strategy in mind.

INTRODUCTION

Thermal building modeling is beginning to make its way into common practice for building design. However, these models can be more than just design tools, and some recent work has focused on making use of them in the operational phase of the building life-cycle. Models can be useful in fault detection and diagnosis, in maintenance management, and in retrofit analysis. Of particular interest here is the use of building models in the integrated control of building systems.

The underlying idea of model-based control is fairly simple. Consider a complex building system with many interacting elements. Instead of devising a complex set of rules for its control (which would be suboptimal), a virtual model of the building or system can be used within a supervisory controller to test possible control configurations at each controller time-step, and optimization techniques can be used to find an optimal (or near optimal) control configuration.

This idea is not new - it was proposed for HVAC control as early as 1988 (Kelly), but it was dismissed at that time as being too computationally complex. But with increases in computation, the idea has begun to appear in various research areas. In the past few years, the basic concept has emerged through the development of better controllers for particular systems. It has been used for daylighting control, ice storage systems, and for some types of HVAC system problems. However, the emergence of the idea in these different fields has generally remained insulated within each of the particular areas, with little cross-referencing or learning from the other developments.

The goal of this current work is to bring these various developments together, to determine the essential underlying concepts, identify the most pressing challenges, and to work towards the development of standard methodologies and tools to support the adoption of this approach. The goal is to develop this approach for use in complex systems that may include many flexible elements (such as combinations of daylighting, thermal storage and flexible HVAC systems, but also such things as natural ventilation, solar walls, etc.). It is felt that such system integration is promising for the design and operation of energy efficient buildings, and for the control of buildings as responsive elements in the electricity grid (decreasing demand at times of high grid stress by responding to signals or electricity prices).

PREVIOUS RESEARCH

The following summary attempts to address some of the key developments in previous research.

Daylighting - Control of Blinds and Lights

Daylighting is a good place to start, in part because it provides a very visual example, but also because of the extensive work and clarity of presentation by Mahdavi in this area (Mahdavi et al., 2005b). (See also Clarke et al., 2002, and Henze et al. 2005, for good descriptions of the basic idea – each in a different field).

The best illustration of Mahdavi's work is perhaps with his description of how to control automated blinds and dimmable lights for an experimental room at Carnegie-Mellon University (Mahdavi, 2001). Each time the central contoller was called upon, it was given the task of determining which combination should be chosen from among the 4 possible louver positions for the blinds (vertical, horizontal, and two configurations in between), and the 10 possible power levels for each of the 4 luminaires. The controller periodically tested possible combinations by running lighting simulations for the room using the combination under consideration, along with the given environmental conditions. The combination which produced the most attractive results (as determined by the use of a weighted objective function that included the consideration of average illumination, uniformity, glare and energy consumption) was chosen by the controller, and the decision was acted on by the system controls.

Although Mahdavi and his colleagues have also ventured into model-based control of natural ventilation (Mahdavi A and Pröglhöf C, 2005a), the focus of the work has been on lighting quality. This focus has influenced how they have applied the idea of model-based control. In particular, their approach is not concerned with any controller timesteps beyond the current one under consideration. This does not allow for the consideration of passive thermal energy storage (as discussed below), nor does it allow for a relatively simple way of considering the energy costs associated with shifting between configurations (as discussed in the challenges section).

Active and Passive Thermal Storage

Henze and his colleagues have done extensive work in the development, testing and analysis of model-based control strategies for active and passive thermal storage systems (Henze et al., 2005). Since the optimal control of storage systems must consider what the future conditions will be, their development of this strategy has included the consideration of predictions over a future horizon.

Henze et al. (2005) describe an installation using model-based control of a building with ice storage and passive thermal storage in the building mass. The system model was done in TRNSYS. A 24-hr horizon was considered at each timestep (1 hour). The control variables were the indoor temperature setpoint and the TES charge/discharge rate. Even though there are just two control variables, the problem is complex, because of the future consideration – choosing the value for each variable at the current timestep depends on the values that the variables will have at future timesteps (one would only charge a store at the current timestep if it can be discharged to advantage at a future timestep). So in this case, the controller must consider 24 temperature setpoint variables (one for each timestep within the horizon), and 24 rate variables. The optimization approach used was to consider the passive and active storage elements separately, using a quasi-Newton method for the optimization of the passive storage, and a dynamic programming approach for the active storage. The optimization (including the interfacing with TRNSYS) was done in Matlab. The objective was to minimize the energy cost while meeting the cooling requirements for the building. The experimental installation ran into two problems during its four days of testing (one technical, one by being stuck in a local minimum), and the TRNSYS model used was not as accurate as it should have been, so the results were not as attractive as expected. But the study was still an important step in the development of the approach for such complex systems, while considering a future horizon.

