Occupant-Aware Control Systems for Energy Efficient Buildings

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1. Introduction

Electricity demand in the US is expected to grow by 1,163 billion kWh from 2009 to 2035. In comparison, renewable electricity generation is expected to increase by only 260 billion kWh over the same period (excluding hydropower, [1]). Thus, in order for the US to make real progress in meeting its sustainable energy goals, it will be necessary to slow the growth in demand. This can be achieved without adversely affecting economic output by increasing efficiency and conservation.

Per capita growth in energy consumption has been slowed by the introduction of improved standards for designing efficient buildings (e.g., LEED). However, "Even as standards for building shells and energy efficiency are being tightened in the commercial sector, the growth rate for commercial energy use …is the fastest rate among the end-use sectors." ([1], p. 63, Figure 1). High efficiency building standards and control approaches *focus heavily on the physical elements of the building* and although the energy efficiency of walls, windows and HVAC systems are extremely important to building system efficiency, *the vast majority of a building's energy usage is related to human occupancy of the building* (e.g., temperature control, lighting, and plug loads). In fact, a recent sensitivity analysis concluded that "a significant percentage of building energy use is driven directly by operational and occupant habits," but that these "are currently outside the scope of energy codes, policy initiatives, and general perceptions in the building industry." ([2], p. 2, 50). Similarly, control strategies for building energy management have, to date, focused almost exclusively on monitoring physical attributes of the building – temperature, humidity, airflow, etc. Current control systems do not incorporate data about the building occupants beyond the projection of occupancy made prior to construction. Thus, current approaches fall far short of addressing the fundamental problem at hand, namely that *the building and its occupants form an integrated system of behavioral and physical components which interact to determine energy use*. Hence, to truly optimize the energy usage of such a system, it will be necessary to devise a control approach which also models, measures and actuates these different components in an integrated fashion, forming a (closed-loop) *Cyber-Physical-Social System* (CPSS).

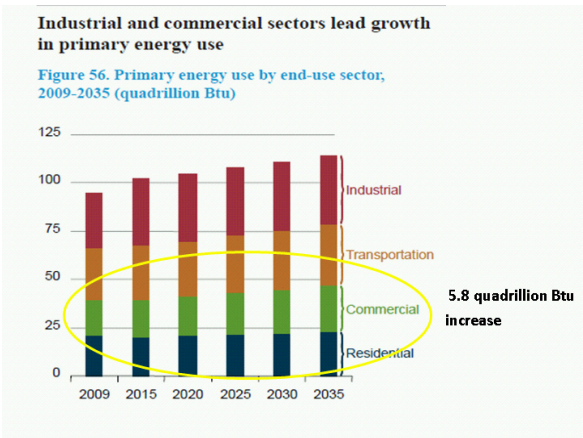

Figure 1 Commercial energy use trajectory

2. Cyber-Physical-Social Systems for Energy Efficient Buildings

Cyber-Physical systems are those in which the cyber and physical components are tightly integrated at all scales and levels. The most sophisticated building energy control systems sample environmental data continuously and build load forecasts [3-6], but even the most advanced of these models seldom include measurements of current or forecasted occupancy, let alone measurements or forecasts of occupant behavior. The addition of the social/behavioral inputs or outputs to the control system is not currently possible. Incorporating real-time behavior is computationally even more complex than environmental data. Temperatures change gradually and there are accurate models for predicting that change. In contrast, building occupants' behavior can change very suddenly and while those changes may be possible to predict, to date, adequate models of occupant behavior do not exist.

The integration of building occupants into the system extends beyond using measurements to gain information about the occupants. Rather, the true potential of the Cyber-Physical-Social System lies in using the control system to not only control the physical systems of the building, but to also encourage behavior change (e.g., energy savings) in building occupants [7]. Given adequate models of occupant behavior the delivery of informational feedback to building occupants can be automated through the control system. We have conceived the first Cyber-Physical-Social systems for efficient building operation which we term, Occupant-Aware Control Systems.

3. Occupant-Aware Control Systems

We are working to create *Occupant-Aware Control Systems* (OACS), which utilize *both technology and people for both sensing and actuation*. Our overall concept for the system architecture is illustrated in Figure 2. The four major subsystems comprise the center four blocks in the diagram. Note that each of these blocks comprises an integrated blend of components from different disciplines. For instance, the first block comprises the physical plant and associated technology, together with the (behavior of the) building occupants. It is not possible to completely separate out the effects of these two components. They interact and depend on each other in many complex ways. Hence, one of the keys in executing such a design is assembling an *interdisciplinary team with expertise in engineering (sensing, power systems, and building systems), computational modeling and controls, and occupant behavior*.

