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The Energy Box: Locally Automated Optimal Control of Residential Electricity Usage

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The Energy Box is proposed as a 24/7 background processor operating on a local computer or in a remote location, silently managing one's home or small business electrical energy usage hour-by-hour and even minute-by-minute. It operates best in an environment of demand-sensitive real-time pricing, now made feasible via 'smart grid' technology. We assume that, in time, virtually every electrical device in a home or small business will be controllable from the Energy Box. There are multiple motivations for an Energy Box: (1) By delaying or pushing forward various uses of electricity (e.g. space conditioning), widespread use of the Energy Box could 'shave the peaks and fill in the valleys of demand,' thereby reducing the need for capacity expansion in electrical power generation and distribution; (2) The system should result in reduced electrical energy costs to the consumer; (3) The system supports local generation, storage and sale of electricity back to the grid; (4) The system supports graceful reductions in power consumption by allowing voluntary partial load shedding as requested by the electric utility during times of extreme high demand; (5) Requiring numerous minute-by-minute decisions over the course of a day, the system alleviates the home owner or small business manager from making such decisions, each only involving pennies but in the aggregate involving significant dollars. The primary integrating method of optimization and control is stochastic dynamic programming.

Key words: electricity; electricity management; demand-dependent pricing; dynamic programming; Energy Box
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1. Motivation for the Energy Box

As many service industries have found, implementing demand-sensitive pricing is a proven strategy that allows the industry in question to provide more service within capacity constraints of the current service system infrastructure. This concept, which was brought into the mainstream in the 1980s by the airline industry as "yield management" and is also sometimes called "dynamic pricing", "demand-sensitive pricing" or "congestion pricing", is now used by numerous service industries to increase the utilization of their service: automobile rentals that charge less during weekends; ski and beach resorts and theme parks that charge higher rates over the holidays and weekends; movie theaters that charge a lower 'matinee' rate for movie showings in the early afternoon hours; mobile phone calling plans that have time-of-day and day-of-week differential pricing, etc. This same concept has long been considered by the electricity service industry, and with the ongoing transformation of electric grids into so-called 'smart grids', there is a strong likelihood that demand-sensitive pricing will soon be implemented as a method to use the electric power infrastructure more efficiently. Since electricity supports the lifestyles of individuals, families and small businesses, its provision and usage is undeniably a service. Electricity utilization management should over the coming years become a vitally important application domain for service science.

The electric power grid has traditionally been built using a "supply follows demand" philosophy, where the consumer has the right to demand any amount of electricity and pays a constant, pre-specified, and infrequently updated or reported price per kilowatt-hour of electricity consumed (Schweppe, Tabors et al. 1980). As long as the peak electricity demand does not exceed the total capacity of dispatchable electricity suppliers, it is possible to generate more electricity to adjust supply to the real-time demand (Aubin, Fougere et al. 1995). Until large-scale electricity storage becomes more cost-effective, electricity generation capacity must always exceed peak electricity demand to ensure continuous service (Black and Larson 2007). However, managing electricity supply and demand in this way leads to inefficient use of fuel supplies, extra system capacity that is only used to meet peak loads, illinformed consumers without any incentive to conserve or plan energy usage, and an electric power system (and natural gas to some degree) vulnerable to failure during adverse weather events, peak-use periods, and fuel supply disruptions (Schweppe, Tabors et al. 1980). With upgrades and improvements likely coming to the electric power grid in the form of 'smart grids', there is a near certainty that demand-sensitive pricing of electricity will soon, within ten years, become the standard pricing mechanism or tariff. As other service industries like the airline industry have found, demand-sensitive pricing is a proven method to encourage a "demand follows supply" philosophy, which allows the service system's infrastructure to be used more efficiently without needing to incur large capital costs to build more infrastructure just to meet peak demands. For decades, utilities have built new generation to meet the short duration, peak electricity demand periods, but the recent push towards 'smart grids' suggests that a transformation of the electric power grid is on the horizon that will place a stronger emphasis on energy efficiency and using demand response to reduce peak electricity demand.

Electricity consumption typically has predictable and cyclical patterns of demand for daily, weekly, and seasonal services (Black and Larson 2007). With no feedback from the electric grid inducing changes to these demand patterns, the aggregate demand pattern oftentimes causes a large portion of the supporting electricity supply infrastructure to remain on stand-by (still consuming power) or sit idle. Fully 30 years ago, in 1980, a team of far-sighted MIT researchers recommended that Homeostatic Utility Control (HUC) be applied to the supply and demand systems to provide a natural state of continuous equilibrium (Schweppe, Tabors et al. 1980). The concept of HUC uses the economic response to price by suppliers and consumers, combined with communication and computation, to develop an efficient, internally correcting scheme (ibid). Underlying the HUC concept is the belief that electricity consumption patterns are not rigid, as the consumers' demand for electricity is for ***services provided*** by appliances and devices that use electricity and ***not*** for the ***electrons themselves***. Electricity consumers often have some flexibility in the timing of their electricity usage; however, with a flat rate for electricity, there is no incentive to induce any change in their electricity-consuming behavior. With the proposed 'smart grid' infrastructure improvements of two-way communication and short-interval meter reading, utilities will soon have the ability to encourage changes in electricity consumption patterns via time-varying electricity pricing. The time-varying pricing signal may be as simple as a two-tier time-of-use rate (similar to mobile phone peak and off-peak minutes) or as complex as real-time pricing of electricity (also called spot pricing) -- reflecting the current state of conditions on the electric grid (Hammerstrom, Ambrosio et al. 2007; Faruqui and Sergici 2008). These time-varying electricity pricing tariffs would provide the needed monetary incentive for electricity consumers to modify their electricity-consuming behavior.

The utilities' primary objective of introducing time-varying pricing is to manage the electricity used during peak demand hours, thus 'shaving the peaks and filling in the valleys' to create a flatter demand curve. By managing the peak and flattening the aggregate demand curve, the current portfolio of generation sources would be able to meet forecasted demand growth for many years, thus delaying the capital expenses of building new generation and transmission. A back-of-the-envelope calculation by Black and Larson found that if demand for electricity could be made perfectly flat across all hours of all days, "a 1.6% growth rate [of electricity demand could] be sustained for almost 28 years without the need to expand capacity over [2007] levels," yielding a net present value of avoided costs on the order of $100 billion (Black and Larson 2007). While this is clearly an extreme scenario, it illustrates the low-hanging fruit of encouraging more efficient usage of electricity. Along these lines, a number of utilities and research organizations have run pilot programs testing the potential of peak management through time-varying pricing, with clear reductions in peak electricity use observed across all pilot programs (Hammerstrom, Ambrosio et al. 2007; Faruqui and Sergici 2008). In addition, the Brattle group's report entitled *'The Power of Experimentation'* discusses how consumers that were given 'enabling technology', i.e. technology that automated their demand response, had clearly larger reductions in their peak demand than consumers without the 'enabling technology' (Faruqui and Sergici 2008).

