## A Cyberphysical Perspective on Energy-Smart Residential Neighborhoods

**Michael Baldea**, McKetta Department of Chemical Engineering, The University of Texas at Austin
mbaldea@che.utexas.edu | http://baldeagroup.cloudaccess.net

Residential buildings account for approximately 30% of the electricity consumption at the national level, and for about 20% of the total U.S. primary energy use. Up to 50% of this vast amount of energy is expended on space cooling [1, 2]. Heating, ventilation and air conditioning (HVAC) systems must maintain occupant comfort within reasonable limits and at a reasonable cost. This should be accomplished in the presence of fluctuations in weather, changes in energy prices, and variations in human occupancy, activity and preferences. Surprisingly, given the challenging nature of their task, most residential HVAC systems still rely on rather rudimentary control strategies (e.g., on/off control coupled with a time-of-day thermostat setpoint schedule [3]).

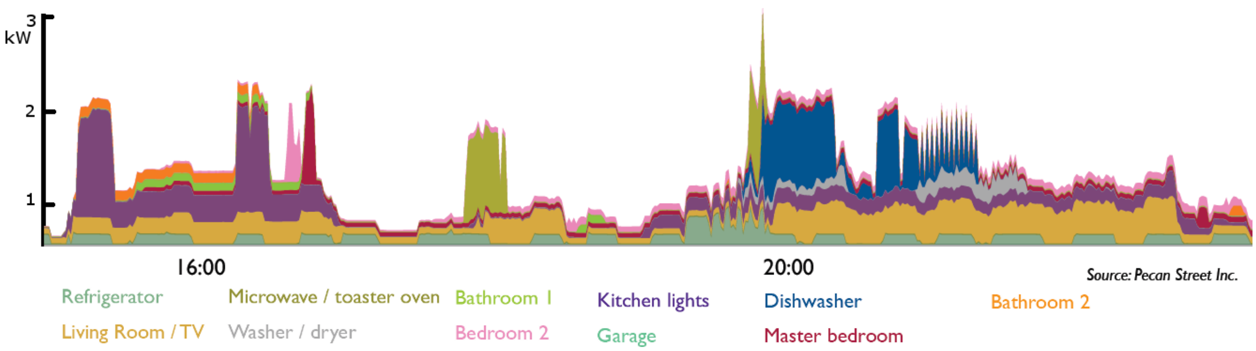


Figure 1: Data collected by Pecan Street, Inc. (a smart grid demonstration project headquartered at The University of Texas) from the Mueller neighborhood in Austin, TX provide an unprecedentedly detailed perspective on residential energy consumption. The data shown here (measured on July 31, 2012 in a typical Mueller home; courtesy of Pecan Street, Inc.) indicate that electricity consumption – note that the contribution of HVAC is not shown – depends strongly on human behavior and varies significantly during the day.

This operating mode (coupled with other energy-intensive human activities – using washers, dryers, water heaters, etc., as shown in Figure 1) gives rise to large daily fluctuations in residential energy use, which are most evident in a late-afternoon and evening peak in energy demand. Extended over large residential neighborhoods, this phehomenon has a significant effect on the operation of the grid, as well as on electricity prices, particularly in the hot weather states of the Southern U.S. (Figure 2).

Grid operators address increased energy demand by using additional, peak-time, generating facilities. Such "peaking plants" are typically designed to be capital-efficient rather than energy-efficient, and are thus more expensive to operate and have a higher environmental impact than the base-load generating facilities.

Fluctuations in residential energy consumption can be significantly diminished by adopting a proactive energy management approach, which entails forecasting energy demand and optimally scheduling the operation of generation (and storage) systems to meet this demand over a future time horizon [4, 5]. Realizing this possibility – and defining the energy-smart neighborhood of the future – requires systematic research efforts on the *cybernetic, software component* of managing energy in the *physical* environment of residential buildings. Ongoing research at The University of Texas at Austin has delineated several directions which present both fundamental challenges and important practical applications:

