Improved Power Grid Stability and Efficiency with a Building-Energy Cyber-Physical System

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Abstract— **This position article outlines some challenges of demand response in the context of the power grid and its interaction with buildings. We describe significant issues in energy-efficient operation of buildings, in particular questions such as system reliability, risk management and environmental impact. We also outline a strategy for the development of new technologies for a cyber-physical infrastructure system that integrates management of smart buildings with management of the power grid. Specific emphasis is given to the interaction of physical and computational processes through sensing, estimation and control.**

I. Background

Electric power grids are large complex systems - currently with centralized power sources and distributed demand. Grid-scale electricity cannot be stored easily, so generation must match demand from instant to instant, all the while maintaining tight tolerances on frequency and supply voltage. Decreasing investments in transmission and distribution (T&D) infrastructure, and in generation capacity, coupled with an aging system, further complicates the demands on a regional power system.

A “peak demand episode” occurs when a rapid rise in load results in a temporary shortage. The rate of generation does not keep up with the rate of demand, resulting in unstable supply or even brownouts. They may occur for seasonal reasons, for example a rapid increase in air conditioner usage during a heat wave, or for sporadic reasons, for example a power plant goes offline unexpectedly (e.g., due to an earthquake or stagnant winds to propel wind turbines). During an episode, the power grid operators must contend with balancing a fast rising demand quickly, while maintaining overall grid stability.

Buildings use approximately 70% of the US’s electricity. In California, weather-caused severe peak-demand episodes are believed to occur 5-10 times annually, with the steepest increase in demand being the first 1-2 hours of an 8-12 hour demand period. The primary power demand is often air conditioning. Efforts to balance capacity during an event include increasing the spot price for power, termed critical peak pricing, and watching building operators respond, or mandating emergency brownouts. The difficulty with either option is an inability to forecast accurately the rate of change in demand. This is caused largely because the power utility and buildings do not exchange information rapidly. Inefficiencies thus result in both power-system stability and energy costs: the utility must wait to observe the response to a price change, and the building operator was unable to “store energy” before an event occurs or must alter demand only after a price change has occurred.

The process of modifying demand in response to price changes or emergency loss of capacity is referred to as “demand response (DR).” In the last few years, LBNL has developed the foundational technologies for a building-energy cyber-physical system. The technologies include (1) establishing an open-standard, secure, robust, protocol for two-way communication between large load centers (large commercial buildings, and industry) and the utility (e.g., PG&E) and (2) automating building responses (for example dimming lights and raising the zone set point temperatures) after a DR communication from the power utility. Currently more than 200 large office and commercial buildings and industrial loads are operating using the Open Automated Demand Response Communication Specification (OpenADR) through a Demand Response Automation Server. California has committed to achieving an early goal for Demand Response in 5% of the system capacity, and a long-term goal of integrating DR into all large-scale power systems. Automated DR has been shown by LBNL researchers to perform better than manual (human-in-the-loop) DR, but California has not yet committed to an Automated DR system.

The problems described earlier embody significant research challenges in the field of cyber-physical systems. With the foundational tools for a cyber-physical energy system being developed and implemented, many opportunities exist to improve grid stability while reducing energy waste and costs. First, for a successful automated DR system to be implemented regionally, it is important for the utility to be able to predict the response for the entire building stock for various levels of price and DR signal. An important research question is how does one determine and then elicit the necessary information to map the demand-response surface for all of the descriptive conditions, such as outdoor temperature, building stock, and geographic location. For DR-subscribing buildings, information may be extracted automatically. For non-DR-subscribing buildings, predictions must be made based on pre-event testing.

Second, when does the utility or building owner recommend/initiate a pre-emptive DR strategy? This decision must be conditioned on forecasts of the expected future demand and future availability. Are there competing objectives for the utility and building operator, based on their unique risk-tolerances? If so, how do we reach optimal decisions? How will DR affect future building designs and construction?

Third, an automated DR system in a building, along with hardware to operate a DR strategy, can have substantial initial costs. What technologies are likely to be most cost effective? For example, can wireless communication technologies improve the performance of various DR strategies and do they reduce initial costs? What DR equipment is needed, and how much should the utility, building operator, or public utility agency contribute for its installation and operation? As a cost-benefit analysis, a utility may find that the expected benefits from regional reliability offsets any initial costs. What classes of buildings should DR first be installed and at what cost?