Henze and his colleagues have also analysed various aspects of model-based control that are peripheral to the central concept, but which are very important to its application. In particular, they have shown the importance of model accuracy (Henze et al. 2004), worked on the development of a method for automated model calibration to ensure continued accuracy over time (Liu and Henze, 2005), and worked on the development of a hybrid control system that attempts to incorporate the aspect of continual updating (found in the learning algorithm approach to control) with the model-based control approach (Liu and Henze, 2006).

HVAC Systems

The most pertinent studies of model-based HVAC system control have been of two types: supervisory control of an entire system, determining optimal setpoint configurations for each timestep; and in determining the optimal start time for heating or cooling, to minimize energy consumption while ensuring occupant comfort when they enter the building in the morning.

Good examples of model-based supervisory control of HVAC systems are provided by Wang and Jin (2000) and Nassif et al. (2005). Both of these studies look at model-based control of VAV systems, and they take a very similar approach. At each timestep, the supervisory controller must determine the supply air temperature setpoint, the supply duct static pressure, the chilled water supply temperature, the outdoor air ventilation rate and the temperature setpoints for each zone. The supervisory controller uses a simplified model of the HVAC system, and determines the collection of setpoints to use at each timestep by using a genetic algorithm.

In the study by Nassif et al. (2005), the HVAC model used was a steady-state model, the building loads were determined outside of the model, and no future horizon was considered, so computation time was not a problem: at each timestep, the genetic algorithm ran through 500 generations of a population of 100, so the model was run 50,000 times – and the total computation time was less than 3 minutes, which is much less than the 15-minute timestep used by the controller. A two-objective approach was used for the optimization, with a separate program module to determine which configuration to choose from along the pareto front.

In the study by Wang and Jin (2000), a one-minute controller timestep was used, and the HVAC model was still simplified but was slightly more complex than that of Nassif et al., with some consideration of the 10 future timesteps (although they did not specify if the optimization considered the effects of possible setpoint modifications over this future horizon). Alongside this increased model complexity and shorter timestep was a smaller population size of 10 for the genetic algorithm, and it was run for just 60-90 generations.

Clarke et al. (2001) provide a very good overview of model-based control and its potential. The work brought together researchers from Honeywell Controls Systems Ltd and the University of Strathclyde, and it worked out some of the interfacing concerns between BEMS systems and simulation tools (ESP-r in particular). Although their discussion was quite broad, the experiments conducted focused only on the problem of determining the optimal start time for heating.

A modification of the optimal start problem was considered by Kummert et al. (2005a and 2005b), who looked at the optimal control of passive solar buildings with night setback, in an attempt to minimize the energy consumption while also minimizing occupant discomfort due to morning undercooling and afternoon overheating. A forecasting horizon was used, along with a simplified model (a linear state-space representation) and the optimization was done by quadratic programming.

ESSENTIAL CONCEPTS

Figure 1 outlines the basic elements of a model-based supervisory control approach.

The approach is applied to a system that contains n flexible elements,

$$\{x_1, x_2, x_3, \ldots x_n\}$$

where each element, x_i, may take on some different states – it may be divided into m_i discrete possible states,

$$\{s_{i1}, s_{i2}, s_{i3}, \ldots s_{im}\}$$

or its state space may be continuous. If all of the elements have discrete state spaces, then the number of possible system states is given by

$$M = \prod m_i$$

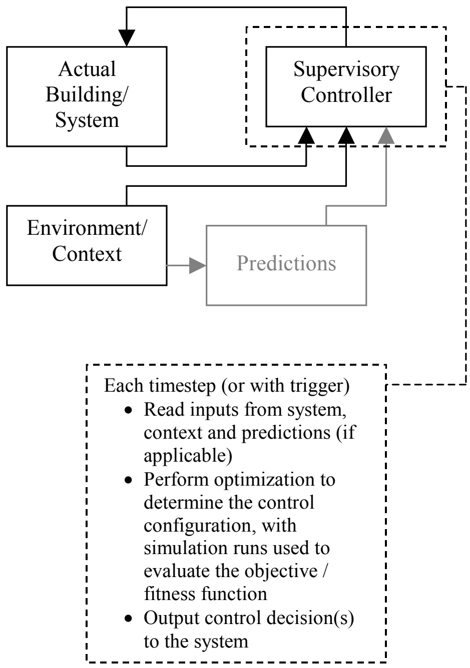

Figure 1. Basic elements

At the beginning of every time interval Δt, the integrated control unit must determine the system state S for that time period,

$$S = \{s_{1?}, s_{2?}, s_{3?}, \ldots s_{n?}\}$$

At a particular time t (where t is an integer multiple of Δt), given the input signals (weather, energy costs, etc.)