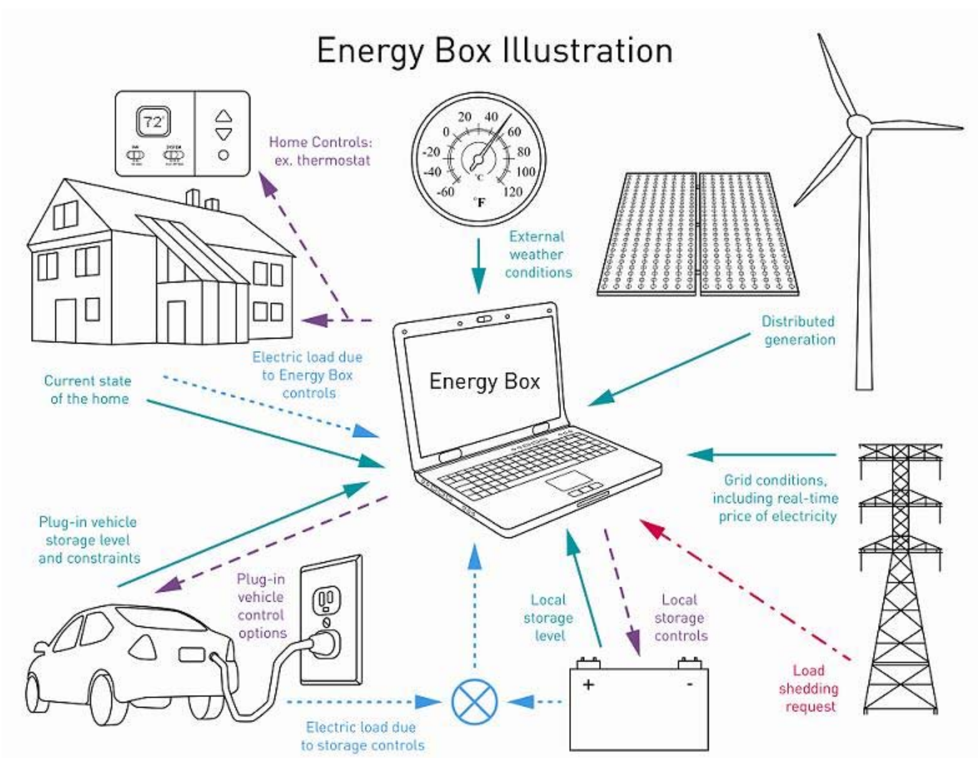
With an eye on the future, electricity from weather-dependent non-dispatchable sources, such as wind, solar and wave sources, are quickly becoming a larger percentage of many utilities' electricity generation portfolio. The variability of these sources is currently balanced by fast-acting dispatchable generation sources, such as natural gas plants, which typically are expensive and an inefficient use of the turbines as the turbines operate most efficiently when they operate at a constant output. Alternatively, spot pricing of electricity would provide an incentive for electricity consumers to modify their electricity consumption pattern so that the variability of these weather-dependent electricity sources is at least partially balanced by price-induced variations in the aggregate demand pattern. By balancing out the variability of the weather-dependent electricity sources via changes in the aggregate demand pattern, the incumbent sources of electricity generation will have a smoother, flatter profile of net electricity demand that they must meet, allowing the overall electric grid to operate more efficiently.

Inducing these changes in the aggregate electricity demand pattern hinges on the ability of electricity consumers to be able to respond to real-time grid conditions without adding significant burden to the consumers' preferred lifestyle. With distributed generation, local electricity storage options, and controllable appliances becoming more common, the average consumer will have a wide range of electricity management options concerning when to use, store, or sell electricity back to the grid in response to current and forecasted electric grid conditions, electricity prices, and weather conditions. This highly repetitive decision-making process under uncertain future conditions would heavily burden the average consumer unless there exists an easy-to-use, automated energy management system that mimics the individual consumer's decision making process under the same grid conditions. Systems such as the proposed Energy Box are necessary for the grid transformation to be sustainable and well received by the average electricity consumer.

Given that the electric grid must balance demand and supply every second of every day, time-varying pricing alone is unlikely to be sufficient for all scenarios. In addition, a valid concern regarding real-time pricing of electricity is that a high penetration of automated responses to frequently changing prices could increase the instability of the electric grid. For these and other reasons, the Energy Box will need to be able to respond automatically to utility-requested demand response signals within pre-existing agreements between the utility and the consumer. For example, during peak hours or hours of unfavorable weather conditions (e.g. lack of wind), the Energy Box platform would coordinate ***graceful load shedding*** to help prevent the demand level from exceeding currently available supply. Unfavorable weather conditions may also arise in the opposite direction (e.g. too much wind), in which case the Energy Box platform would also coordinate graceful load increases by turning on appliances and storing electricity in local storage devices to help maintain a reliably functioning electric grid.

Just as the 'enabling technology' helped increase consumers' peak load reduction during the pilot studies mentioned earlier, we hypothesize that an easy-to-use, automated energy management system will effectively and accurately automate the consumers' electricity use, store and sell decisions in response to real-time grid conditions while allowing the consumer to balance her preferred comfort level and lifestyle with a minimized bill for the electricity used to meet these preferences. Furthermore, we hypothesize that an energy management system that is designed with systemic integrating algorithms will be a major advance over the many "one-appliance-at-a-time" devices that currently exist or that have been proposed. This will lead to a total system optimal control rather than a mixed set of local controls that collectively are likely far from a global optimum.

Figure 1 Energy Box Illustration



The instantiation of our energy management system is herein called the Energy Box, illustrated in Figure 1, and is the main focus of section 2 of this paper. Section 3 introduces our energy management algorithm framework, followed in section 4 by an example energy management algorithm illustrating how it would operate under a range of potential pricing and weather conditions. We then close in section 5 with a discussion of the simulation results and further development of the Energy Box.

2. The Energy Box and its Algorithm Bank

The Energy Box is a software energy management system consisting of a suite of algorithms that will coordinate the management of electricity use, storage and selling back to the grid for the typical small consumer of electricity. Many large commercial and industrial consumers already use sophisticated energy management systems, and oftentimes hire a dedicated employee to oversee the operation of these systems. The average residential consumer and small commercial and industrial consumers, on the other hand, do not have the resources to implement such elaborate systems. As discussed in the previous section, there is strong motivation for incorporating demand-sensitive pricing to encourage responsive demand from all consumers as a resource on the electric grid, both for managing peak demand as well as mitigating the variability of weather-dependent sources that are quickly becoming a large part of the grid's electricity generation portfolio. In a news release accompanying a December 2008 report from the Federal Energy Regulatory Commission, a FERC Commissioner stated that "[d]emand response is clearly the 'killer application' for the smart grid" (O'Driscoll 2008). The challenge is in creating a system to incorporate this responsive demand without creating a significant burden to the average small consumer of electricity.

As the penetration of automated response systems like the Energy Box increases, there are at least two grid management concerns that must be addressed. The first concerns changing the price of electricity too frequently. With a pricing tariff that changes too frequently, there is a potential for inducing an unstable oscillation in demand for electricity should the automated responses become inadvertently synchronized across the system. While the authors do not posit what the appropriate limit will be for the frequency of price changes, the assumption made here for the paper's later sections is that retail electricity prices will change hourly. The other grid management concern is of many appliances simultaneously turning on or off at a price change event. Many strategies could solve this second problem, such as staggering the price changes amongst consumers and/or randomly delaying the Energy Box responses to price changes. While this is necessary to address in a fully implemented system, it will not be discussed further here.

Assuming that a time-varying pricing tariff is ultimately enabled and implemented in a region, there will be a monetary incentive to control net electricity consumption from one hour to another over the course of a day. Controlling the net electricity consumption will include some combination of: scheduling and shifting electricity consumption in the home or business; charging or discharging local storage devices (including electric vehicles when they are plugged-in at the home or business) to store electricity during less-expensive hours and use or sell the electricity during more-expensive hours; and storing, using or selling electricity generated by distributed generation sources at the home or business. While many controls already exist to manage these devices 'one-appliance-at-a-time', the authors hypothesize that significant gains are possible by coordinating these controls to achieve a global optimum.