***Predicting energy-relevant human behavior:*** Neighborhood-level monitoring projects (including Pecan Street, Inc. – see Figure 1) are producing highly granular data on energy-related human activity. The multi-scale nature of the phenomena captured in these data (owing, e.g., to the superposition of hourly, daily and seasonal variations), as well as the sheer volume of the data sets, constitute a substantial barrier in the development of reliable models for analyzing and predicting residential activity. New, computationally efficient methods and mechanisms are urgently needed, that would allow for mining these data, and for forecasting energy-relevant human activity and preferences such as (variations in) HVAC temperature

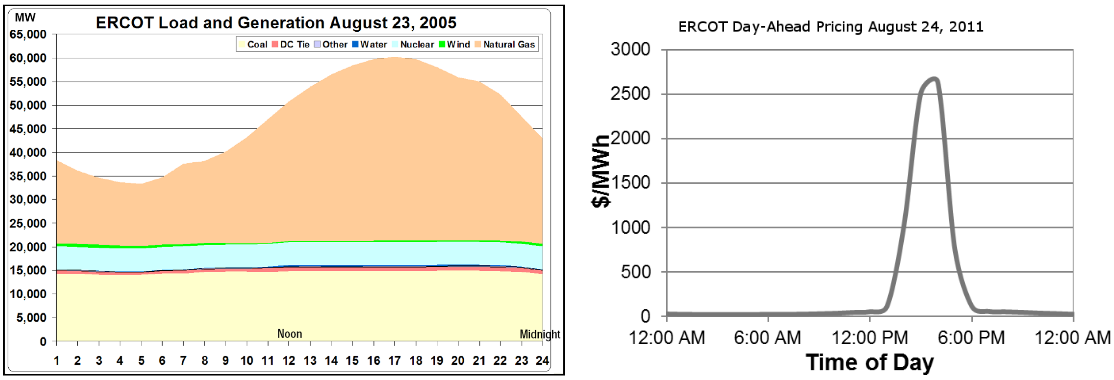


Figure 2: (a) Electricity demand and generation exhibit significant variations during the day. (b) Unusually high (105-110°F/40.5-43.3°C) mid-afternoon temperatures on August 24, 2011 considerably increased AC energy use, causing a large peak in the Texas grid load. As a consequence, spot electricity prices (the prices charged to large consumers) increased by two orders of magnitude. Data source: Electric Reliability Council of Texas (ERCOT).

setpoints, the operation of appliances (including electric vehicle charging) as well as emerging behaviors (e.g., working from home, home schooling). Recent analyses (Figure 3) suggest an increased variability of energy-relevant human preferences when overall energy demand is high. Further work is thus required to understand the potential influence of information streams (e.g., real-time energy prices, real-time billing) on human behavior. In a broader context, this information should serve as the basis for structuring the energy market in a way that encourages producers and consumers to engage in actions and behaviors that lead to reducing the peak energy demand.

***Optimization-oriented building models:*** Time-shifting and leveling peak residential energy consumption is vitally dependent on predictions of energy use based on human behavioral models (as described above), weather and price forecasts. In turn, this requires accurate mathematical models of the temperature dynamics of a home. Currently, most modeling and simulation tools use detailed models derived from the fundamental partial-differential equations describing material and energy balances in a building. Such models are well-suited for design purposes, but are too large (and, typically, in an unwieldy "black-box" format) for use in energy optimization calculations that are performed on-line.

Thus, further progress in optimal energy management in residential buildings depends on the availability on accurate *low-order* models of the building dynamics, which can be solved rapidly and reliably in real-time [6]. Further, such models should be easy to derive and portable, requiring the estimation of a minimal number of parameters from experimental data.

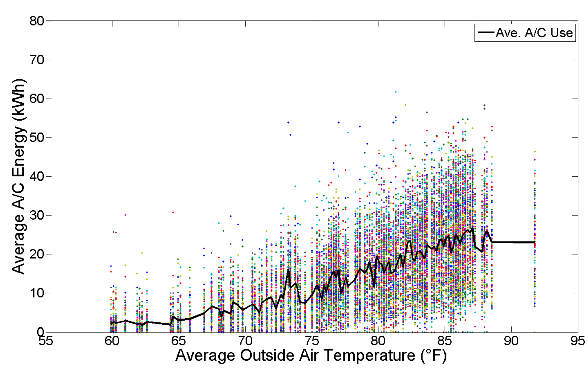


Figure 3: HVAC energy consumption in 88 homes monitored by Pecan Street, Inc. as a function of outside temperature. For each temperature value, an individual home is represented as a point on the graph. Note the (intuitive) increase in energy use in hotter weather. The increased "spread" of the points at higher outside temperatures is suggestive of a strong variability in human preference - in this case, related to AC temperature setpoints [7]. Data collected July 2012 - June 2013, provided courtesy of Pecan Street.

