The Energy Box: Comparing Locally Automated Control Strategies of Residential Electricity Consumption under Uncertainty

by

Daniel James Livengood

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Author . . . .

Engineering Systems Division

May 16, 2011

Certified by . . . .

Richard C. Larson

Mitsui Professor of Engineering Systems

Thesis Supervisor

Certified by . . . .

Stephen C. Graves

Abraham J. Siegel Professor of Management Science Professor of Engineering Systems and Mechanical Engineering

Certified by . . . .

James L. Kirtley, Jr.

Professor of Electrical Engineering

Accepted by . . . .

Warren P. Seering

Weber-Shaughness Professor of Mechanical Engineering and Engineering Systems

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Abstract

The Energy Box is an always-on background processor automating the temporal management of one's home or small business electrical energy usage. Cost savings are achieved in a variety of environments, ranging from flat pricing of electricity to real-time demand-sensitive pricing. Further cost savings derive from utilizing weather forecasts to manage local rooftop wind turbines or solar photovoltaics and/or to anticipate price swings from central utilities.

The main motivation of this research is to design, construct and test a prototype software architecture for the Energy Box that can accommodate a wide variety of local energy management environments and user preferences. Under some scenarios, appliances can be optimally controlled one at a time, independent of each other. In other scenarios, coordinated control of appliances, either simultaneous or time-sequenced, provide better outcomes.

Stochastic dynamic programming is the primary optimization engine. The optimization goal is to balance cost minimization with thermal comfort as specified by consumer preferences.

The results demonstrate that the desired general energy management platform is feasible as well as desirable for saving money on electricity while maintaining comfort preferences. Scaling up to neighborhoods, towns and cities, a key contribution is improved understanding of single-home electricity demand dynamics induced by automated decisions. Further research will determine how such local automated decisions affect the broader smart grid with regard to resilience, stability and pricing.

Thesis Supervisor: Richard C. Larson
Title: Mitsui Professor of Engineering Systems

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Chapter 1

Introduction and Dissertation Overview

1.1 Motivation

According to the National Academy of Engineering, electrification was the greatest engineering achievement of the 20^{th} century[1]. Considering how much of our daily lives depend on electricity, few would disagree. Supplying electricity has its challenges, though. In particular, electricity is almost immediately perishable, so the supply and demand of electricity must be balanced on the electric grid at every moment of every day. Unlike other energy sources like oil and gasoline, electricity cannot yet be stored cost-effectively over a long time and at a large scale.

Throughout the 20^{th} century, balancing electricity supply and demand typically was a problem solved by supply-focused strategies. One of the reasons for this was simply that measuring and communicating details of electricity demand was costly for the majority of electricity customers. The original electromechnical meters required a meter reader to walk up to each individual meter to write down and report back the amount of electric

[1] http://www.greatachievements.org/

energy (measured in kilowatt-hours (kWh)) consumed by the residence or business on the other side of the electromechanical meter. The expense of this process meant it was cost-prohibitive to take these measurements more frequently than once a month, and thus demand-focused strategies of balancing electricity supply and demand were originally impractical.

Moving into the 21^{st} century, the cost of modern digital electric meters (often called 'smart meters') has dropped substantially, which has sparked an interest in developing a so-called 'smart electric grid' or 'smart grid'. Current discussion regarding what should be included in a 'smart grid' varies, though many would argue that integrating responsive electricity demand into the wholesale and retail electricity markets is certainly one preferred element of the smart grid. Pilot programs around the U.S., Canada and Europe have been and are testing a multitude of ways to better integrate responsive demand into the retail electricity market, with some form of time-varying, demand-sensitive pricing of electricity a leading candidate. Demand-sensitive pricing, also known as yield management or revenue management, is well established in other service industries like airlines, movie theaters and restaurants as a way to use the existing infrastructure as efficiently as possible.

For the pilot programs of time-varying pricing of electricity, the goals of a subset of these pilots were collected and summarized by the Brattle group where the focus was mostly on peak electricity demand management [Faruqui et al., 2007, Faruqui and Sergici, 2008]. Time-varying pricing policies, such as time-of-use rates (TOU) (similar to cell phone plans' peak and off-peak minutes), critical peak pricing (CPP), and hourly real-time pricing (RTP) (also called spot pricing of electricity) were implemented to meet this peak management goal. As Faruqui et al. [2007] and Faruqui and Sergici [2008] discuss, 'enabling technology' clearly increased residents' peak load reductions by automating the responses to these pricing policies. The exact implementation of the 'enabling technology' varied by pilot, but generally this included smart thermostats that 'automatically raise the temperature setting on the thermostat by two or four degrees' Fahrenheit and 'always-on gateway systems' that would automatically shed electric load whenever the price of electricity surpassed a pre-set threshold [Faruqui et al., 2007].