Determining the global optimum control of using, storing and selling electricity will require a sequential decision-making process that balances the end-user's comfort, cost and lifestyle preferences in the face of uncertain conditions regarding the price of electricity, weather conditions, and electricity available from weather-dependent generation sources. The authors view **stochastic dynamic programming** as the appropriate framework for this process of sequential decision-making under uncertainty. The inventor of dynamic programming was Dr. Richard Bellman, who brought it to reality in the 1950's (Bellman 1957; Bellman and Dreyfus 1962). As an honor to its inventor, the recursive equations used in the dynamic programming approach are sometimes called the "Bellman Equations". With this decision-integrating algorithmic approach, the Energy Box will use the forecasted information of weather, price, and occupancy patterns to determine the optimal control signals of use, store and sell for the current moment in time. The frequency with which these algorithms will run and send new control signals will depend on the frequency of updated information to the current and forecasted weather, grid and home or building conditions. Prior art of the applicability of the stochastic dynamic programming concept for electricity management is best represented in publications by Constantopoulos, et al, and Black (Constantopoulos, Schweppe, Larson 1991; Black 2005). Similarly, Black and this paper's senior author have discussed some of the very general concepts described here in previous work as well (Black and Larson 2007; Larson 2007; Larson 2008).

An illustration of how stochastic dynamic programming will be used by the Energy Box will be discussed in more detail in the next section. While this is the authors' algorithm of choice, the Energy Box's Algorithm Bank will support other algorithmic structures so that other developers may add their supporting algorithms to the Algorithm Bank. The authors intend for the Energy Box to be a modular platform that will allow for the collective creativity of interested persons to create as many 'smart' demand management applications as possible.

While algorithms like stochastic dynamic programming will coordinate net electricity consumption on an hourly and daily time scale, the Energy Box will also be able to coordinate net electricity consumption on time scales of seconds and minutes as well. Due to the grid management concerns discussed earlier, the authors suspect that these are less likely to be coordinated by real-time price changes. Instead, coordinating net electricity consumption on the second-by-second and minute-by-minute time scales will more likely occur via automated responses to grid conditions and utility-requested responses via pre-existing contracts between the distribution utility and consumers. For example, a pilot study in 2006 in the Pacific Northwest by PNNL and Whirlpool tested the short-term interruptible nature of dryers in response to grid frequency fluctuations (Hammerstrom, Brous et al. 2007). Similarly, continuing research at MIT on Frequency Adaptive Power Energy Reschedulers, which was originally introduced in the Homeostatic Utility Control paper, controls the operation of appliances such as refrigerators in response to changes in the grid's frequency (Schweppe, Tabors et al. 1980; Black and Ilic 2002). While the authors expect that some of the sensing and control for these and other rapid response applications to be housed in the appliances themselves, the Energy Box role will be to coordinate when this automated response is enabled, as there may be times when the grid or homeowner would prefer that the automated response not occur.

Another grid management strategy that will require careful coordination of appliances, storage devices and distributed generation at the second and minute time scales is the policy of limiting the total power draw from a residence or office building during times when the grid is stressed. These limits would be established via contracts between the electricity consumer and their distribution utility, and the penalty for exceeding these limits could range from a financial penalty to a temporary blackout at the home or business. In these situations, automated control of net electricity consumption is paramount to ensuring that this maximum power limit is not breached. Among other options, one strategy to ensure that this limit is not breached is the coordination of appliances with regular on/off cycles. Refrigerators, water heaters, air conditioners, and so on could have the Energy Box coordinate their cycles so that only a limited number operate simultaneously. While this addresses cycle control at the individual consumer scale, community coordination of cycle control is also being researched as a potential strategy for managing peak demand on the grid (Gomes, Antunes et al. 2007). By centrally-coordinating the cycles of appliances across a large number of consumers, a distribution utility would have better control of preventing the coincident peak demand from exceeding the available supply in a region, on a specific feeder, or on an islanded microgrid.

The number of potential grid management strategies is clearly more numerous than can be discussed here, and the exact combination of strategies that will be implemented in a region may vary widely and will change as new strategies are developed. Allowing consumers to manage their automated responses and adapt to new strategies without adding a significant burden to their lifestyle will require an easily adaptable and increasingly mobile user-interface for users of the Energy Box and any other energy management system. The ability of the Internet, computers and 3G phones to support such a system has been clearly demonstrated, and many groups have begun work in this area for energy management.

Another key piece of the enabling infrastructure for an energy management system is the communications and computation infrastructure necessary to send and receive information and control signals. This infrastructure will connect the Energy Box to appliances, storage devices, distributed generation sources, smart meters, smart plugs and external sources of information on the Internet via any number of current or future communication standards. A colleague of the authors recently completed a technical report reviewing a wide range of communications standards, with a successful implementation of commercial off-the-shelf hardware demonstrating that the communication and control concept necessary for implementing the Energy Box is indeed feasible (Leow 2008). Storage of the consumer's preferences, as well as the running of the algorithms, may occur locally on a computer or server or externally on the Internet via cloud computing. With the enabling infrastructure essentially independent of the building itself, the Energy Box can be added as a retrofit to existing residences and office buildings as well as being fully integrated into new construction. While the user-interface, communications and computation infrastructure are clearly integral pieces of a fully functioning energy management system, the authors leave the development of these parts of the system to others.

3. Stochastic Dynamic Programming for the Energy Box

The stochastic dynamic programming framing for determining optimal control decisions builds off of the work by Constantopoulos, Larson and Schweppe, that two decades ago considered an automated real-time response by space conditioning appliances with respect to spot pricing for electricity (Constantopoulos, Schweppe, Larson 1991). In the context of dynamic programming fundamentals, we expand the framing of the system to include much more than just thermostat control in a home.

In dynamic programming there are five main concepts: **decisions, states, stages, stage-to-stage state transition rules and rules for following an optimal policy** (Bellman and Dreyfus 1962). Here in the Energy Box context, **decisions** are the control options at hand for a resident to determine how much electricity she will use, store in local storage devices, and sell back to the grid (when applicable). **States** refer to the current conditions at the home and on the grid -- including current price of electricity -- as well as current weather conditions. Each **stage** is seen as a decision-making point in time. The time duration between successive stages will vary by location depending on the frequency of information updates available for the states of the system. **Stage-to-stage state transition rules** are used in the dynamic programming model to calculate the probability of a state variable attaining a certain value at the next stage based on the state of the system at the current stage and the immediate decision(s) implemented at the current stage. These rules are mathematical, probabilistic depictions of weather conditions, electricity price, other conditions on the electric grid, and conditions at the home evolving over time. For example, if the current outdoor temperature were 85^{o}F, the stage-to-stage state transition rule would give us the probability that the temperature could increase to 86^{o}F (or higher), stay at 85^{o}F, or drop to 84^{o}F (or lower) by the next stage. The **rule for following an optimal policy** guides the dynamic programming algorithm's decision-making process by balancing the homeowner's comfort, lifestyle and cost preferences both now and in the future via the optimal sequence of use, store and sell control decisions given the current and forecasted states of the system. The dynamic program is 'solved' via the principle of optimality by working backwards from the terminal stage of the process to generate optimal decision rules for each preceding stage, culminating with the optimal decision for the current moment in time. Given the homeowner's comfort, lifestyle and cost preferences, the control decisions returned by the stochastic dynamic program reflect what the homeowner would have done if she had the time and "lifestyle bandwidth" to consider all of her use, store and sell options when faced with the same information.