II. Value of a Cyber-Physical System for Demand Response

DR strategies include increasing building energy efficiency, limiting demand when pre-set limits may be exceeded, and shifting demand from peak to off-peak times (e.g., using energy storage). Controls to limit demand involve a sequence of automated or manually performed changes to the building HVAC (e.g., relaxing temperature and system set points) and lighting systems (e.g., dimming and bi-level switching). The value of DR include the following:

- System reliability: Poor power quality and power interruptions are estimated to cost \$100 billion to the nation per year. In the New York Independent System Operator (NYISO) 2002 Emergency Demand Response Program, a 670 MW load curtailment for a 31-GW power system provided system reliability benefits estimated at \$1.7 to \$17 million over the year.
- Cost savings: Reduced load during times of rapidly increasing demand will lower costs for energy generation, transmission, and distribution.
- System efficiency: Overall peak demand for the utility may be reduced if utility-wide DR systems can shift some on-peak usage to off-peak periods. The literature suggests that a 10% reduction in electricity demand in California may reduce the number of wholesale price spikes by 50%.
- Risk Management: Prices in wholesale markets vary from day to day, and hour to hour, and are difficult to predict. Improved price stability and system reliability reduces uncertainty for the facility operator, which improves load management and planning.
- Environmental Impact: Demand response can help reduce environmental burdens placed on the air, land, and water by reducing or delaying new power plant developments, and by allows the use of the current generation capacity more effectively. These benefits are highly regional and can be large in some areas and negligible in others.

III. Advanced Controls for a Building-Energy Cyber-Physical System

For brevity, we will discuss the technology and infrastructure required for developing and managing a building cyber-physical-system (CPS). We refer the reader to http://certs.lbl.gov/ and http://drrc.lbl.gov/ for an overview of our research on grid stability and competitive pricing.

CPS integrate computational and physical processes, using embedded computers and networks to monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa. Using the motion of humans, materials, and energy in the built environment, the notion of CPS can be extended to infrastructure such as transportation networks, water distribution networks, the power grid, instrumented bridges, intelligent buildings, etc. The development of integration schemes for intelligent buildings into power systems is a specific example of a infrastructure cyber-physical system, for which several layers of physical processes need to be integrated into active control schemes. Three layers of physical processes constitute the description of the system of interest:

- *The power network.* At the core of the energy problem is the power supply system, which is coupled to the control system of the building, through an automated demand response utility interface.
- *The physical building*, i.e. its temperature, ventilation, the state of charge of its thermal energy storage, the state of its interface with the outside environment (via control of daylight, outside air supply rate, ground-coupled heat pumps, etc.) and more generally the resource control system, which adjusts itself to the demand inside the building by the users (currently with little regulation beyond directly actuated demand from the users).
- *The human activity*, which creates the energy demand (in particular ventilation, lighting, electricity, end-use, and air temperature control).

The development of efficient actuation mechanisms for systems in which automation layers have to be built on top of physical processes can follow the steps below.

- *Physical modeling.* Each of the physical components above must be modeled at the appropriate level of aggregation for analysis and control to be possible. For example, power usage must be abstracted; temperature and air ventilation models cannot incorporate small scale phenomena, while human activity is described in an aggregated manner. Integration requires the development of appropriate models for coupling models of electrical power transmission and physical grid infrastructure, with models of human occupancy, activity, and electricity demand. This is usually performed by developing proper constitutive equations, in the form of statistical and control-theoretic models.
- *State estimation.* At the core of any active control mechanism is a sensing layer, which generates the information (cyber) used to control the system. In the present case, a crucial issue in sensing is sensor placement, since most of the buildings today do not come with a "state monitoring" infrastructure. While dedicated sensing infrastructure systems might be needed to provide adequate level of monitoring, these come at a cost. The proper deployment of the sensor and communication equipment must be optimized, taking into account (1) costs of deployment and maintenance, and (2) nature of the information required for operational needs. With proper sensing infrastructure

in place, state estimation can be performed using various system models such as Bayesian inference models, and inverse modeling and data assimilation for control-theoretic models.