The focus of this dissertation is to expand upon the automated control options provided by this ‘enabling technology’ to understand the dynamics induced by time-varying pricing electricity tariffs during all hours of the day and week (not just the peak) and to consider other applications of this automated responsive demand. Generally speaking, residents are interested in the services provided by appliances and devices, not for the electrons themselves [Black, 2005, Livengood and Larson, 2009], and there is often some flexibility in the timing of when residents complete these services. One potential application of this flexibility is the integration of local weather-dependent sources of electricity generation, such as rooftop wind turbines or solar photovoltaic systems. A resident may benefit from coordinating her or his electricity consumption with windy or sunny hours, and this dissertation explores how much benefit could be realized when ‘demand follows supply’ [Schweppe et al., 1980, Chao et al., 1986, Chao and Wilson, 1987].

1.2 Research Objective and Question

The main motivation of this research was to design, construct and test a prototype software architecture for the Energy Box that can accommodate a wide variety of local energy management environments and user preferences. When implemented in a home, the Energy Box would be an always-on background processor automating the temporal management of one’s home or small business electrical energy usage.

Once the prototype software architecture was developed, one of the specific research questions investigated for this dissertation was determining when **coordinated** control of appliances and devices **within** a single residence or business provides additional benefits to the consumer relative to independent control of appliances and devices.

Stochastic dynamic programming is the primary optimization engine for local energy management under uncertainty, and the optimization goal is to balance cost minimization with thermal comfort as specified by consumer preferences. Cost savings are achieved in a variety of environments, ranging from flat pricing of electricity to real-time, demand-sensitive pricing. Further cost savings derive from managing electricity consumption in response to weather forecasts that predict when electricity production from local rooftop wind turbines or solar photovoltaics will be available.

Ultimately, it was found that under some scenarios, appliances can be optimally controlled one at a time, independent of each other. In other scenarios, coordinated control of appliances, either simultaneous or time-sequenced, provide better outcomes.

1.3 Research Approach and Methods

Whether due to some of the time-varying pricing tariffs tested or from forecasts of weather-dependent sources of local electricity generation, the Energy Box model inevitably will be making local energy management decisions under uncertainty. For this implementation of the Energy Box, the primary method used for decision making under uncertainty is stochastic dynamic programming [Bellman, 1957, Bellman and Dreyfus, 1962, Constantopoulos et al., 1991, Powell, 2007]. Details of the dynamic programming decision method's implementation in the Energy Box context are discussed in full detail in chapter 3.

Once the independent and coordinated decision methods were established, a Monte Carlo simulation collected measures of the two key outputs, cost and thermal comfort, to determine which decision making process best managed the competing objectives of minimizing cost and maximizing thermal comfort. Constraints were also included to manage how much flexibility was permitted by the simulated resident for each type of service included in the model (e.g. dishwashing must be completed by a certain hour). Though the focus of this dissertation is on the two competing objectives of cost and thermal comfort, the Energy Box simulation process could easily be expanded in future research to include other competing objectives, such as minimizing emissions or maximizing usage of locally-generated electricity (e.g. rooftop wind turbines or rooftop solar photovoltaics).

Models of the random variables were carefully managed to ensure that variations of simulated consumers faced the same uncertain conditions so that variations in the results arose exclusively from changes in the decision making process or the controllable parameters in the Energy Box model. The sensitivity of these results with respect to the decision making process and with respect to a few other parameters modeled in the Energy Box simulations were explored and will be discussed in chapters 4 and 5. The controllable parameters modeled are introduced in detail in chapter 3.

1.4 Scope and Limitations

Electricity must be balanced at all time scales: years, days, hours, minutes and seconds. Different strategies and markets are in place to accomplish the goal of balancing electricity supply and demand at each time scale. The Energy Box and other 'enabling technology' could conceivably manage one's home or small business electrical energy usage across all time scales in response to whatever market and/or system design is implemented.

The focus of this dissertation is specifically on the dynamics of electrical energy usage at an hourly time step. One reason for focusing on an hourly time step is that many utilities are beginning to install 'smart meters' across their service territories, which typically measure electricity usage at time steps of an hour or even as frequently as every five minutes. Another of the leading reasons for the choice of an hourly time step in this Energy Box model was that the affect of the algorithms' hourly decisions would be easily visible to residents, particularly if the algorithm performs poorly from the resident's perspective. Though beyond the scope of this dissertation, the goal of an in-home implementation of the Energy Box would be to collect feedback from the occupants regarding perceived thermal comfort or the timing of when appliances started, leading to an automatic update of parameters for the algorithms with the goal of reaching a set of parameters where the algorithms' decisions are simply not noticed by the resident (i.e. the resident's lifestyle is no longer noticeably affected).

Due to computational complexity constraints, the Energy Box model implemented for this dissertation only coordinates decisions between a dishwasher, clothes washing machine, air conditioner, and wind turbine. A commercially implemented Energy Box would certainly include energy management algorithms for many more appliances, storage devices and distributed electricity generation sources. However, for exploring the benefits of coordinated control within a single residence or business, this small set of appliances along with the wind turbine provides a sufficiently rich set of results for this dissertation.

The Energy Box model for this dissertation assumes that the resident is a price taker in the electricity market and that changes to a single resident's load are so small that they will not affect the price of electricity. Bidding and other interactions with the market are beyond the scope of this dissertation, though these alternative approaches are certainly a topic of interest for research in this area and will be discussed further in section 2.4.