Looking at each of these main concepts in more detail for our model, we begin with the range of **decisions** that could be available to a typical homeowner. All homeowners already make many decisions regarding when and how they will use electricity. This includes scheduling the time to run the dishwasher, deciding at what temperature to set the thermostat, deciding which lights to turn on and off, and so forth. As storage devices such as plug-in vehicles and dedicated batteries become more common at the home, the homeowner will have decisions to make regarding when to charge or discharge her storage devices. If the local grid supports the option, these storage devices as well as any distributed generation sources located at the home could sell electricity back to the grid. The exact set of use, store and sell options available will obviously vary from home to home, and thus we will generalize these decisions into three vectors of decision options, represented by d_i^{use}, d_i^{store}, and d_i^{sell} for our model. The subscript i differentiates these decisions by the stage at which this decision is made. Stages will be discussed in more detail shortly.

The use, store and sell decisions chosen will ultimately depend on the current and forecasted **states** of the system, which for our model includes the home, electric grid and weather. At the home, we assume that a host of sensors, appliances and devices will be able to communicate information about the state of the home to the Energy Box. A few examples of the information that might be collected and sent to the Energy Box are occupancy patterns, the temperature inside the house, the amount of electricity currently in a storage device, whether or not a plug-in vehicle is currently plugged-in, and whether an appliance such as the dishwasher is loaded and ready to run. Moving to the electric grid, information may include the current price and forecasted prices of electricity, the portfolio of generation sources producing electricity, and the emissions from the portfolio of generation sources. Last but not least is the weather, from which temperature, wind speed and sunlight intensity are a few examples of the information that would be collected when considering the thermal comfort of the home's occupants, the amount of electricity available from wind (via the utility and/or a local small wind turbine), and the amount of electricity available from the sun (again, via the utility and/or solar panels on the roof). Again, a wide range of states may be involved, and for the model we will aggregate these states into three state vectors: s_i^{home}, s_i^{grid}, and $s_i^{weather}$.

Since most aspects of the home, grid and weather will never enjoy perfect forecasts, updates to the current and forecasted states are essential, and the control decisions will need to be recalculated as different combinations of settings prove to be optimal given new state information. Recall that the moments in time at which the control decisions are made are called **stages**. The frequency with which the state information changes will dictate the time between stages. The authors anticipate the time between stages to be on the order of a few minutes to an hour. In the model, the stages are reflected by the subscript i in order to differentiate the states and decisions made at each stage.

With whatever length of time between stages is used, the dynamic programming model will need to model the expected changes to the state information from one stage to the next. These changes are captured in the **stage-to-stage state transition rules**, which are mathematical, probabilistic depictions of Energy Box decisions, weather conditions, electric grid conditions, and conditions at the home evolving over time. For the grid and weather state information, the authors anticipate that at least a portion of the current and forecasted information will be available from the Internet. The information available online would ideally be in the form of a probability distribution of the states of the grid and weather conditions. A key assumption is that the grid and weather transitions depend only on state information and exogenous forecasts, and not on the use, store and sell decisions made by the homeowner. This assumption may not be valid for grid conditions if there is a high penetration of automated control methods.

Calculating the transition of the states at the home from one stage to the next, on the other hand, will be affected by both state information and the decisions made by the homeowner. A few illustrative examples will be discussed in more detail in the next section. For modeling purposes, these transition rules are captured in the following equations:

$$s_{i+1}^{home} = f_{i,i+1}^{home}\left(s_i^{home} , d_i^{use} , d_i^{store} , d_i^{sell} \right)$$

$$s_{i+1}^{grid} = f_{i,i+1}^{grid}\left(s_i^{grid} \right)$$

$$s_{i+1}^{weather} = f_{i,i+1}^{weather}\left(s_i^{weather} \right)$$

The final main concept of dynamic programming is the **rule for following an optimal policy**, which guides the dynamic programming algorithm's decision-making process by balancing the homeowner's comfort, lifestyle and cost preferences both now and in the future via the optimal sequence of use, store and sell control decisions given the current and forecasted states of the system. In order to accomplish this task, the dynamic program needs a mathematical function that reflects the homeowner's preferences regarding comfort, lifestyle and cost, which will be represented as utility functions $u_i^{comfort}(s_i , d_i)$, $u_i^{lifestyle}(s_i , d_i)$, and $u_i^{cost}(s_i , d_i)$ in the model. Two examples of how these functions map the states and decisions to consumer preferences are illustrated in the next section's example algorithm. Once each individual preference function is defined, the three preference functions need to be balanced with one another. The authors' preferred approach at this time is a weighted linear relationship, so that the rule for following an optimal policy equates to finding a sequence of decisions that maximizes the expected value of the following function:

$$\underset{d_i}{maximize} \left\{ \underset{s_i}{E} \left[\lambda_i^{comfort} * u_i^{comfort}(s_i , d_i) + \lambda_i^{lifestyle} * u_i^{lifestyle}(s_i , d_i) + \lambda_i^{cost} * u_i^{cost}(s_i , d_i) \right] \right\}$$

$$\text{where} \quad \lambda_i^{comfort} + \lambda_i^{lifestyle} + \lambda_i^{cost} = 1$$

With the optimal policy rule in place, the dynamic program uses the principle of optimality to calculate recursively optimal decisions, culminating with the optimal decision for the current moment in time.

Implementing the stochastic dynamic programming model described here faces a number of challenges, however, that must be addressed. Many of the decisions and states could theoretically take on an infinite number of values. Taking all forecasts of future state values into consideration would require considering an infinite number of stages. These challenges underlie many dynamic programming models, and the challenges as a whole are often referred to as the **curse of dimensionality** (Powell 2007). Many strategies exist to prevent the dynamic program from succumbing to the curse of dimensionality, including discretizing the continuous state and decision variables as well as fixing a time horizon after which all future forecasts of state information will be ignored (Powell 2007). These strategies will be employed in the example in the next section, which will illustrate the ability of the approximate stochastic dynamic program to balance the consumer's preferences when faced with uncertain forecasts of future state information.

4. Implementing Approximate Stochastic Dynamic Programming

For illustrative purposes, we describe a prototype model to illustrate how an approximate stochastic dynamic programming model would optimally control a few devices at the home on a warm day when faced with demand-sensitive pricing on the grid and uncertain weather forecasts. This illustrative model is limited to three devices at the home: an air conditioner with a controllable thermostat, an always-connected battery array, and a wind turbine on the roof. The wind turbine is assumed to generate electricity whenever the wind is blowing with sufficient speed, so there is in reality no decision to be made regarding the wind turbine. Thus, the **decisions** available to the dynamic programming model are

$d_i^{use.temp}$: setting the set point of the thermostat,
$d_i^{store.battery}$: charging or discharging the battery array, and
d_i^{sell} : selling or not selling electricity back to the grid.

