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Data flow requirements for integrating smart buildings and a smart grid through model predictive control

Thomas M. Lawrence[a,*], Richard T. Watson[b], Marie-Claude Boudreau[b], Javad Mohammadpour[a]

[a]College of Engineering, University of Georgia, Athens, Georgia 30602 USA
[b]Dept. of Management Information Systems, Terry College of Business, University of Georgia, Athens, Georgia 30602 USA

Abstract

A truly energy efficient and sustainable society requires intelligence embedded at all levels within energy production and consumption systems. The 'smartness' of a smart grid is wasted if major consumption locations, ranging from individual buildings to larger collection of buildings (such as campuses or cities) don't have a comparable level of intelligence. Model predictive control (MPC) is an effective tool for integrating the smart grid with future smart buildings. Interest is growing about the need to research the application of MPC to the operation of building systems; however, full-scale MPC concepts have not made it yet into commercially available building energy management systems. Much of the prior published work uses a simplified description of building and systems performance in order to reduce computational complexity. We describe in this paper a vision for data flow and modeling developments that a future, high level control system will need. This would allow a smart building or connected campus of buildings to effectively integrate an overall operational strategy for a future time horizon of 24-48 hours to minimize the energy consumption and cost, enable integration of regional renewable energy sources, and, importantly, consider human factors such as building indoor environmental quality (thermal comfort indoor air quality, etc.). This idealized data exchange and systems control network would obtain or predict data on parameters such as the real-time cost of electricity, renewable energy production, building cooling and heating loads, and current system disruptions (such as equipment maintenance). System monitoring would provide feedback for advanced features such as adaptive learning and automated fault detection and diagnostics. In addition to the idealized future system that is fully capable as described, we discuss some of the issues involved with trying to implement these concepts in older, existing building systems.

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* Corresponding Author.
E-mail Address: lawrence@engr.uga.edu

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1. Background and motivation

A major challenge for the built environment in the 21st century is matching electrical energy supply with demand in a world within the presence of:

- Growing demand due to population increases and emerging developing economies;
- An increasing fraction of intermittent electrical energy supply due to the growth in renewable energy produced by solar photovoltaics and wind energy;
- Concerns about the carbon emissions associated with burning fossil fuels.

Electric utilities employ various methods for managing demand, including price-based programs such as time of use or real-time pricing and incentive or event-based agreements with customers, particularly those with large loads who have flexible operations [1]. Often repeated statistics are: (a) buildings are approximately 40% of the world's total energy consumption, and (b) heating, refrigeration and air conditioning (HVAC) systems represent about 50% of a typical building's total energy consumption [2] with this being representative of buildings in most of the developed economies. Thus, HVAC systems in buildings represent about 20% of total global energy demand [3]. More recently, the concern is with not just the total energy consumption (kWh) but also the current rate of consumption (kW) by a building. Organizations that operate a collection of buildings with a large combined electrical demand are prime candidates for participation in demand response programs. These include campuses, medical centers, military bases, and large office complexes. Demand response can also be considered for energy systems other than electricity (e.g., a chilled water district cooling system), however the focus of this paper is only on electricity demand.

This article summarizes the state-of-the-art in how buildings may implement demand response programs and describes initial findings from an ongoing study at the University of Georgia (UGA) into how an automated demand response system (DRS) could be implemented within a campus that contains a wide mix of building system control technologies, ranging from older, simple pneumatic systems that have no connectivity to those with newer, web-connected building energy management systems.

1.1. The "Smart Grid" and associated control system development

A "smart grid" is a combination of sophisticated communication networks and controls for the generation, transmission, distribution and consumption of electricity, with some segments operating independently and some interconnected. Each of these segments requires a complex control network that can manage the combined functioning of new and older equipment working together under the direction of both a centralized system and various localized control networks. In a fully functional smart grid, interconnected systems, such as buildings and their control networks, will be integrated. The development and full-scale implementation of such a grid as envisioned is still years away due to technological, as well as economic and societal, limitations. Thus, there is a very definite need for the development of techniques and methodologies that allow for the effective control and integration of these major energy consuming systems. In addition, knowledge gains and energy savings can come from learning how to control distributed heterogeneous energy consuming systems, such as building HVAC systems.