The results demonstrate that for the scenarios tested in this dissertation, the desired general energy management platform is feasible as well as desirable for saving money on electricity while maintaining comfort preferences. Scaling up to neighborhoods, towns and cities, a key contribution is improved understanding of single-home electricity demand dynamics induced by automated decisions. Further research will determine how such local automated decisions affect the broader smart grid with regard to resilience, stability and pricing. Ultimately, a large-scale smart grid simulator that integrates the actions **across** thousands or hundreds of thousands of Energy Boxes in response to various market designs and system architectures would be necessary to fully analyze the aggregate demand-side dynamics, however that is beyond the scope of this dissertation. The focus of this dissertation is on developing the prototype Energy Box software architecture and determining when **coordinated** control of appliances and devices **within** a single residence or business provides additional benefits to the consumer relative to independent control of appliances and devices.

1.5 Dissertation Structure

The dissertation structure is laid out as follows. Chapter 2 provides an overview of relevant literature, including a summary of the history of responsive demand in electricity markets. Chapter 3 discusses the details of the Energy Box model, including the coordinated and independent decision methods under uncertainty. The results pertaining to electricity consumers are presented in chapter 4, followed by a discussion of the results pertaining to electricity prosumers in chapter 5. Chapter 6 closes the dissertation with some concluding observations and remarks.

1.6 Glossary of frequently used acronyms

CWM	Clothes Washing Machine
DG	Distributed Generation
DH	Decision Horizon
DP	Dynamic Programming
DW	Dishwasher
EBA	Event-based Appliance
FC	Flexibility Constraint
FD	Full Distribution
FP	Fixed Prices
MV	Median Value of the Distribution
PF	Perfect Forecast
RI	Run Immediately
RTP	Real-time Pricing
ST	Schedule for a Specific Starting Time
TCA	Thermostatically-controlled Appliance
TOU	Time-of-use

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Chapter 2

Literature Review

2.1 Balancing Electricity Supply and Demand

With modern life so dependent on electricity, entities such as Independent System Operators or regulated utilities exist to ensure that the balance of electricity supply and demand is always maintained. These entities use both supply-focused and demand-focused strategies in order to meet this balancing objective, as noted in Table 2.1.

Supply-focused strategies, like building new power plants, are well studied in the literature and are more commonly employed for balancing electricity on the electric grid than demand-focused strategies. However, some demand-focused strategies have received much attention in scientific literature. In particular, demand-focused strategies for peak management, such as demand response programs for commercial and industrial customers and direct load control programs of residential appliances (typically hot water heaters and air conditioners), have even segued from literary discussion to implementation [Neufeld, 1987, Taylor and Schwarz, 1990, Cappers et al., 2010, Rahimi and Ipakchi, 2010, Le et al., 1983, Lee and Wilkins, 1983, Lee and Breipohl, 1984, Rautenbach and Lane, 1996, Wei and Chen, 1995]. Using interruptible demand to help ensure the grid's frequency remains at 60 Hz in the United States (50 Hz in Europe) is also well studied in the literature, ranging from Frequency Adaptive Power Energy Reschedulers (FAPERs) to Grid Friendly[1] Appliances^{TM} [Schweppe et al., 1980, Black and Ilic, 2002, Hammerstrom et al., 2007b, Brokish, 2009].

Table 2.1: Representative Strategies for Balancing Electricity Supply and Demand

	Peak Management	Days, Hours and Minutes	Seconds
Demand- focused strategies	• Direct load control • Energy efficiency programs • Demand Response	• **Time-varying demand-sensitive pricing**	• FAPERs • Grid Friendly Appliances^{TM}
Supply- focused strategies	• Build new power plants	• Schedule power plant operations	• Automatic generation control (AGC)

The focus of this dissertation, as highlighted in bold in Table 2.1, is on the demand-focused strategy of time-varying, demand-sensitive pricing that new digital 'smart' electric meters enable. Demand-sensitive pricing, also called yield management or revenue management, is common in many service industries where the objective is to use the existing infrastructure as efficiently as possible. Airlines were among the first entities to implement demand-sensitive pricing in the 1980s. As many travelers are aware, the price of a flight differs by day and by the time of day. Oftentimes Monday morning and Friday evening flights are more expensive than a Wednesday afternoon flight because of the higher demand from business travelers at the beginning and end of each week. The price difference encourages those travelers with flexibility to shift their travel plans to times of low demand and away from times of high demand, enabling the airlines to use existing infrastructure more efficiently, avoid the cost of building new infrastructure, and as a result, maximize profits. This same concept is applied in many other service industries, including movie theaters (prices for matinee movies are often lower), rental cars, hotels, sporting events and restaurants [Kimes, 1989, Weatherford and Bodily, 1992, McGill and Van Ryzin, 1999, Desiraju and Shugan, 1999, Talluri and Van Ryzin, 2005]. Interest in applying demand-sensitive pricing to electricity became a leading topic of discussion in the 1970s

[1] Grid Friendly Appliance^{TM} is a trademark of Pacific Northwest National Laboratory and Battelle: see http://www.pnl.gov/news/release.aspx?id=856 and http://availabletechnologies.pnnl.gov/technology.asp?id=61 for more details.

and 1980s and will be discussed further in the next section [Vickrey, 1971, Schweppe et al., 1980].