The options available for each of these decisions will be limited in order to avoid the curse of dimensionality. For instance, the thermostat's decision options, $d_i^{use.temp}$, will be limited to integral temperatures in the range of 72°F to 78°F. Similarly, the battery array's decision options, $d_i^{store.battery}$, will be modeled as decisions of whether to charge the battery at a fixed charge rate, discharge the battery at a fixed discharge rate, or maintain the current charge level in the battery (losses of charge over time are neglected for this model). For the decision of selling electricity back to the grid, d_i^{sell}, the model will assume that any electricity generated by the wind turbine and/or discharged by the battery array that is not used at the home nor used to charge the battery array will be sold to the grid. A wider range of options and decisions will be considered in future models, but the objective here is to illustrate that the set of decisions need not be overly complicated to quickly see benefits to the homeowner.

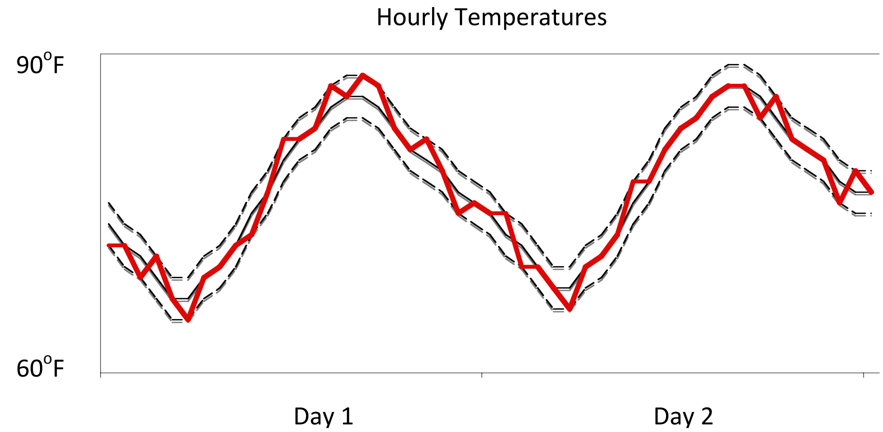
Given the devices at the home, a set of seven **states** will be of interest to the model:

$s_i^{home.temp}$: the indoor temperature of the home,
$s_i^{home.store}$: the amount of electricity stored in the battery array,
$s_i^{home.otherLoads}$: the amount of uncontrolled electricity being used in the home,
$s_i^{home.windDG}$: the amount of power generated by the wind turbine,
$s_i^{weather.temp}$: the temperature outside the home,
$s_i^{weather.wind}$: the wind speed, and
$s_i^{grid.price}$: the price of electricity from the electric grid.

The model will assume that the indoor temperature and amount of electricity stored in the battery array, $s_i^{home.temp}$ and $s_i^{home.store}$, are known perfectly at the present moment in time, and that all future states will be calculated by the stage-to-stage state transition rules to be discussed later. The amount of uncontrolled electricity being used in the home, $s_i^{home.otherLoads}$, is assumed for simplicity to be known perfectly at all times. The amount of power generated by the wind turbine, $s_i^{home.windDG}$, is simply a function of the wind speed, and thus depends directly on $s_i^{weather.wind}$. The three weather and grid state variables, $s_i^{weather.temp}$, $s_i^{weather.wind}$, and $s_i^{grid.price}$, are modeled as random variables, reflecting the uncertainty inherent in forecasts of temperature, wind speed and price of electricity. For simplicity, each of the random variables considered in this illustrative implementation are simplified in the model to take on one of three discrete values: the forecasted mean, μ_i; a deviation above the mean, $\mu_i + \Delta$; or a deviation below the mean, $\mu_i - \Delta$. The time varying forecasted mean μ_i of each random variable is assumed to be retrievable from a weather forecast service (for temperature and wind speed) or the utility (for price of electricity). Again for simplicity, the random variables' distribution for this illustrative implementation is that there is a 60% chance of the random variable being at the forecasted mean at stage i and a 20% chance each of the random variable being at the deviation above the mean or below the mean at stage i. More detailed distributions and stage-to-stage modeling and updating of deviations from the mean are being developed for future implementations of the model.

For this model, the interval between **stages** is set at one hour. Thus, the **stage-to-stage state transition rules** will reflect hourly changes in the state information. For the weather and grid state variables, we have assumed that the expected value for each stage is available from an online service or the utility. Thus, we assume that the stage-to-stage state transition for the mean of each of these state variables is accurately reflected by the forecast from the online service or from the utility. We then add a simple uncertainty band for each of the state variables, as discussed earlier and illustrated here for the forecasted temperature, μ_i°F. At each hour, we model the distribution of potential temperatures as having a 20% chance of being μ_i + 1°F, a 60% chance of being μ_i°F, and a 20% chance of being μ_i - 1°F. Future implementations will use more discrete temperature states and will have time-varying uncertainty bands, as the forecasted temperatures typically become less certain when looking further into the future. Since the weather and grid state variables depend only on previous weather and grid states and are assumed to be independent of the decisions made at the home, we can simulate a full sequence of temperatures, wind speeds and electricity prices in advance of running the dynamic program. For example, the temperature forecast and simulated actual temperature sequence used for two of the simulated days in this implementation is illustrated in Figure 2.

Figure 2 Two Days of Hourly Simulated Temperatures



Assuming that updates to the hourly temperature forecasts from the online service are unlikely to occur more frequently than every six hours, the authors will be developing a method to incorporate observed real-time deviations from the expected temperature via a Markov transition process. For example, at 5:00AM on Day 1 in Figure 2, the simulated actual temperature is one deviation below the forecasted temperature. With this information in hand, future implementations of this model will modify the distribution of potential temperatures at 6:00AM via a Markov transition matrix to account for the observed temperature deviation at 5:00 AM. The updated distribution of potential temperatures for 6:00AM will be skewed towards the lower-than-expected temperatures, as one would expect the actual temperature at 6:00AM to have an increased likelihood of being below the 6:00 AM forecasted temperature when the actual temperature at 5:00AM is below the 5:00 AM forecasted temperature. This adjustment will then propagate through the rest of the forecasted distributions of potential temperatures. Although not implemented for this model, the modeling approach described here will be a key piece of the junior author's dissertation. The wind speeds and electricity prices will be modeled in a similar fashion.

Figure 3 Two Days of Simulated Hourly Wind Speeds

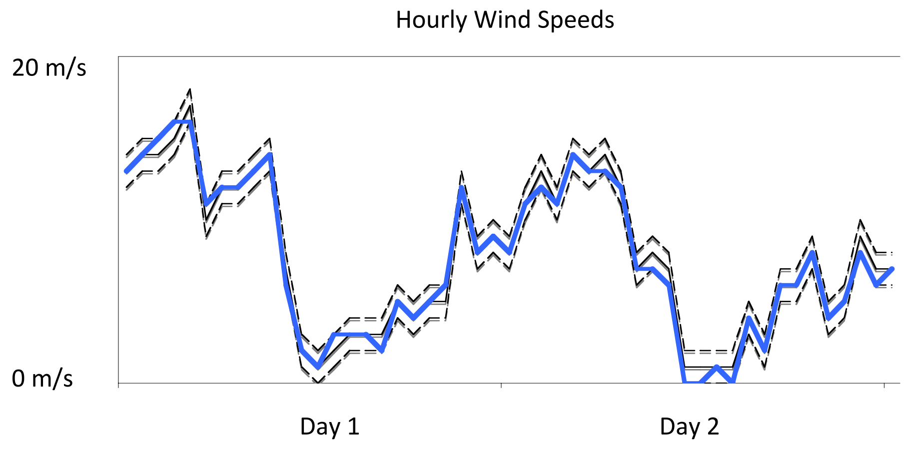
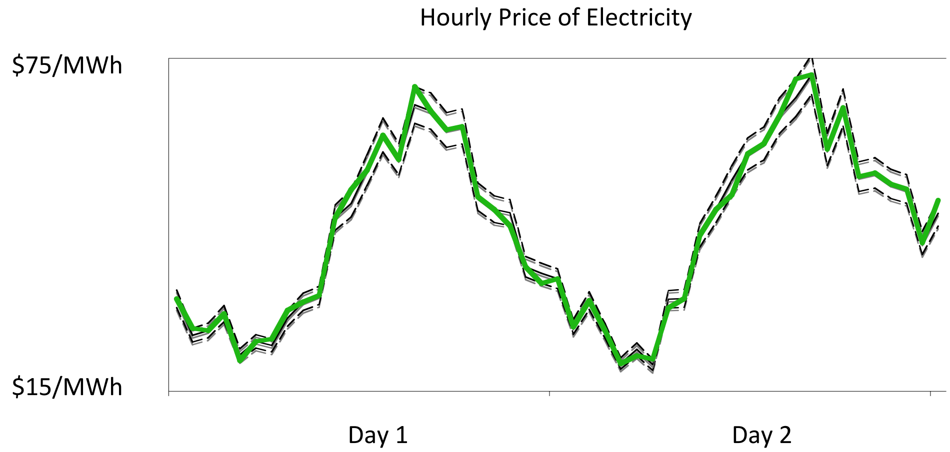