1.2. Evolution of building controls and energy management systems

Control systems for building HVACs have evolved from simple on-off switching control laws. For much of the 20th century, pneumatic controls were the dominant technology. They offered adapting proportional, integrative and derivative (PID) control logic and remained popular until the 1990s. They provide reliable and steady control functions but have limited flexibility and are reliant on a steady supply of compressed air, which requires energy. Recently, a large-scale change in the way that building systems are designed, operated, and controlled has developed. Direct digital control (DDC) development began in the 1960s, but it took time for DDC systems to replace pneumatic control. In addition, the need for a standardized data output for hardware from different manufacturers to communicate digitally with each other and centralized control systems became apparent. This led to communication protocols such as BACnet [4] and the proprietary LONworks [5], which paved the way for a 'plug and play' interchange of systems and control hardware through building automation systems (BAS). The ability for building systems to communicate with each other and with a central control system is vital for the successful development and deployment of a building energy management system (EMS) that can minimize energy consumption by adjusting set points and operations based on time of day and use schedules. An illustration of the varying levels of functionality within building systems is given in Figure 1. At the lowest level are the connectivity and communication requirements between the varying pieces of equipment; this allows for the development of automatic control systems. As these become more sophisticated, the operation could be optimized for energy performance via an energy management system. Figure 1 also indicates the likely connection point of the building with a smart grid, where input from a model predictive control (MPC) system would come in.

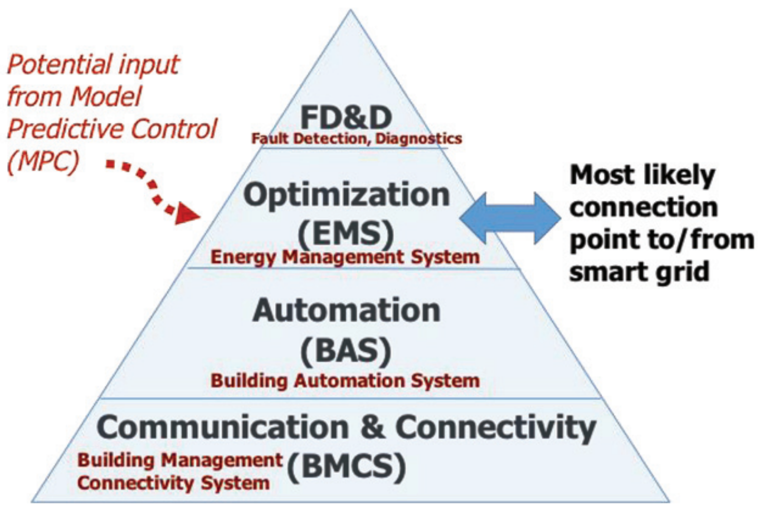

Fig. 1. Building controls and functionality pyramid featured in operation and interactions with grid.

The following characteristics of HVAC systems make their control more challenging than other process control systems [6]: nonlinear dynamics; time-varying system dynamics and set-points; time-varying disturbances; poor quality data due to the low resolution of analog-to-digital converter devices, sampling rates, accuracy of sensors, and lack of access to network forecasting and environmental information; interacting and at times conflicting control loops; and lack of supervisory control (in many buildings).

The increase in control system functionality available during the past decade or so has led to research into more advanced concepts. For example, the concept of Energy Informatics was proposed [7] for this purpose at the beginning of this decade. Others have furnished related visions of future high level data management and control concepts, for example the concept of Facility Management and Modeling (FMM) control in [8]. FMM would combine the measurement of building systems and processes along with modeling of the systems (via MPC) to create a more powerful and robust means of managing buildings and their energy consuming systems.