2.2 History of Methods to Induce Responsive Electricity Demand

The discussion of how to price electricity has a long history, dating back at least to the 1890s as presented by Neufeld [1987]. One of the early debates that continues today is how to balance the costs imposed by electricity demand for both electric energy (measured in kilowatt-hours (kWh)) and electric power (measured in kilowatts (kW)). Even then, concerns over peak management arose amongst key stakeholders in the electricity industry, with the discussion continuing throughout the 1900s [Houthakker, 1951, Steiner, 1957]. Neufeld [1987] and Crew et al. [1995] provide a survey of this history for those interested in the historical details.

However, the functionality of the original electromechanical meters limited the options available to electricity service providers in regards to pricing electricity. The constraint was the cost and time of using a meter reader to walk up to each individual meter, write down and report back the amount of electric energy (kWh) consumed. Given labor costs and the amount of time required for the meter reader to complete this process, it was cost-prohibitive to take these measurements more frequently than once a month. The electricity service providers were thus limited to charging a monthly rate for electric energy, even though the cost of supplying electric energy did, and still does, vary by the hour of the day and day of the month.

In addition to the monthly rate for electric energy (kWh), a concept commonly referred to as a demand charge was added by many electricity service providers to charge end users for the maximum amount of electric power (kW) that they consumed over a month. Taylor and Schwarz [1990] expand on the distinction between the two: "Traditional residential rate structures price electricity by units of energy consumption in cents per kilowatt-hour (kWh). A demand charge places a price on the maximum level of power consumed in the billing period. Power, measured in kilowatts (kW), is the rate of energy consumption at a given point in time and is the quantity that determines generating capacity requirements. The rationale for including a demand charge is to price capacity and energy separately and thereby encourage efficient use of power so that construction of excess capacity may be avoided" [Taylor and Schwarz, 1990]. Though originally included to ensure utilities received fair compensation for their capital investments, the demand charge essentially encouraged end users to minimize their peak electricity demand. Minimizing costs in response to this demand charge via automated technology that coordinates appliances within a home was the motivation for one of the initial business products of the company Sequentric. Sequentric recently received a patent for their system implementation [Flohr, 2010].

Perhaps the most extreme implementation of a 'demand charge' is commonly referred to as a 'power limit'. The electricity distribution system designed by some utilities trips a circuit breaker and causes a house to be blacked out if power consumption exceeds some threshold for too long. According to Morganti et al. [2009a], in Italy this power limit is 3 kW. Morganti goes on to discuss a few algorithms that will coordinate electricity demand at the residence in order to ensure this threshold is not breached for too long, thus preventing the undesirable local blackouts [Morganti et al., 2009a,b].

When electricity tariffs include demand charges, power limits and other strategies for inducing responsive demand while circumventing the electromechnical meter's limitations, coordination **within** a home has been shown to be beneficial [Flohr, 2010, Morganti et al., 2009a,b]. However, as metering and computing technology have improved in the last 30 years, the limitations of the electromechanical meter have begun to dissipate. With this change, it is possible that time-varying, demand-sensitive pricing[2] of electric energy, defined to be prices of electric energy ($/kWh) that change every five minutes or an

[2]Spot pricing and real-time pricing are often used interchangeably with demand-sensitive pricing in the electricity context.

hour, will replace the current flat price of electric energy. Demand-sensitive pricing of electric energy may in turn render demand charges, power limits, and other strategies circumventing the electromechanical meter's limitations obsolete. According to Peddie [1992], with smart meters in place, "true spot pricing can be introduced; this would flatten the load curve and reduce both thermal cycling of system components and the expensive startup and shutdown of generating equipment." If, or when, demand charges, power limits and other strategies are phased out, will coordination **within** a home remain beneficial under spot pricing of electricity? The answer to that question is the focus of the rest of this dissertation.

As mentioned previously, spot pricing of electricity has been a leading topic of discussion since the 1970s and 1980s [Vickrey, 1971, Schweppe et al., 1980] and was the focus of the seminal book *Spot Pricing* by Schweppe in 1988 [Schweppe, 1988]. In order to implement spot pricing for electricity consumption, markets that could communicate the 5-minute or hourly price of supplying electricity had to be developed. The original process for this was known as 'restructuring' (also called 'deregulation' [Bohn, 1982] or sometimes 'reregulation' [Borenstein and Bushnell, 2000]) and focused on wholesale electricity markets as opposed to the retail electricity markets. Much of the relevant literature available for those interested in the details of 'restructuring' can be found in Joskow [1997], Borenstein and Bushnell [2000] and Huneault et al. [1999] and their references.