Figure 4 Two Days of Simulated Hourly Electricity Prices



For the illustrative model used in this paper, Figure 3 and Figure 4 illustrate two days of the sequences of forecasted and simulated actual wind speeds and electricity prices, respectively, that were used during the model's runs. The one difference in the electricity price model is that instead of using a constant difference to capture the deviations from the forecasted price, a fixed scaling factor of plus or minus 5% is used, so that lower expected prices have smaller uncertainty bands than higher expected prices. The uncertainty band for the forecasted wind speed, on the other hand, is a constant plus or minus one meter per second (with the obvious minimum of 0 meters per second).

For modeling the indoor temperature of the home and amount of storage in the battery array, the stage-to-stage state transition rules will in these cases depend on the current state of the system as well as the decisions made at each stage. For the indoor temperature of the home, the stage-to-stage state transition rule is as follows:

$$s_{i+1}^{home.temp} = \begin{cases} s_i^{home.maxTemp} & if\ d_i^{use.temp} > s_i^{home.maxTemp} \\ d_i^{use.temp} & s_i^{home.minTemp} \le d_i^{use.temp} \le s_i^{home.maxTemp} \\ s_i^{home.minTemp} & if\ d_i^{use.temp} < s_i^{home.minTemp} \end{cases}$$

The new state variables $s_i^{home.maxTemp}$ and $s_i^{home.minTemp}$ are the highest and lowest temperatures, respectively, that are reachable in the home when the air conditioner is either running for the entire hour or not at all. These maximum and minimum reachable temperatures depend on a number of factors, which for our simple model includes the starting temperature of the home, the outdoor temperature, the thermal characteristics of the home and the efficiency of the air conditioner. The thermal model we are using for this initial model is a simple exponential decay building thermal model used by Constantopoulos (Constantopoulos, Schweppe et al. 1991):

$$s_{i+1}^{home.temp} = \varepsilon * s_i^{home.temp} + (1-\varepsilon) * \left(s_i^{weather.temp} - \gamma * s_i^{home.elec.AC} \right)$$

In this building thermal model, ε is the thermal time constant of the building, γ is a factor capturing the efficiency of the air conditioning unit at cooling the air in the home, and $s_i^{home.elec.AC}$ is the amount of electricity used during the hour by the air conditioning unit to drive the home's indoor temperature from $s_i^{home.temp}$ to $s_{i+1}^{home.temp}$, given that the outdoor temperature is $s_i^{weather.temp}$. This is clearly an overly simplified building thermal model, and in future instantiations of the dynamic programming model, we will shift to more detailed building thermal models, such as ones by Glicksman and Taub or by Wit. (Glicksman and Taub 1997; Wit 2006) Ultimately we hope to develop and incorporate a 'learning' thermal model for buildings that adjusts its parameters automatically based on information collected from temperature sensors around the house to yield a truly house-specific thermal model.

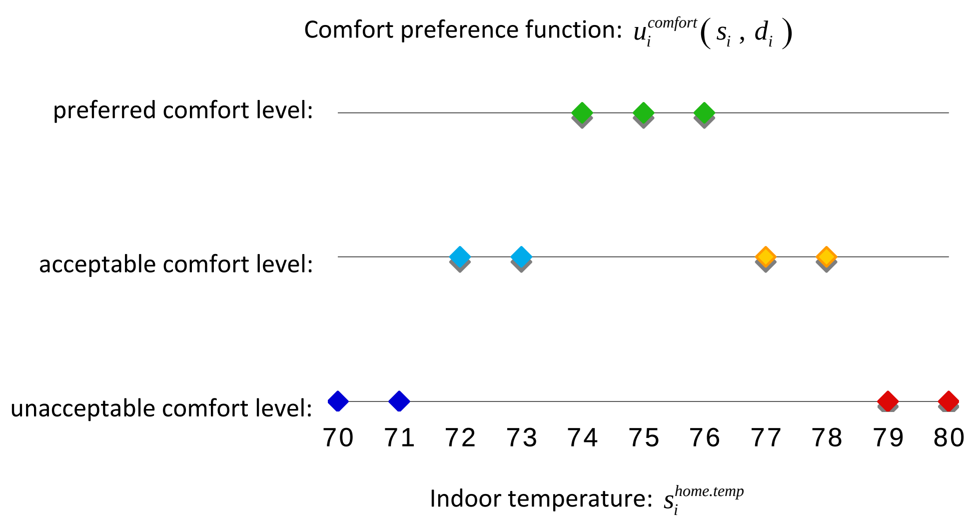
Moving to the battery array, the type of battery used in the array will have a significant effect on the charge and discharge rates of the battery array. Whatever the appropriate charge and discharge rates are for a specific battery type, there will always be a maximum charging capacity, from which the appropriate charge and discharge rates can be compared in order to create discrete states for the dynamic program to use. For example, assume that the battery array's maximum charge capacity is C. While any number of charge and discharge rates may be possible, we will simplify the battery and assume that the battery array will charge and discharge at equivalent rates of $C/4$. Thus, the battery array's states of charge are easily modeled as $0*C/4$, $1*C/4$, $2*C/4$, $3*C/4$ and $4*C/4$, which is further simplified to the set of integers from 0 to 4 inclusively. With this simplification, the stage-to-stage state transition rule is also greatly simplified:

$$s_{i+1}^{home.store} = \begin{cases} s_{i+1}^{home.store} + 1 & \text{if } d_i^{store.battery} = \text{ charge and the battery is not full in stage } i \\ s_{i+1}^{home.store} - 1 & \text{if } d_i^{store.battery} = \text{ discharge and the battery is not empty in stage } i \\ s_{i+1}^{home.store} & \text{otherwise} \end{cases}$$

While this potentially oversimplifies the operation of the battery array, more detailed models could easily be used for this dynamic program so long as the modeling allows for the discretization of the battery's state so as to avoid the curse of dimensionality in the dynamic program. More detailed controls of storage devices at the second-by-second and minute-by-minute time scales are also expected to be a part of the suite of Energy Box algorithms, which may affect the actual state of the battery at the next stage for this dynamic program. Updated information on the battery's storage state would be easily included as it becomes available from sensors on the battery array.