1.3. The role of model predictive control for smart buildings connected to a smart grid

MPC is an invaluable tool for the development and implementation of the emerging smart grids and the associated smart buildings and equipment systems; a few examples are included in [9-15]. Electric utilities have been developing tools to control the future generation of power grids for several years now, but limited work exists on the end user demand side of the equation. BAS and EMS controls companies are exploring and developing sophisticated systems using MPC to more effectively control and manage the HVAC, lighting and other energy systems within buildings.

The use of MPC has been studied as a potentially powerful tool for building cooling systems and has shown the potential to cope with challenges that other control approaches fail to overcome. The design of MPC laws has been the center of interest for a number of years in industry and academia because of its ability to yield high performance control systems capable of operating without expert intervention for long periods of time [16]. A wide variety of comparisons made recently show that an MPC approach outperforms most control techniques from different aspects such as energy and cost saving, peak load shifting, satisfying complicated operational constraints, improvement in efficiency and transient response [11], [17-18]. From the control point of the view, MPC could be one of the better candidates for supervisory control of building cooling systems. The application of MPC to minimize operational cost considering potentials of active and passive energy storage has been investigated during the past decade, for example in [19-20]. A low complexity MPC scheme designed to be robust against uncertainties in buildings load demands was given in [11]. The model is also used to demonstrate a fundamental trade-off involving savings, losses, and uncertainty in load shifting using active thermal energy storage. Although different MPC-based design methods have been introduced and implemented in the recent years to optimize the operation of HVAC systems, the contribution of MPC as a control tool at a higher level or supervisory control to optimize the operation and schedule of a network of chillers tied to the thermal energy storage (active or passive) has remained largely unexplored.

Any MPC-based building control must be able to predict efficiently and accurately the change in energy consumption if a combination of demand response measures (such as changing set points in some or all of the zones, or supply air temperature and flow rate) are temporarily implemented to handle, for example, high real-time prices. A limited work, however, has been reported to date on developing MPC-based schemes for district energy systems that provide chilled water for cooling and hot water or steam for heating for relatively large areas such as university campuses or shopping centers [11].

Another major development challenge that our work aims to address is the incorporation of human factors into the MPC scheme. For example, peak demand response strategies often include making changes to the building zone temperature set points by temporarily raising them to decrease the overall cooling demand (and hence electrical energy consumption). The fear of causing too much of a temperature swing leading to thermal comfort complaints is one of the major barriers to maximizing the practical implementation of demand response measures by facility operational staff. A recent paper summarizes the technical, societal and human factors issues associated with connecting smart buildings into a smart grid [21].

2. Developing a model predictive control approach for smart buildings integrated into a smart grid

We see MPC as a supplement to, not a replacement for, existing building energy management systems. Some functions of building EMS would be assumed to normally happen, for example having temperature set points adjusted when a zone is unoccupied or scheduled to be unoccupied. This adjustment could be achieved by a local thermostat with occupancy sensor control or centrally through a building EMS. We see MPC techniques as being most helpful when operations that are outside the 'normal' are desired, for example with participation in automated demand response events.

This section outlines how smart buildings can be integrated into a smart grid, and our vision for the application of MPC techniques to help achieve this.

2.1. Four-layer model of integrating smart buildings with a smart grid

The information flow of control systems for integrating smart building(s) and their associated equipment with a smart grid (and potentially for automated demand response) that takes advantage of the communication capabilities that exist in newer systems can be modeled (Figure 2). While our work focuses more on campus-wide facilities, it relies on sound modeling and description of the lower level components as well.