Glossing over many details, the main purpose of 'restructuring' was to implement wholesale electricity markets with time-varying prices of electricity. Generally speaking, only industrial and large commercial customers participated in the wholesale markets. This was because installing smart meters was cost-effective given the amount of electric power and energy consumed by these large customers. Various other methods have also been pursued to integrate large sources of electricity demand (typically industrial and large commercial customers) into wholesale markets, sometimes via demand response programs or bilateral agreements [Philpott and Pettersen, 2006]. Demand response, as shown in Table 2.1, is typically used for peak management [Cappers et al., 2010, Rahimi and Ipakchi, 2010]. A bilateral agreement, on the other hand, is a contract between one or more power plants and large consumers of electricity to coordinate a portion of the supply and demand of electricity independent of the wholesale market [Carrión et al., 2007]. Essentially, the large consumer tells the power plant(s) when they will need electricity, and the power plant(s) will schedule their generation to coincide with that specific demand. In general, coordinating electricity consumption of large commercial and industrial customers provides the biggest "bang for the buck", hence these customers are often the focus of responsive demand programs like time-varying pricing.

On the other hand, retail electricity rates for residents and small commercial customers often remained regulated during 'restructuring' and were kept at a flat, monthly rate because the expected benefits of time-varying pricing for these smaller customers did not surpass the cost of replacing the old electromechanical meters with smart meters. However, the utilities providing electricity service to these retail customers had to pay the time-varying wholesale market rates. The regulated, flat price of electricity on the retail market meant that the retail customers had no incentive to reduce consumption when prices in the wholesale market were high, leaving the utilities with little choice but to buy electricity at high wholesale market prices and to sell at the much lower retail price. This mismatch where electricity service providers buy electricity at the time-varying wholesale market rate and then sell that electricity to the retail customers at a flat rate helped lead to the California electricity market failure and rolling brownouts in the summers of 2000 and 2001, which in turn effectively stopped restructuring in its tracks across the United States [Joskow and Kahn, 2002, Borenstein, 2005, Borenstein et al., 2002, Hirst, 2001, Hirst and Kirby, 2001, Caves et al., 2000, Wilson, 2002, Spees and Lave, 2007, Chao et al., 2006].

As the cost of digital smart meters continues to decrease, smaller customers in the retail electricity market may soon face time-varying pricing of electricity as smart meters become cost-effective for these smaller customers as well. This would help eliminate the mismatch of the wholesale and retail markets that created the problems in California and other places during the initial attempts at 'restructuring'. How these smaller customers might respond to time-varying pricing in the retail markets is a key focus of this dissertation.

Section 2.3 provides an overview of some of the time-varying retail electricity tariffs in existence and under consideration today.

2.3 Time-varying Retail Electricity Tariffs and 'Enabling Technology'

The most basic time-varying pricing of electricity is the *time-of-use* (TOU) tariff. The TOU tariff charges different prices for peak and off-peak electricity consumption, similar to how mobile phone plans have peak and off-peak minutes. The ratio between the peak and off-peak price varies, and the hours defined as 'peak' hours also vary by each electricity service provider, depending on the demand pattern in that region.

A variation of the time-of-use tariff is the *critical-peak pricing* (CPP) tariff. In the CPP tariff, peak and off-peak prices are set as described for the TOU tariff. However, whenever the electricity service provider believes that the next day's electricity demand will cross a critical threshold, an announcement is made by the electricity service provider that the next day's peak price will be an extremely high 'critical peak' price. As with TOU tariffs, the ratio from critical peak to peak to off-peak prices varies by region. In addition, oftentimes there is a limit on the number of times in a season that a 'critical peak' day can be called.

Many other tariff structures, including peak-time rebates and inclining block rates, could be implemented as well. For a broader overview of the range of possibilities, the interested reader is directed to Mohsenian-Rad and Leon-Garcia [2010] and Faruqui and Sergici [2008].

Last but not least for the discussion here, real-time pricing (RTP) of electricity (also called spot pricing or demand-sensitive pricing) is an electricity tariff where the price of electricity changes at a regular interval throughout the day (e.g. every five minutes or one hour). Economic theory suggests that real-time pricing will let the electricity market operate most efficiently: “Retail real-time pricing (RTP) of electricity – retail pricing that changes hourly to reflect the changing supply/demand balance – is very appealing to economists because it ‘sends the right price signals’ ” [Borenstein, 2005, Borenstein et al., 2002]. Integrating responsive demand via real-time pricing was recommended decades ago by numerous researchers, from a 1971 RAND study [Vickrey, 1971] and the Homeostatic Utility Control team [Schweppe et al., 1980] to the CALMU [Rosenfeld et al., 1986] and early work from Chao [Chao et al., 1986, Chao and Wilson, 1987]. The common element was to implement time-varying, demand-sensitive pricing so that ‘demand follows supply’, allowing the electric grid to reach a state of homeostasis [Schweppe et al., 1980, Chao et al., 1986, Chao and Wilson, 1987]. Though the electromechanical meters were unable to support the real-time pricing electricity tariff at that time, the decreasing cost of digital smart meters means that such a pricing tariff could potentially be introduced into retail markets today.