$$C = \{c_1, c_2, c_3, \ldots c_u\}$$

the controller must determine S to

$$\text{minimize } Z = f(C,S)$$

where Z is the objective function (which may be a weighted function of various performance aspects), and $f(C,S)$ is approximated by a simulation.

Calls to the supervisory controller are discrete in time. As assumed above, the controller may be called at regular intervals (which is the case with most of the previous studies), or it may be called whenever a trigger condition is reached (this possibility was studied by Mahdavi and Pröglhöf [2005a]).

The prediction component is coloured grey in Figure 1 to denote that it may be required in some cases and not in others. In general, if future timesteps are considered, then some sort of prediction is required for the conditions at these timesteps. But given that a control decision requires some time to calculate, the controller should be using model inputs that reflect what the conditions will be when the control action occurs, rather than when the calculations begin. So, in general, the controller must be looking ahead to the next timestep. If, however, the optimization is quick relative to the changes in conditions, then the current condition information can be used.

If the system's state space is discrete, and if the number of possible configurations is small and the simulation time (T_s) is relatively short,

$$M*T_s < \Delta t$$

then it might be possible to use an exhaustive generate-and-test algorithm to determine the optimal configuration at each time step. Otherwise, some other approach must be used to determine an optimal or near-optimal configuration. Some possibilities are discussed in the section on Optimization Approaches.

If the controller is considering a future horizon, then the optimization becomes more complex. Consider a horizon of h timesteps. When choosing the state for the current timestep, the optimization must also consider the states over the following h timesteps.

S	S	S	…	S	S
t_1	t_2	t_3	…	t_{h-1}	t_h

Figure 2. Future horizon of h timesteps

So the optimization must consider n·h variables. (If all of the variables are discrete, then the number of possible configuration sets to consider is M^h.)

However, when considering the optimization that must be done by the controller at the next timestep (Figure 3), there is an overlap between the states considered by the controller at successive timesteps. (The horizon is perhaps best imagined as a 24-hour window that keeps moving forward in time, bringing a new timepoint into consideration at each step, and having one timepoint falling out of consideration as it falls into the past.)

S	S	S	…	S	S
t_2	t_3	t_4	…	t_h	t_{h+1}

Figure 3. Future horizon for next timestep

Depending on the optimization algorithm used, this overlap might be used to advantage. This is discussed in the section on Optimization Approaches.

The choices of using a discrete or continuous state-space, the length of the controller timestep (or the use of a control trigger), and whether or not to consider a future horizon, will all depend on the system under consideration. But the basic structure in Figure 1 remains the same in each case.

Comparison with learning algorithms for control

The use of neural networks and learning algorithms within HVAC control is very similar to the model-based approach. EDIFICIO (Priolo et al., 2001) is a good example of a neural network and learning algorithm approach to system control. An article by (Clarke et al., 2001) does well in outlining the differences between this approach and the model-based approach, and discusses the advantages and disadvantages of each. In general, learning-algorithm based controllers are easier to install and operate, and do not have the same concerns about model accuracy or computation time that the model-based control approach has. But they do require an in-situ learning period before they can be used (which the model-based approach does not), they do not deal well with physical or use changes to the building (which the model-based control can, if the model is adjusted accordingly), and they do not perform as well as the model-based approach can in conditions that they have not seen before (such as extreme weather conditions). The model-based approach also has the benefit of using and continually updating a building-physics-based model of the building, which can be used in maintenance management and retrofit analysis.

CHALLENGES

Using a model with enough accuracy, and keeping it updated, is often a big concern. Mahdavi noted it briefly. Henze looked at it in more detail, and suggested an approach to automated model calibration. Wang and Jin developed a method to have their simple VAV models be continuously auto-calibrated. But automated calibration of detailed models is not simple, since determining the important parameters is difficult (Kummert et al. 2005b). The development of this field will have an important impact on the use of model-based control.