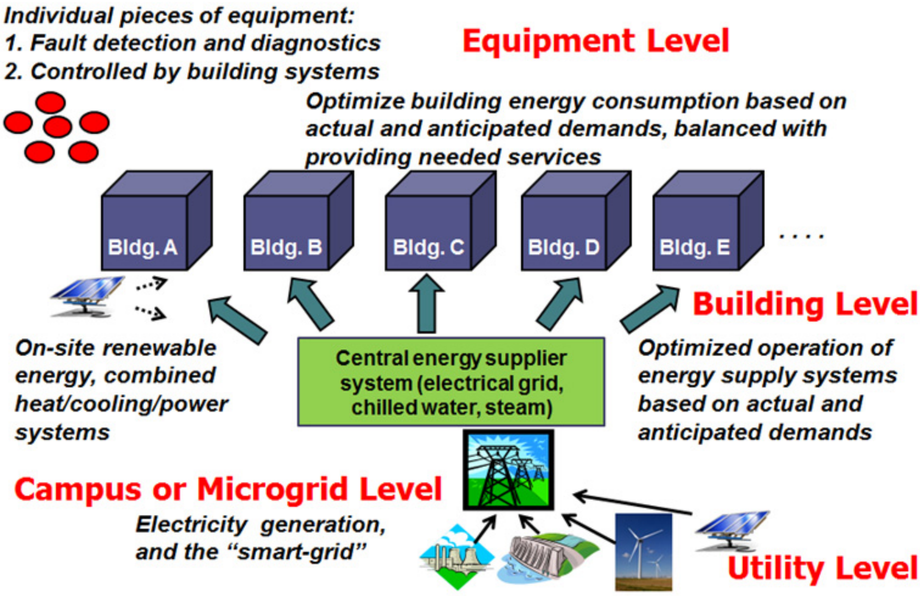

Fig. 2. Four-layer model for integrating smart buildings with a smart grid.

2.2. Data flow requirements for model predictive control for a building or campus of buildings

Our vision for the data flow requirements when integrating smart buildings with a smart grid is presented in Figure 3. This concept would be applicable to individual buildings or to a campus of buildings that may or may not have district energy systems for cooling and/or heating. The campus of buildings may also interact independently with the grid or be operated as part of a separate micro- or nano-grid.

The MPC 'system' will receive inputs from various information sources, such as: monitoring of the building(s) operation during the current day and recent history (say the past 24-48 hours); real-time energy prices or demand response signals; and weather. It also could potentially receive input about other systems such as renewable energy production at the campus or regional level and energy storage system capacity, if installed. MPC output will be the set of recommendations for how the individual buildings and their equipment should operate based on an optimization scheme that would minimize energy peak demand, overall energy consumption while minimizing any negative effects on occupant thermal comfort perceptions and other building operations. The optimization could also potentially include the predicted carbon footprint for that system operation. The MPC controller is not used to directly control equipment and systems in the building or set of buildings, but rather is an input to the building's energy management system control as illustrated earlier in Figure 1.

Other features in this vision for an overall, high level MPC based system include fault detection and diagnostics (FD&D) of the system operation or individual pieces of equipment, as well as the potential for adaptive machine learning of the systems and how they operate.