With this push towards implementing time-varying pricing into retail electricity tariffs, many pilot programs over the last few decades were developed to explore their opportunities and challenges. One of the earliest pilot programs presented in the literature is Aigner [1985], which also discusses an early estimate of electricity demand elasticity. Other electricity demand elasticity measurements are studied in Lijesen [2007], Kirschen et al. [2000], Kirschen [2003] and Taylor et al. [2005]. A summary of many recent pilots presented in Faruqui et al. [2007] and Faruqui and Sergici [2008] focused on the effectiveness of time-varying pricing to induce load shifting and/or load shedding for peak management purposes. Most studies assume residents will be price takers, though the study by Hammerstrom et al. [2007a] implemented a bidding system, which is another alternative that has been proposed by some researchers [Williams and Schweppe, 1986, Hammerstrom et al., 2007a]. The main assumption surrounding time-varying pricing in particular is that retail customers will curtail some of their electricity demand when prices go up and increase their electricity demand when prices go down, thus flattening the aggregate electricity demand curve [Braithwait, 2005, Martinez and Russell, 2004, Holland and Mansur, 2006, Faruqui and George, 2005, Spees and Lave, 2007]. Evidence from the pilot programs presented in Faruqui et al. [2007] and Faruqui and Sergici [2008] suggests initially that this will indeed occur. An extension to this result in Faruqui and George [2005] and [Chassin, 2010] is that responses from retail customers to time-varying pricing clearly improved when 'enabling technology' is included at homes.

The 'enabling technology' used by different pricing pilot programs unsurprisingly varies, though the core 'enabling technology' is any device that automates a program participants' response to whatever time-varying pricing tariff (s)he faces in the pilot program. For the California Statewide Pricing Pilot, Faruqui et al. [2007] and Martinez and Russell [2004] discuss that one part of the 'enabling technology' was smart thermostats that would "automatically raise the temperature setting on the thermostat by two or four degrees when the price becomes critical." In the Pacific Northwest National Laboratory's (PNNL) Olympic Peninsula project, Hammerstrom et al. [2007a] and Chassin [2010] present their inclusion of a smart thermostat that effectively used an automated bidding process to determine the thermostat's temperature setting.

The key element in both of these examples of 'enabling technology' is the word 'automated'. The desire expressed by residential customers in PNNL's Olympic Peninsula pilot was to have the ability to set up the home's energy management system and forget it, or to "fire and forget" as stated by Chassin [2010]. The "forget" part of this statement was perhaps most surprising from PNNL's Olympic Peninsula project: 55% of the consumers at the exit survey did not remember which pricing tariff they were on [Chassin, 2010]. This suggests that residents and small business owners feel that they have "better things to do" than manually manage their electricity consumption. In other words, the savings available are not large enough for people to take the time to actively manage their electricity consumption. However, using 'enabling technology' to automatically respond and react to real-time information in ways the consumer may never realize or notice was acceptable as long as the consumer's comfort and lifestyle were not adversely affected. A key desire from these same consumers was to be able to maintain control of the home's energy management system via an intuitive process for modifying and changing their preference settings whenever they wish [Mert et al., 2008]. The concept of using 'enabling technology' for home energy management is certainly not new. Some early ideas of home energy management systems were proposed decades ago [Schweppe et al., 1989], with recent ideas involving the management of additional competing objectives like minimizing emissions while also balancing the traditional objectives of minimizing cost and maximizing comfort [Ramchurn et al., 2011b].

This dissertation builds in particular upon work begun over two decades ago by Panos Constantopoulos, Richard Larson and the late Fred Schweppe in Constantopoulos et al. [1991], in which they identified a range of automated decision methods for controlling electricity consumption in response to hourly time-varying pricing and uncertain weather conditions. One of the best methods identified for making sequential decision making under uncertainty was stochastic dynamic programming. The inventor of dynamic programming was Dr. Richard Bellman, who brought it to reality in the 1950s [Bellman, 1957, Bellman and Dreyfus, 1962]. As an honor to its inventor, the recursive equations used in the dynamic programming approach are often called the 'Bellman Equations'. Though Constantopoulos et. al. identified dynamic programming as the preferred automated decision making method, implementing it on the computers of the time was too computationally expensive for any detailed testing. Because of this, Constantopoulos et. al. were forced to use a 'certainty equivalent controller' that used the expected value of the uncertainty distribution for the weather variables to approximate the uncertain future conditions. Modern computers can now efficiently process a stochastic dynamic programming model for a problem of this scale, so part of this dissertation will look at how the performance of the 'certainty equivalent controller' and the stochastic dynamic programming process using the full uncertainty distribution compare with one another. In addition, Constantopoulos et. al. decomposed the automated decision making into independent decision processes, focusing in particular on space conditioning (e.g. air conditioning and heating). A leading reason for this decision was likely again caused by the computational limitations at the time. With that constraint lifted, this dissertation expands upon these independent decision methods to explore when coordinated decision making for more than one appliance (e.g. an air conditioner and a dishwasher) provides additional benefits over the decomposed, independent decision making methods presented in Constantopoulos et al. [1991].