If the system under consideration includes elements that the occupants may want to control themselves (such as blinds, lights and window openings), then the strategy should include the possibility for manual overrides. And depending on how the system is configured, modeling the behaviour of the occupants may be important (Kummertet al., 2005b).

One aspect that was not considered in any of the previously mentioned studies, but which can play an important role in some systems (such as with mechanically actuated windows or automated blinds), is the energy cost associated with changing between system states. If a future horizon is considered, this cost penalty can be incorporated into the optimization – a change might not be energy efficient over just one timestep, but worthwhile if one considers the energy that can be saved over the future timesteps. (This is demonstrated in the simulation example below.)

In many cases, and particularly in the cases of building systems with many controllable variables, using detailed building models, and considering a future horizon, the biggest concern is that the optimization must occur within the time constraint given by the supervisory control timestep.

OPTIMIZATION APPROACHES

Optimization approaches in previous research

A number of different optimization approaches were used in the previous research discussed above. One key element of many of the approaches (particularly for HVAC control) was to use a simplified model of the system (Kummert et al., 2005; Nassif et al., 2005; Wang and Jin, 2000). This allows for easier optimization: in some cases, the model might be simplified to the point that analytical gradient-based optimization techniques can be used; in other cases, using a simplified model just decreases the computation time required for a simulation run in a generate-and-test algorithm.

However, a more detailed model is often desired. The HVAC control strategies considered often avoided detail by considering very simplified load estimations rather than a detailed transient simulation of the building physics. This works fairly well for the HVAC problems considered, but it is not suitable for studies of passive storage in the building mass (Henze et al., 2005), or for other more complex systems.

When using a detailed model, if the number of possible system states is small and the simulations can be run quickly, it may be possible to test all of the possible configurations. This, however, is rarely the case. In some cases, it may be possible to provide a rule that choses a reasonable subset of the possibilities to test, and then to test all of the possibilities in this subset (as done by Mahdavi et al., 2005b). Other generate-and-test optimization approaches that may be used include genetic algorithms (as were used on simplified models by Nassif et al., 2005, and Wang and Jin, 2000) – but with the longer simulation run times associated with more detailed models, the population size and number of generations would have to be very small.

Some gradient-based methods have also been considered, such as quadratic programming (Kummert et al., 2005), and the quasi-Newton method (Henze et al., 2005). The general trade-offs to be made between precise gradient-based methods and genetic algorithms (or other heuristic methods) are: gradient-based methods can more easily get stuck in local mimima than can genetic algorithms; genetic algorithms are conceptually simpler and often easier to configure than are gradient-based methods; and some gradient-based methods can optimize much faster than genetic algorithms.

If one is considering future timesteps, then the optimization problem might be amenable to the use of dynamic programming, as was the case for the active storage component in the study by Henze et al. (2005).

Other possibilities for optimization

Aside from the computation time associated with many simulation calls, the genetic algorithm approach is an attractive option, since it can be easily applied to a wide variety of systems. For the consideration of a future horizon, the standard genetic algorithm can also be modified slightly to take advantage of the overlap between the state-sets from one timestep to the next. Instead of using a random initial population, the initial population can include at least some possibilities that are based on the optimal set of configurations found during the optimization at the previous timestep, to decrease the computation time needed to find a near-optimal solution.

Another way of modifying the standard genetic algorithm approach is to use a simplified model for the first several generations, to get into range, and then switch to using the detailed model to refine and verify the solution obtained. Instead of having to manually define a simplified model for the system, the detailed model could be used to train a neural network, which could then be used as the simplified model.

PROPOSED TOOL

In order to make model-based control easier to use for researchers (and eventually for building operators and designers), it would be helpful to have software that could facilitate the model-based approach. The proposed program would, at each timestep, receive inputs from the sensors in the system and context, and from a prediction module (if applicable). It would set up the optimization problem appropriately for that timestep, and perform the optimization by interfacing with the virtual building model. It would then send the decision output back to the system.

Ideally, the tool would be configured such that it could use a building model created by any commercial building software, and it would be flexible enough to be used with different optimization strategies. The genetic algorithm approach outlined above for the cases with a future horizon, with the initial population based on the findings of the previous optimization, would also be a worthwhile inclusion within this tool.

As noted above, the computational challenges might be diminished if a simplified model can be used to ‘get into range’, before the detailed model is used to verify and refine the result. The proposed software tool should thus facilitate the automated production of a neural network based on the detailed building model. The variables for the inputs to the network are defined by the condition variables (the sensors and predictions) and the control variables (the flexible elements under supervisory control), and the output is defined by the objective function. The software tool must also be able to run the hybrid optimization approach (using the ANN at first and then switching to the detailed model).