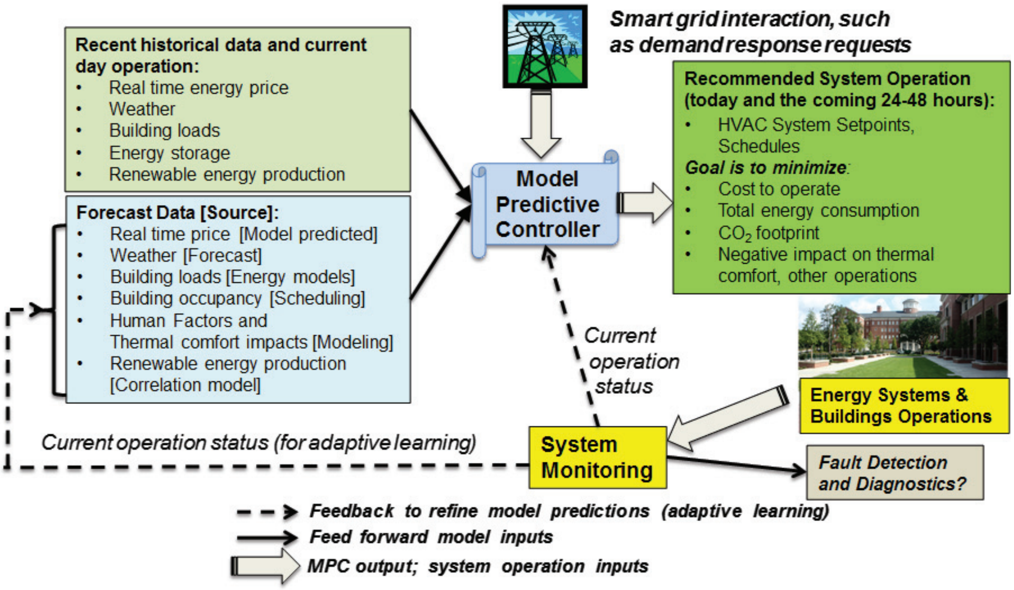

Fig. 3. Data flow diagram: Integrating smart buildings with a smart grid.

2.3. Application of model predictive control concepts at a campus level

Large-scale electricity consumers that operate a number of co-located buildings are good candidates for an automated DRS. However, unless a campus is a newly built facility, it is likely that there will be a mix of older buildings with legacy control systems of limited if any connectivity alongside newer buildings with more modern ‘smart’ controls incorporating BAS and EMS.

There is an exponential increase in modeling complexity when shifting focus from a single system serving a single building to one serving a diverse set of many interconnected buildings. This level of complexity also increases greatly if the buildings are served by a distributed district energy system. District energy systems can generate all the cooling or heating energy in one central location or utilize distributed generation with the buildings interconnected, or a combination of both. Some instances of district energy systems operate like a utility with the cooling or heating energy generated and distributed by one entity and the consumption made by buildings that pay for the amount of energy used. Other cases involve the combined functions of generation and consumption by one common entity and thus provide an opportunity to coordinate the operation in order to improve efficiency and minimize overall energy consumption. Such systems are commonly installed in university campuses, military bases, medical complexes or other facilities that include a collection of buildings operating under common ownership.

2.4. Predictive control system development

When applying MPC to buildings and their associated systems, one complexity to handle is the various sources of stochasticity, such as the actual building occupancy and operation schedules, actual building cooling or heating loads, the interaction of the various cooling or heating system operations, the population makeup and its individual thermal comfort perception patterns, etc.

The predictive controller would be designed to minimizing a cost function (J in Equation 1 below) subject to bounds on states (or outputs) and inputs that is a finite horizon optimization problem with T being the horizon length. The presence of the stochastic disturbance inputs, as well as the stochastic nature of the building equipment models due to the model uncertainties and environmental factors, provide a challenge in solving the MPC problem. A second challenge is associated with the existence of input and state constraints resulting in the minimization of the cost function expected value over a finite horizon that becomes difficult to solve. In these situations, where an analytical solution does not exist, Monte Carlo methods have received wide attention in the literature for example [22-24].

$$J_t = \sum_{k=0}^{T-1} J(x(k), u(k)) \tag{1}$$

The optimization problem can be solved using various methods, for example stochastic dynamic programming. Further details on methods for how MPC would be developed and derived for systems such as a campus of buildings are left to other articles and venues.

3. Challenges and recommendations for integrating existing building facilities into a smart grid

Large-scale electricity consumers that operate a number of co-located buildings are good candidates for an automated DRS. However, unless this is a newly built facility, it is likely that there will be a mix of older buildings with legacy control systems of limited if any connectivity alongside newer buildings with more modern 'smart' controls incorporating building automation systems (BAS) and energy management systems (EMS). With limited budgets for major system upgrades, the challenge is to identify what facilities can be incorporated and where future investments should be made.

3.1. Identifying equipment modernization and upgrade needs

There are two main areas of concern when dealing with older, legacy systems in the context of integrating them into the smart grid. One is their actual capability of providing varying levels of control or set point overrides. The second, and probably most important, is the communication and connectivity of the equipment with the building energy management systems and/or the grid. Some products are coming on the market, which will allow communication and connectivity without the need for a costly and disruptive total change of the building controls. For example, one product allows for wireless communication with legacy pneumatic thermostats that give direct digital control-like functionality. However, there appears to be limited options to an overall control system modernization if full-level automated demand response capability is desired.