2.4 Smart Grid Structure and Simulation

Interest in developing a so-called smart grid has risen dramatically in recent years, as evidenced at least partially by the large investments provided via the American Recovery and Reinvestment Act (ARRA) of 2009. The Smart Grid Information Clearinghouse website[3] provides an overview of the smart-grid related projects in existence around the U.S., which includes the projects funded by ARRA and projects funded by other sources. The scale and scope of each smart grid project varies with each project testing different ideas of how the smart grid could be structured. The component of these smart grid projects that is most related to the research from this dissertation is how to coordinate electricity consumption **across** residential, commercial and industrial customers.

As discussed throughout this chapter, charging time-varying, demand-sensitive pricing to retail electricity customers is certainly one structure being studied in some of the smart grid projects. Depending on the project, the ‘enabling technology’ presented in section 2.3 could be controlled locally by the customer with no external coordination other than through the influence of the time-varying electricity tariffs. The same ‘enabling technology’ could also be coordinated via a subscription or contract with an aggregator that plays an intermediary role to ensure electricity supply and demand remain balanced at all times [Medina et al., 2010, Brooks et al., 2010, Chao, 2010]. These aggregators could provide a range of services to the grid from peak management to frequency regulation. Many proposals for the aggregator’s role focus on coordinating the cycles across thermal appliances (e.g. fridges, freezers, air conditioners and hot water heaters) or focus on coordinating the charging of plug-in electric vehicles [Koch et al., 2009b,a, Alves et al., 2008, Gomes et al., 2007, 2008, 2004, Jorge et al., 2000, Brooks et al., 2010]. Essentially,

[3] http://www.sgiclearinghouse.org/

the aggregators could help manage a large number of clients to ensure that the aggregate demand curve is desirable for the grid operators.

Microgrids that can automatically island themselves from the larger grid have also received considerable attention in both the U.S. and Europe as another potential smart grid structural element. Hierarchical control structures are often proposed as the preferred method for sending appropriate coordination signals to the retail customers' 'enabling technology' [Peças Lopes et al., 2006, Lasseter et al., 2002, Marnay and Venkataramanan, 2006, Jiayi et al., 2008, Hatziargyriou et al., 2002, Vandoorn et al., 2011]. Another option proposed for coordinating distributed energy resources (DER) in a microgrid is to use decentralized or distributed bidding in a microgrid market [Costa and Kariniotakis, 2007].

A decentralized control structure that has been proposed and researched for many years uses appliances that automatically sense and react to frequency fluctuations on the grid. Since the frequency on the grid must be maintained within tight technical bounds at all times, the appliances' reaction could be used to provide important second-by-second balancing services to the electric grid. Similar ideas under different names such as the Frequency Adaptive Power Energy Rescheduler (FAPER) and Grid Friendly Appliances^{TM} abound, all providing some variant of an automated response from appliances to provide this frequency regulation service to the grid [Schweppe et al., 1980, Hammerstrom et al., 2007b, Kirby, 2003, 2007, Ilic et al., 2002, Black and Ilic, 2002, Brokish, 2009].

All of the aforementioned smart grid structures are not necessarily mutually exclusive, and in some instances using a combination of two or more will be desirable. These and other new structural ideas for the smart grid led researchers to call for the need to develop large-scale smart grid simulators that test these options at scale before implementing the proposed ideas in the physical system [Podmore and Robinson, 2010, Kok et al., 2008, 2005, Chassin et al., 2008, Burke and Auslander, 2008]. Agent-based simulations are currently a leading choice for smart grid simulation environments being developed at this time, though other smart grid simulation structures will undoubtedly develop over time [Lamparter et al., 2010, Spees and Lave, 2007, Kok et al., 2005, Karnouskos and de Holanda, 2009, Ramchurn et al., 2011b,a, Vytelingum et al., 2010].

Whatever structure and accompanying ‘enabling technology’ is included in the smart grid, scaling up the automated responses of the ‘enabling technology’ is critical for understanding what will happen at scale for the smart grid. For instance, Faruqui et al. [2007] and Faruqui and Sergici [2008] suggest that retail time-varying pricing will lead to significant peak load reductions, and many of the pilot programs cited support this claim. However, as briefly mentioned earlier, the details of how a retail time-varying pricing tariff is implemented play a key role in assessing the conclusion that retail electricity load will be smoothed out by the real-time pricing tariff. For hourly real-time pricing of electricity in particular, a leading factor is whether the hourly prices of electricity are set the day ahead or only an hour or two in advance [Hirst and Kirby, 2001]. Schweppe et al. [1980] calls for hourly prices to be set less than an hour in advance. However, consumer preferences for having certainty in the hourly prices have influenced some programs to use day-ahead hourly prices based on the expected costs of electricity [Spees and Lave, 2007, Energy, 2011]. The details in how real-time pricing is implemented may, though may not, cause undesirable outcomes as more retail customers participate in real-time pricing programs with automated ‘enabling technology’. In particular, chapter 4 from this dissertation along with recently published work from an independently developed model by Ramchurn et al. [2011a] show that the choice of ‘enabling technology’ along with the implementation of a retail time-varying pricing tariff plays a significant role in whether or not retail customers’ ‘enabling technology’ will actually reduce peak electricity demand and flatten the aggregate electricity demand profile. The seemingly contradictory results are likely explained by the ’enabling technology’ used by most of the pilot programs cited by Faruqui et al. [2007] and Faruqui and Sergici [2008]. From what has been published, the ‘enabling technology’ in those pilot programs used a threshold control strategy that reduced electricity consumption whenever the price of electricity exceeded some threshold. Thus, the conclusion that peak electricity consumption would decrease was tautologically guaranteed given the specific ‘enabling technology’ used. The control methods of the energy management system from this dissertation and Ramchurn et al.