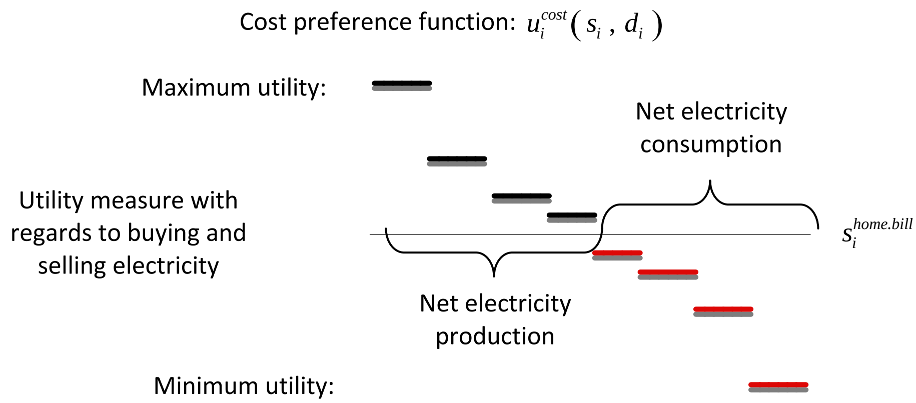
Last but not least, the **rule for following an optimal policy** must be defined. To keep the implementation straightforward at this time, the authors have chosen to consider only comfort and cost in this model. For comfort preferences, represented by $u_i^{comfort}(s_i, d_i)$ in the model, a simple relation between the expected indoor temperature at the end of the stage and the homeowner's utility is illustrated in Figure 5. What this represents is that the homeowner prefers an indoor temperature between 74°F and 76°F. In certain cases, she is willing to allow the temperature to either drop to 72°F or 73°F or to rise to 77°F or 78°F, but at a lower preference level. For this model, anything outside of this range is deemed unacceptable. Hence, the set points on the thermostat are limited to the 72°F to 78°F range.

Figure 5 Illustration of Comfort Preference Function



The cost preference function used in this model, represented by $u_i^{cost}(s_i, d_i)$, is illustrated in Figure 6, which assumes that a homeowner will be displeased if she must purchase electricity from the grid (as modeled by the *'net electricity consumption'* portion of the cost preference function) and will be pleased if she is able to sell electricity to the grid (as modeled by the *'net electricity production'* portion of the cost preference function). The cost of electricity increases from left to right on the x-axis, and a negative cost is equivalent to when the homeowner is making money by selling her excess electricity to the grid.

Figure 6 Illustration of Cost Preference Function



The exact cost of electricity in a given hour, shown on the *x*-axis of the cost preference figure, Figure 6, is calculated by the function

$$s_i^{home.bill} = s_i^{grid.price} * \left(s_i^{home.allLoads} + \frac{C}{4} * \left(s_{i+1}^{home.store} - s_i^{home.store} \right) - s_i^{home.windDG} \right),$$

where the variable $s_i^{home.allLoads}$ captures the electric load from the air conditioner as well as the other uncontrollable loads. Of note is that it is possible for $s_i^{home.bill}$ to be negative, should the amount of electricity generated by the wind turbine and discharged by the storage device exceed the total electric load of the home. Similarly, a homeowner's $s_i^{home.bill}$ could be negative even without a wind turbine if the homeowner has a storage device that she charges during low-priced hours and sells back to the grid during high-priced hours. For cases in our model where the option of selling the excess electricity to the grid is available, we implement the policy of net metering, whereby the homeowner is paid at the same rate for selling electricity to the grid as she would be charged when using electricity. Other pricing models for selling electricity to the grid exist and could also be modeled. If selling electricity to the grid is not possible and the home has nonetheless produced more electricity than it consumes (which may be the case in a very strong wind), then the model simply 'dissipates' the extra electricity. This 'lost' electricity will be tracked in these cases to illustrate scenarios where insufficient balancing is available to fully take advantage of the electricity generated by the wind turbine at the home. With the two individual preference functions now defined, the dynamic program's rule for following an optimal policy over a 24-hour planning horizon can now be written as

Rule for following an optimal policy:

$$\underset{d_0,\, d_1,\, \ldots\, d_{24}}{maximize} \left\{ \sum_{i=0}^{24} \left(\underset{s_i^{weather},\ s_i^{grid}}{E} \left[\lambda_i^{comfort} * u_i^{comfort}(s_i, d_i) + \lambda_i^{cost} * u_i^{cost}(s_i, d_i) \right] \right) \right\},$$

where $\lambda_i^{comfort} = \lambda_i^{cost} = ½$ for this instance of the model. These relative weightings will be adjustable to individual homeowner preferences regarding comfort and cost. In addition, a range of preference functions will be considered for both the cost and comfort preferences, as well as for the lifestyle preference when that is included in future dynamic programs.

With the rule for following an optimal policy established, the dynamic program structure is now complete. From here, the dynamic program will use the principle of optimality to calculate the optimal sequence of decisions given the state information at hand. At each stage, we will consider all reachable states that the dynamic program's decisions directly affect, which are the states $s_i^{home.temp}$ and $s_i^{home.store}$. For this implementation, this yields a set of 35 possible state combinations at each stage that the home could be in at that time. For each of these possible 35 state combinations, each combination of the decisions $d_i^{use.temp}$ and $d_i^{store.battery}$ are considered, of which there are 21 in this implementation. After calculating the expected utility for each of these, the decision combination with the maximum utility will be stored as the optimal decision combination for that state at that stage.

Assuming that we limit our time horizon to 24 hours, we will begin the dynamic programming algorithm at the 24th stage and work our way backwards in the following process. This modeling decision assumes that all information beyond 24 hours from now has a negligible affect on the current optimal decision, although this assumption will be tested in future implementations. For all 35 possible state combinations at that 24th hour, the combination of decisions that maximizes

$$\underset{s_{24}^{weather},\ s_{24}^{grid}}{E}\left[\lambda_{24}^{comfort} * u_{24}^{comfort}(s_{24}, d_{24}) + \lambda_{24}^{cost} * u_{24}^{cost}(s_{24}, d_{24})\right],$$

is stored as the optimal decision combination for that particular state combination at the 24th stage. The optimal value and decision combination are stored as $J_{24}\left(s_i^{home.temp}, s_i^{home.store}\right)$ for all of the 35 state combinations, yielding

$$J_{24}\left(s_{24}^{home}\right) = \max_{d_{24}}\left\{\underset{s_{24}^{weather},\ s_{24}^{grid}}{E}\left[\lambda_{24}^{comfort} * u_{24}^{comfort}(s_{24}, d_{24}) + \lambda_{24}^{cost} * u_{24}^{cost}(s_{24}, d_{24})\right]\right\}.$$

Once the optimal decisions are established for stage 24, the process is repeated for stage 23 via the recursive form of the above equation, yielding

$$J_{23}\left(s_{23}^{home}\right) = \max_{d_{23}}\left\{\underset{s_{23}^{weather},\ s_{23}^{grid}}{E}\left[\lambda_{23}^{comfort} * u_{23}^{comfort}(s_{23}, d_{23}) + \lambda_{23}^{cost} * u_{23}^{cost}(s_{23}, d_{23}) + J_{24}\left(f_{23,24}^{home}(s_{23}, d_{23})\right)\right]\right\}.$$

This process is repeated for each stage until the optimal decision for the current moment in time is determined for all state combinations. Then, for whatever state combination the home is currently in, the optimal control decisions as determined by the dynamic programming process will be sent to the thermostat and battery array to be set for the next hour.