- *Control.* A successful estimation procedure leads to accurate real-time knowledge of the state of the system, which is a prerequisite for "closing the loop" in large scale infrastructure systems, i.e. adding a control layer to regulate the corresponding system. Based on the selected model, optimal control schemes can be developed, and may include the costs for sensor deployment and operation.

In the context of smart buildings, the following tasks seems of particular importance.

- *Development of privacy-aware sampling strategies for modeling human activity in smart buildings*. Today, almost all human activities in modern industrial countries are closely tied to numerous electronic devices in their environment that can be used to create real-time activity maps. This information may be directly usable for quantifying activity-linked energy demand, but such analysis must be privacy-aware. With smartphones, RFID-equipped badges, or other devices such as iPods, smartwatches, etc., it becomes possible to map human activity using numerous sensing mechanisms, such as wireless signals, Bluetooth signals, RFID, infrared, etc.
- *Development of privacy-aware human activity models.* With privacy-aware sampling, appropriate models can be used to estimate human activity, without "tracking", which is a significant concern for privacy.
- *Mapping human motion and activity into energy consumption.* Based on the modeling of the system physical layers, human activity can be mapped to energy consumption requirements (for example ventilation or heating/cooling), which in turn can be aggregated to the proper building-level scale.
- *Mapping energy consumption into metrics for DR.* Power demand must be categorized in bins such as (i) essential (e.g., internet routers and servers), (ii) DR-responsive within limits (e.g., some dimming of ambient lights and some widening of thermostat deadbands), (iii) fully DR-responsive (e.g., short-term turning off of decorative lighting, fountains, etc.), and (iv) anticipatory DR-responsive (e.g., pre-cooling the building structure, charging thermal storage). Each activity has a "depth" (i.e., KW), a utility-cost, and a price-point at which it can be triggered. Aggregation of these categories across participating buildings will lead to a supply curve for DR-responsive demand for categories i, ii, and iii, and a supply surface for category iv depending on the confidence associated with the DR-anticipatory signal and how early it is provided before the anticipated event.
- *Active control schemes.* The challenge in developing active control schemes using the framework developed before is the notion of 'forecast' vs. 'nowcast'. While nowcast is possible using estimation, it is very likely that most of the energy efficiency gains are to be made by anticipation of the energy consumption, rather than reading of the current state. This is particularly challenging, given that the human activity forecast models can only be used for anticipation by integrating historical (statistical) models of activity with current readings.

Biographies

MA Piette is Staff Scientist at LBNL and Research Director of the PIER Demand Response Research Center. The DRRC is a 3-year old Center to plan, manage, conduct and disseminate DR research for the California Energy Commission. Piette receieved an MS Degree in Mechanical Engineering from UC Berkeley and a Licentiate from the Chalmers University of Technology in Gothenburg, Sweden.

M. Sohn is Staff Scientist and Group Leader of the Airflow and Pollutant Transport Group at LBNL. He leads research in mathematical modeling of environmental systems and quality, human exposure assessment, Bayesian uncertainty analysis, and value-of-information decision analysis. Sohn received a PhD in Civil and Env. Eng., and an MS degree in Engineering and Public Policy from Carnegie Mellon Univ.

A. Gadgil is Senior Scientist and Deputy Director for the Environmental Technologies Division at LBNL, and Professor of CEE at UC Berkeley. He has a PhD in Physics from UC Berkeley. His expertise ranges from computational fluid dynamics of indoor air and pollutant flows, simulation of entry and transport of indoor radon, building energy efficiency, and methods to treat drinking water to make it potable.

A. Bayen received the Engineering Degree in applied mathematics from the Ecole Polytechnique, France, in 1998, the M.S. degree in aeronautics and astronautics from Stanford University in 1999, and the Ph.D. in aeronautics and astronautics from Stanford University in 2003. He was a Visiting Researcher at NASA Ames Research Center from 2000 to 2003. In 2004, he worked as the Research Director of the Autonomous Navigation Laboratory at the Laboratoire de Recherches Balistiques et Aerodynamiques, (Ministere de la Defense, Vernon, France), where he holds the rank of Major. He has been an Assistant Professor in the Department of Civil and Environmental Engineering at UC Berkeley since January 2005.