3.2. Identifying demand response opportunities and priorities

Within buildings, the best potential for temporarily adjusting energy demand is with the HVAC, lighting systems, and in some situations other services such as water heating and plug loads. Zone temperature set points can be adjusted to reduce cooling or heating demand, but there are concerns with occupants' thermal comfort perceptions and humidity control. Supply air temperatures and flow rates can also be adjusted. Temporary adjustments can be made in the chilled and hot water or variable refrigerant flow systems. In all cases, there is a need to coordinate action to achieve the desired demand reduction. Also, the timing for any changes and transitions need to avoid problems such as a rebound effect when the demand response event is over.

3.3. Identifying benefits and priorities

We are studying how to efficiently manage peak electrical demand for a central district cooling systems at the UGA campus. The focus is on electrical demand, although ultimately similar concepts can be applied to a central steam heating system. Electrical demand management is a high priority since the campus is on a real-time price tariff, whereas the steam heating system is primarily from fixed price natural gas. The challenge of trying to maximize the effectiveness of energy demand reduction with a mix of buildings with a mix of control systems is difficult. We have run demonstration tests to help document the potential savings and to identify areas where upgrade renovation budgets should be focused. The next section briefly describes tests run on a portion of the campus facilities that identify the potential benefits and challenges for implementing MPC and a DRS on campus.

4. Case study from a university campus

4.1. Example application of simulated demand response measures

In late August 2015, we conducted a test on the main central chilled water loop and two of the connected buildings, which have modern, centralized control systems. There is a total of 10 buildings currently linked to the district energy system, with more planned for connection in 2016 and 2017, and three of those buildings have their own chillers that operate semi-independently. This test was run when classes were in session and the cooling demand was near peak. Testing was done on a Wednesday, and the next day the ambient weather and high temperature reached was nearly identical, so we used Thursday as the baseline. We scheduled HVAC control set point changes and also scheduled the chilled water system to take advantage of the inherent thermal energy storage potential within the large distribution pipe network. HVAC set point changes include increasing the thermostat set point by 1.7ºC, changing the supply air temperature upward also by 1.7ºC and (when possible) adjusting the total cooling air supply maximum flow rate downward by 10%. Not all of the zones were subject to the HVAC changes due to the need for these to be set manually at the central control station, so the resulting energy savings were less than the full potential if the changes were applied universally. These changes were relatively small with the hope that they would be totally transparent to the building occupants.

The results of this test are promising. Figure 4 shows a comparison plot of the district energy chiller power for the baseline and test day. It also shows the chilled water supply temperature that was selected during the test day, with pre-cooling starting in the morning and then drawing on the stored 'coldness' during the afternoon peak. Table 1 gives a comparison of the peak demand (kW) and total overall energy consumption (kWh) for the test and baseline days, with approximately 11% savings in each category. This is promising, in that only a portion of the total system was adjusted. Detailed analysis indicates that approximately two-thirds of the savings were from the chilled water system adjustments and the remaining one-third came from the air side HVAC adjustments. If HVAC temperature set point changes were done in all buildings on this district energy system, we estimate that the breakdown would likely be roughly reversed although we caution against making too much of a generalization from this due to the specific nature of each district energy system. We also conducted thermal comfort surveys in the two test buildings and there were no significant differences in the occupant's perception of thermal comfort between the test and baseline days.

MPC could be applied to this particular district energy system that would produce an optimized operation schedule for the HVAC system based on peak grid demand (using the predicted real-time pricing), known room occupancy patterns. Optimization would balance energy costs, total energy consumption within constraints of thermal comfort.