Table 1 Simulation Output

Scenario Number	Thermostat Control	Battery Array (16 kWh)	Wind Turbine (3 kW)	Option to Sell Back to the Grid	Total Cost ($)	Cost Reduction Compared with Baseline	Number of Hours in [72, 73] indoor temperature range	Number of Hours in [74, 76] indoor temperature range	Number of Hours in [77, 78] indoor temperature range	Percent of wind energy used
1	N	N	N	N	182	-	12	708	-	n/a
2	Y	N	N	N	145	20%	5	618	97	n/a
3	Y	Y	N	N	139	24%	8	655	57	n/a
4	Y	Y	N	Y	139	24%	9	646	65	n/a
5	N	Y	N	N	173	5%	12	708	-	n/a
6	N	Y	N	Y	170	7%	12	708	-	n/a
7	N	N	Y	N	166	9%	12	708	-	38%
8	Y	N	Y	N	131	28%	17	603	100	38%
9	N	Y	Y	N	151	17%	12	708	-	49%
10	Y	Y	Y	N	120	34%	13	641	66	59%
11	N	N	Y	Y	150	18%	12	708	-	100%
12	Y	N	Y	Y	112	38%	16	601	103	100%
13	N	Y	Y	Y	139	24%	12	708	-	100%
14	Y	Y	Y	Y	102	44%	14	612	94	100%

After an hour of time has passed (i.e. the time interval between two successive stages in this implementation), this entire process is repeated as the home's state information and the forecasts of future weather and grid state information will be updated, yielding the potential for the sequence of optimal decisions to have changed.

For the simulation considered in this paper, 30 days of optimal control decisions are calculated for 14 different combinations of devices and options in the home in response to the forecasted weather and price information illustrated earlier. The simulated actual values of the weather and grid conditions are used to update the home's states for each simulated hour, from which we calculate and collect the cost to the homeowner as well as a measure of the number of hours that the home remained in her preferred temperature range of 74^{o}F to 76^{o}F. The same sequence of forecasted and simulated weather and price data was used for each of the 14 scenarios, so that the cost and comfort output is comparable from one scenario to another. Table 1 presents the output of these 14 scenarios, where each scenario considers a different combination of the following set of devices and options: a controllable thermostat, a battery array with storage capacity of 16 kWh, a wind turbine with a 3 kW peak capacity (slightly oversized for a typical home, but used for illustrative purposes), and whether or not the homeowner is allowed to sell any excess electricity back to the grid. These are all compared to the baseline scenario of a single, fixed set point of a preferred temperature (75^{o}F in this case).

5. Simulation Results and Future Work

From the simulation output in Table 1, a wide range of comparisons is visible, with a few worthy of direct inspection. For all scenarios, the total cost calculated for each scenario decreases relative to the baseline scenario. Of the three scenarios with only one device included in the simulation (scenarios 2, 5 and 7), the thermostat control provides the largest cost reduction of 20%, although the comfort tradeoff for this cost reduction is that for 97 of the simulated 720 hours (~13% in this case), the indoor temperature reached the range of 77^{o}F to 78^{o}F. One note about the simulated temperature profile that was used is that at times, the simulated temperature remained below 74^{o}F overnight, which is what caused a handful of the simulated hours (no more than 17 hours, or ~2%) to have indoor temperatures in the range of 72^{o}F to 73^{o}F. Whether or not the tradeoff in comfort for reductions in cost is acceptable is ultimately up to the homeowner and the home's occupants to decide. Adjusting the individual comfort and cost preference functions, $u_i^{comfort}(s_i, d_i)$ and $u_i^{cost}(s_i, d_i)$, and/or adjusting the relative weighting of the individual preference functions, $\lambda_i^{comfort}$ and λ_i^{cost}, will give the homeowner control over her preferred balance of the competing objectives of maximizing comfort and minimizing cost. Future work with this model will compare variations of the preference functions and their relative weighting.

For each additional device and option included, there is at worst no improvement in the cost reduction, and typically a further cost reduction is realized as the number of control options increases. Again, whenever temperature control is included in a scenario, the deviation of the indoor temperature from the preferred range of 74^{o}F to 76^{o}F would have to be assessed by the homeowner and home's occupants to decide whether the gains in cost reduction outweigh the increased number of hours that the home's indoor temperature is outside this range. Future work will also look at the timing of the hours when the home's indoor temperature is outside the preferred temperature range and what the corresponding outdoor temperature is at that time, as the interaction between the two may affect the perceived comfort levels.

Looking at the 'one-appliance-at-a-time' versus global optimum hypothesis, consider combining the output of scenarios 2, 5 and 7 versus scenario 10. The total cost reduction of the three 'one-appliance-at-a-time' scenarios is 37 + 9 + 16 = 62, which is the same as the total cost reduction of the global control scenario (all scenarios do not allow the selling of electricity back to the grid). However, the benefit of the global control is that the number of hours that the indoor temperature is above the preferred temperature range drops from 97 to 66 (~13% to ~9%). Hence, the homeowner obtains the same cost reduction with less of a deviation from her preferred comfort level.

Switching the focus to the last column of 'percent of wind energy used', scenarios 7 through 10 illustrate cases when the home has a wind turbine but is not allowed to sell electricity back to the grid. As only around half of the electricity generated by the wind turbine was ultimately used in these cases, a competing objective that will be considered in future work involves maximizing the usage of electricity from the wind turbine jointly with maximizing comfort and minimizing cost. This would add another preference function and relative weighting factor to the mix, which may change the output of the algorithm. One caveat here is that this objective may be satisfied when a full contingent of the home's demand pattern is included in the simulation or if a smaller wind turbine is installed. Nonetheless, there may still be times even then when a portion of the electricity generated by the wind turbine is wasted if responsive demand and storage devices are not included in the control process.

Last but not least, the 30-day simulation output in Table 1 was calculated using a 24-hour look-ahead as discussed in Section 4. Another simulation run was completed using a 48-hour look-ahead, ultimately yielding essentially equivalent results. This suggests that in this case, a 24-hour look-ahead is sufficient given the dynamics of the weather and price of electricity. As more devices and options are included, though, this result will continue to be checked, as there may be cases when a longer look-ahead will provide better performance by the algorithm.

As mentioned throughout the paper, the authors and their colleagues are considering a wide range of extensions and enhancements to this model. Incorporating the home occupants' daily patterns down to the scale of room-by-room control is the current research focus of the authors' colleague Woei Ling Leow. Other extensions and enhancements being considered include: more detailed models of storage devices (including electric vehicles) and building thermal characteristics; more distributed generation sources at the home; more controllable appliances; better knowledge of the daily electricity profile for uncontrollable appliances and devices; other consumer preference functions and relative weighting of these functions; and time-varying preferences based on daily occupancy patterns. In addition to developing a more detailed model of an individual home, the authors intend to develop a simulation that will explore how a large-scale implementation of automated energy management systems like the Energy Box affects the aggregate demand curve on the electric grid. Last but certainly not least, the question that will determine whether or not a system like the Energy Box is successful is: Do the Energy Box's automated control decisions meet the expectations of the homeowner? After all, the consumers' demand for electricity is for ***services provided*** by appliances and devices that use electricity and ***not*** for the ***electrons themselves***.

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