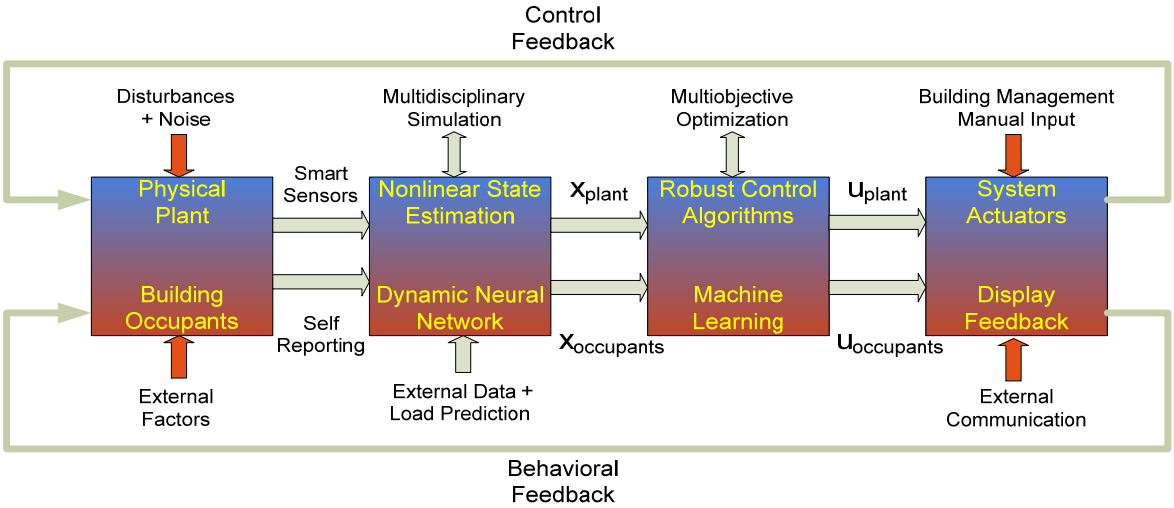

Figure 2 Occupant-aware control system architecture

In the second block (of Figure 2), nonlinear observer theory, signal detection methods, and dynamic neural networks are combined to generate state estimates for the entire system, i.e., both the physical plant states (x_{plant} - temperature, power etc.) and building occupant states ($x_{occupants}$ - comfort, productivity etc.). The data available to this block comes from smart sensors, and also self-report data directly from occupants (see the light-green arrows in Figure 2, which represent data streams in our system).

There are many different tools from different disciplines being brought to bear on this problem. However, it is important to note that we do not divide the problem into distinct components which operate separately from one another, nor do we partition the input space. Rather we take an integrated systems approach. It is clear that the overall system will be subject to many uncertainties (e.g., modeling and prediction errors, state estimation inaccuracies, all of which are unavoidable for tractable algorithms) and external disturbances, such as someone propping open a door (see the red arrows in Figure 2, which represent disturbances to our system). Hence it will be necessary to design the overall system to be robust to these uncertainties and disturbances.

The third block (in Figure 2) computes the control strategy, utilizing a combination of tools from robust control and machine learning. Note that the resulting controller will be unique in many ways. In particular it outputs control commands intended to be executed by a combination of technical (u_{plant} - actuators) and behavioral ($u_{occupants}$ - people) means. This approach differs substantially from a purely technical control approach, requiring us to combine engineering tools with behavioral systems/models/data (see [8] for an overview of control theory in the behavioral sciences).

The fourth block then 'executes' these commands via signals to physical actuators (e.g., lighting level, boiler temperature) and communication with occupants (e.g., informational feedback displays). However, the building occupants are not guaranteed to react as desired: Essentially, the system 'actuators' (people, in this case) may choose to ignore the control command! Thus the control algorithm has to cope with the fact that the $u_{occupants}$ control command may not always produce the desired effect, and this may vary with time. That is one reason why our approach utilizes a combination of tools from robust control and machine learning, to cope with uncertainty, whilst also maintaining the flexibility of adaptation.

We have now closed two feedback loops around the system, one based primarily in the technical world, and the other in the behavioral world (where we are using building occupants as both sensors and actuators). These technical/behavioral pathways are interdependent, and both are crucial to the overall system performance. Our entire system - comprising subsystems associated with the plant, sensing, estimation, control, actuation, and feedback - is an integrated mix of technical and behavioral facets.

4. Conclusion

Occupant-Aware Control Systems will need to adapt to physical conditions and occupant behavior to optimize the performance of the *overall* Cyber-Physical-Social System. This observation is paramount – most of us have observed buildings where people use space heaters in summer because the HVAC system has their space too cold for them. As a result, the *overall* system is performing poorly. Indeed, it is not useful to command a temperature drop via the building HVAC system at a time and place that has consistently prompted users to plug in additional local heating, *unless* a corresponding informational feedback has been identified that effectively prevents this behavior. The OACS energy management is aware of this, and always able to take/adapt appropriate action that optimizes the occupant/technology interactions to deliver true (energy) savings, often during circumstances where traditional control approaches would fail.

5. References

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