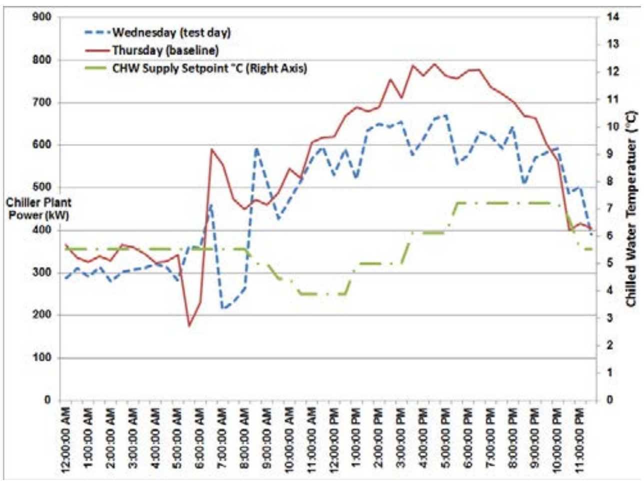

Fig. 4. Total District Energy Plant Chiller Power, Test Day vs. Baseline.

Table 1. District energy plant comparison analysis.

			% Compared to Test Day		
Day	Total kWh	Peak kW	Total kWh	Peak kW	High T (ºC)
Monday	42,507	2,447	129.0%	128.0%	33.7
Tuesday	36,109	2,211	109.6%	115.7%	32.2
Wednesday	32,939	1,911	-	-	30.5
Thursday	36,584	2,132	111.1%	111.5%	30.6

4.2. Barriers to implementation

The barriers to connecting the complete set of even the 10 buildings in this case study example to a smart grid for automated demand response capability are fairly large and costly. Four of the buildings were built in the past decade with modern digital control systems installed, but the others contain a variety of legacy digital or pneumatic control systems. One purpose of our studies is to develop a technical and business case for control system upgrades, potentially to include MPC capability (even if done just as a research project).

Other barriers to a full-scale implementation of MPC to the buildings on this district energy loop for automated demand response is the uncertainty of the impact on thermal comfort perceptions of the buildings occupants and a general reluctance of building operations staff to risk hot or cold call complaints.

5. Development Needed

Based on our experience over the past few years in exploring how a local or campus wide model predictive control or DRS could be expanded, we now discuss briefly needed additional research and policy changes.

5.1 Software and modeling

Since a large portion of the existing built environment contains older control systems, there is a need for add-on technologies that allow cost-effective retrofits. These may serve as an intermediate step before a costly full-scale control upgrade. One such existing product is previously mentioned wireless retrofit for conventional pneumatic thermostats, but there is a need for more competition and different products that will allow other energy systems to be incorporated into automatic demand response programs.

Although there has been a great deal of research into modeling of buildings to predict their resulting cooling and heating loads, there is a need for techniques that will provide simple but accurate predictions of the impact on building cooling and heating loads of temporary future control set point changes. For example, the MPC optimization will need to know what is the estimated energy demand change if an “X” degree change is made to building thermostat settings, and ideally would combine this with the predicted impact on thermal comfort perceptions of the occupants. In addition, the MPC optimization would also provide direction on the optimal way to return to ‘normal’ operation once a demand response event is past.

5.2 Retrofit of enabling technologies

Since a large portion of the existing built environment contains older control systems, there is a need for add-on technologies that allow cost-effective retrofits. These may serve as an intermediate step before a costly full-scale control upgrade. One such existing product is a wireless retrofit for conventional pneumatic thermostats, but there is a need for more competition and different products that will allow other energy systems to be incorporated into automatic demand response programs.

5.3. Human factors considerations and modeling

Much of the recent research and development work has focused on technologies that will automatically control systems. If such changes can be totally transparent without the building occupants noticing, that is well and good. However, to maximize the potential savings in demand and consumption, occupant notification and buy-in will be needed. In some situations, it may be best if the occupants or operators of the buildings are integrated with the demand response measures [25]. In addition, there is a need for research into the human thermal comfort perception in real-world (i.e., outside a test laboratory) situations, accounting for factors such as how long a person is actually in the particular zone, their transient nature (whether they just came in from outside), etc. The relationship between impact on thermal comfort perception and zone air temperature in these various real-world settings would be an important contribution to the MPC optimization function.

5.4. Standards and regulations development, adaptation and adoption

The challenges of modernizing the standards and regulations vary with different regions. One of the more significant, non-technical barriers to demand response programs is how end-user price regulation is conducted, and differences exist between how this approached in Europe, the United States and various areas of Austral-Asia.

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