The building optimization program GenOpt (developed by M Wetter when at Lawrence Berkeley Labs, usually used for design and research purposes, not for control) provides a good basis around which the proposed tool can be built. However, a number of elements will have to be added on, including: a main module which reads sensor inputs, modifies the 'conditions text file' (as discussed in the next section), calls GenOpt and processes the results; and elements that can carry out the modified genetic algorithm approach outlined above. The authors are currently investigating these possibilities.

SIMULATION EXAMPLE

To better illustrate the concepts outlined herein, a simple example has been devised. Although the simplicity of this example allows for clarity in outlining the process, that simplicity also makes it difficult to imagine how this control strategy could be much better than using a simpler control approach for this particular system. There are some cases where this method would catch possible energy savings that rules of thumb might not, but the reader is encourage to consider instead how this approach can be applied to more complex systems that are more difficult to control by rule of thumb.

Consider a fictitious building, 5m x 5m, 3m tall, with opaque walls (brick, 10cm fibreglass insulation, gypsum) on the north, east and west, and a glass curtain wall on the south with external horizontal venetian blinds. The building has electric resistance heating and an electric air conditioning unit that keep the indoor temperature at a constant 22^{o}C. Dimmable light fixtures, with an illuminance sensor and autonomous control unit, are set to supplement any daylight as needed to maintain 500 lux on the floor.

The blinds on the south wall are controlled by actuators which are connected to a personal computer. The goal is to minimize energy consumption through the optimal control of the blinds. Information is passed to the personal computer from temperature and humidity sensors outside the building, and also from solar radiation sensors on all four walls and on the roof. The computer can also have access to weather predictions through an internet connection.

The model-based approach begins with the creation of a virtual building model, so the building has been modeled using TRNSYS. To facilitate its use in real-time control, two input text files and one output text file are specified within the model. The input files are: (1) the 'conditions text file', containing real-time and/or predicted weather information, as gathered from the internet and from temperature, humidity and radiation sensors around the building; and (2) the 'control state text file', with a control signal for the blinds. The 'output text file' notes the total energy consumed over the period tested. The supervisory controller operates on a 1-hour timestep. Five possible blind configurations are considered: fully open, ¾ open, ½ open, ¼ open and fully closed.

To demonstrate some of the concepts outlined herein, the controller's operation is simulated and discussed under two different sets of assumptions: (1) the effects of passive thermal storage and the energy use associated with changing states are both assumed negligible, and the supervisory controller does not consider a future horizon; (2) passive storage and the cost of state-changes are considered, and three hours into the future horizon are considered.

Without future horizon considerations

Consider a particular controller timestep on a clear sunny summer day, with an ambient temperature of 28^{o}C, a relative humidity of 50% and a solar gain of 300 W/m^{2} on the south façade. The supervisory controller would use these inputs to modify the 'conditions text file'. It would then test each of the five possible blind configurations by modifying the 'control state text file', running a simulation, and reading the 'output text file'. In this case, with the TRNSYS model used for this example, it would get the results shown in Table 1. With these results, it would choose to have the blinds closed, and it would send this command to the control system for the actuators.

Table 1
Energy Use for Possible Blind Configurations
No Horizon, Summer Noon

STATE	Open	¾	½	¼	Closed
ENERGY USE (kJ)	627	538	449	360	260

The opposite decision would occur during a clear sunny winter day, at a point where the ambient temperature is -10^{o}C, with the same relative humidity and solar gains as above.

Table 2
Energy Use for Possible Blind Configurations
No Horizon, Winter Noon

STATE	Open	¾	½	¼	Closed
ENERGY USE	419	858	1297	1736	2175

With future horizon considerations

Consider a point in time on a summer morning, where the blinds are currently open. The temperature is currently 18^{o}C, and expected to stay at about 18^{o}C over the current hour, and is predicted to rise to 20^{o}C, 22^{o}C and 24^{o}C over the following three hours. The solar gain on the south wall is also expected to rise over the time horizon – is is currently 100 W/m^{2}, and will likely be 150 W/m^2, 200 W/m^2 amd 250 W/m^2 over the following three hours.

It is assumed for this example that the energy cost associated with changing configurations is 150 kJ (approximately 0.042 kWh) for each ¼ change. (So to go from fully closed to fully open, or visa versa, the actuators use 600 kJ of electricity.) This cost is included in the building model's calculations.