***Cooperative strategies for peak load reduction and reallocation:*** Energy storage is an effective means for reassigning high grid demand from residential buildings to off-peak times. Of particular interest is the use of cost-effective home- or community-level *thermal* energy storage (TES), either in the form of sensible heat (e.g., chilled water) or latent heat (using ice or other phase-change materials) [8]. Managing TES systems requires devising optimal operating policies, which include decisions on the charge and discharge times as a function of (forecasts of) occupancy, weather and energy prices. Recent results [9] show that optimally scheduled home-level TES systems have excellent potential for peak-load reduction via energy storage and precooling of the structural elements of the buildings in anticipation of the afternoon peak. Intuitively, implementing this approach in *every* home in a neighborhood would simply translate the peak energy consumption to a different time of the day. A *leveling* effect can only be achieved via cooperation between the control systems of individual homes. Thus, future work should target the development of cooperative control strategies that enforce load equalization during the day at the community level. Specific research areas include achieving load-leveling with decentralized controllers that require minimal communication and coordination, minimizing computational requirements, and ensuring the stability of the ensemble of homes and controllers. The operational integration of local generation (e.g., combined heat and power, solar panels, fuel cells) and the influence of human behavior on the design, operation and control of such microgrids is also of elevated interest.

***Education and community outreach:*** Modern society has a symbiotic relationship with energy, in all of its forms. Awareness of the nexus of human behavior, energy and the environment should be instilled in the young generations at an early age. Educational and outreach initiatives aimed at contextualizing energy use (particularly at home) and encouraging responsible stewardship of energy resources by the youngest members of our society should thus be an integral part of our research efforts.

Optimal management of energy use in residential buildings is therefore a rich topic for fundamental research and provides a plethora of exciting practical applications. Research in this field is highly interdisciplinary, as it requires new developments in the *cybernetic* realm, including data mining, mathematical modeling, optimization, computation and control, as well as in the *physical* domain, where new means for understanding and modulating energy generation, consumption and storage must be developed.

## References


[1] Department of Energy, Buildings Energy Data Book. `http://buildingsdatabook.eren.doe.gov/` (last retrieved 10/23/2013).

[2] P. Wattles. ERCOT Demand Response Report, May 3, 2011. `http://www.ercot.com/content/meetings/lts/keydocs/2011/0503/LTSTF%20DR%20Slides%20050311_FINAL.pdf` (last retrieved 11/6/2013).

[3] T. Salsbury. A Survey of Control Technologies in the Building Automation Industry. In Proceedings of the 16th IFAC World Congress, pages 1396–1396, 2005.

[4] California Energy Commission. Source energy & environmental impacts of thermal energy storage. Report P500-95-005, 1996.

[5] W.J. Cole, T.F. Edgar, and A. Novoselac. Use of model predictive control to enhance flexibility of thermal storage cooling systems. In Proceedings of American Control Conference, pages 2788 – 2793, 2012.

[6] C. Touretzky and M. Baldea. Nonlinear Model Reduction and Model Predictive Control of Residential Buildings with Energy Recovery. J. Proc. Contr., In Press, 2013.

[7] K.X. Perez, W.J. Cole, J.D. Rhodes, A.D. Ondeck, M. Weber, M. Baldea, and T.F. Edgar. Nonintrusive disaggregation of residential air-conditioning loads from smart meter data. Energy and Buildings, submitted.

[8] W.J. Cole, K.M. Powell, and T.F. Edgar. Optimization and advanced control of thermal energy storage systems. Reviews in Chemical Engineering, 28(2-3):81–99, 2012.

[9] C. Touretzky and M. Baldea. A Hierarchical MPC Strategy for Control of Buildings with Thermal Energy Storage Systems. In European Control Conference, 2014, submitted.