The supervisory controller alters the 'conditions text file', and then sets up the optimization problem. In this case, it must consider the future timesteps when determining its action for the current timestep, so it cannot simply test the five configurations as it did in the previous case. In order to test all of the possible configurations over the future horizon for this example case, these 5^4 = 625 simulations were carried out with the help of GenOpt (using its parametric option). The simulations took 40 minutes on a desktop PC, which is less than the hour timestep used in this example, so the parametric approach would be feasible for this case. (In most cases, some other optimization strategy would have to be used.) Table 3 shows the most promising sets of states. The states are denoted as follows: open = 1; closed = 0; in between is partially open. The hour before the decision hour, the blinds were open.

Table 3
Energy Use for Possible Blind Configurations
Future Horizon, Summer Morning

DECISION HOUR STATE	NEXT HR ST	2ND HR ST.	3RD HR ST.	ENERGY USE (KJ)
0	0	0	0	1587
¼	0	0	0	1632
½	0	0	0	1677
¼	¼	0	0	1685
¾	0	0	0	1722

In this case, the configurations that resulted in the least energy consumption were those that focused on shading – the energy savings over the four hours from solar shading outweighed the cost of switching configurations in the current hour. With these results, the supervisory controller would choose to close the blinds. It would then start to consider what decision to make for the next timestep, and it could use these results as a good starting point for that search.

This decision would have been different, however, if the future horizon was not considered, and a shorter timestep was used. For example, with no future horizon and a 6 minute timestep, the supervisory controller would have chosen to keep the blinds open (total energy use of 67kJ over the timestep) instead of closing them (total energy use of 100kJ). In such a case, the control system might never choose to change configurations unless considering the future.

DISCUSSION

The examples given from the previous research show a wide variety of applications for this supervisory control strategy. However, it is felt that the most promising applications have not yet been fully explored – these are complex building systems that may include some or all of the systems considered thus far, and use a supervisory control approach to optimize the energy efficiency and/or thermal comfort of the building as a whole.

Another possible use of model-based control is for load shedding and load leveling by buildings in response to peak demand on the electricity grid, to avoid blackouts and to decrease the need for further capital expenditures on production capacity. Responding to a signal from a central grid manager, or simply responding to electricity prices in a deregulated market, the supervisory control system can be told to shed or shift a certain amount of the load – and the model-based control strategy can help it determine the method that would cause the least inconvenience or discomfort for the occupants (or that would maximize the load reduction while staying within certain comfort limits). Again, such an approach works best with systems that have many possible ways of decreasing or shifting their electricity load, such as by solar shading, thermal storage, light dimming or on-site cogeneration.

Development of this control strategy helps in making more flexible and responsive building systems feasible and beneficial. The model-based approach is particularly interesting in that it can be applied directly in the design phase as well as in the operational phase – the same building models that are used for testing possible designs can be used by the simulated supervisory control element within the simulated building (as long as two separate versions of the simulation software can be run simultaneously). Using this approach in building design might lead to some interesting synergies.

CONCLUSIONS

Previous research in the field of model-based supervisory control has grown out of attempts to optimize particular systems. This paper has tried to bring some of these developments together, and to underline the essential concepts for model-based control. The approach has shown promise when applied to some of these previously-studied systems, but it is felt that its most promising application is with complex systems that contain many flexible and responsive elements. Such flexible and responsive systems have potential benefits for both energy efficiency and for occupant comfort. They also have potential in allowing buildings to act as responsive elements in the electricity grid, shifting or shedding loads to decrease peak demand on the electricity grid.

The main challenges to be dealt with in future model-based control research are: dealing effectively with the computational challenge of optimization within the tight timeframe required for supervisory control; ensuring the accuracy and continual recalibration of the building model being used (the possibility of using methods of automated calibration is of particular interest); and, if applicable, ensuring the possibility for user override of the system, and proper consideration of human actions in the models.

In an attempt to make the general application of model-based control easier for researchers, and to aid progress on the computational challenge of quick and repeated optimizations, a software tool has been proposed for development. This tool would fulfill the basic actions of a supervisory controller: receiving and outputing information to the sensors and building control system; setting up the optimization; applying the optimization algorithm being used; and interfacing with the simulation software being used for the virtual building model. An optimization approach has also been proposed, based on a genetic algorithm, which makes use of the optimization from the previous timestep, uses a neural network model to 'get in range' and uses a detailed model to refine and verify the solution.

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