[2011a] don't use threshold control, hence the outcome of a pilot program with a variation in the 'enabling technology' may or may not find the same conclusion that peak electricity load is reduced.

Mohsenian-Rad et al. [2010] states that a retail real-time pricing tariff implemented at individual homes may not satisfy the global objective of smoothing out the aggregate electricity demand curve. Ramchurn et al. [2011a] goes further and states that "... [electricity] demand *cannot be flattened* by applying *only* a real-time pricing mechanism, while completely ignoring the behaviour of the agents. This is because if the agents are signalled a low price for the next 30-minute period, they will all switch on their devices, which then results in a peak in demand at the next time period. When such a mechanism is rolled out on a large scale, such reactive behaviours can cause significant peaks." A key figure in Ramchurn et al. [2011a] shows the results of this behavior for a simulation of "500 smart homes". This figure illustrates that the demand curve resulting from responses to the real-time pricing tariff is less smooth than it was under a flat electricity tariff. In addition, the model by Ramchurn et al. [2011a] shows another behavior induced by hourly real-time prices when the prices are set a day in advance: all automated, single-event appliances with sufficient flexibility in their starting time congregated at the lowest priced hour, creating the largest peak of all from these 500 customers at a traditionally off-peak hour. Both of these are examples of problems that could emerge if automated home energy management systems make consumption decisions based on real-time pricing tariffs and appropriate feedback or learning mechanisms are not included in the tariff and system design. Ramchurn et al. [2011a] continue on to present a Widrow-Huff learning mechanism that smooths out the aggregate electricity demand under real-time pricing rates. Measuring and incorporating the price elasticity of electricity demand into the process that establishes real-time electricity prices could also provide a feedback mechanism that would mitigate these issues. A bidding process such as the one proposed by Wang et al. [2010] would explicitly include price elasticity of demand into electricity markets via a Price Elasticity Matrix [Wang, 2009, Wang et al., 2010]. Other strategies to mitigate these emergent issues certainly exist, adding further incentive to develop large-scale smart grid simulators to experiment with proposed electricity management programs and retail electricity tariffs to truly see what consequences result as more demand-side resources are integrated into the smart grid.

Whatever underlying structure ultimately is chosen for the smart grid, one of the leading motivators of developing the smart grid and demand-sensitive pricing in particular is to decrease the volatility of the cost of supplying electricity throughout the day. Charging wholesale and retail prices of electricity that more closely resemble the actual time-varying cost of supplying electricity should improve the utilization of the electricity infrastructure [Vickrey, 1971, Schweppe et al., 1980, Peddie, 1992, Borenstein, 2005, Borenstein et al., 2002]. Looking ahead, the smart grid and time-varying pricing likely will also prove beneficial for integrating weather-dependent sources of electricity generation (like wind and solar) onto the grid. Many states and countries have encouraged the use of these sources of electricity generation via feed-in tariffs, bringing with them some operational challenges as the supply from these sources is uncontrollable [Cory et al., 2009, Klein et al., 2007]. The smart grid simulators could test methods of integrating these distributed energy resources (DER), ranging from distributed generation (DG) (e.g. rooftop wind turbines, rooftop solar panels, micro-combined heat and power (μCHP)) to controllable demand via 'enabling technology' to energy storage devices [Kok et al., 2008, Klein et al., 2007, Pillai and Heussen, 2009, Ramchurn et al., 2011b]. Kok et al. [2005] in particular calls for developing methods of distributed coordination over central coordination, particularly as distributed generation becomes more prevalent, which again could be simulated and tested via these large-scale smart grid simulators.

Ultimately, regional details likely will influence what system design is best for each geographic area [Chao et al., 2006]. These system designs should be simulated and tested at large scale to better understand the dynamics that emerge on the smart grid under each system design [Podmore and Robinson, 2010]. As part of the development of these large smart grid simulators, knowledge of how electricity consumption from retail electricity consumers might change in response to time-varying pricing and other real-time information (such as weather forecasts) is important if the results from these smart grid simulators are to be realistic and useful. Hence, the focus of this dissertation is to obtain a better understanding of how individual consumers with ‘enabling technology’ might respond to time-varying pricing.

Chapter 3

The Energy Box Model

As discussed in section 2.4, many models are under development to better understand the dynamics of the evolving smart grid for electricity. These models must simulate the grid at varying scales of time and space. Building a model that could capture the dynamics at all time steps and scales would be the ideal goal for a smart grid model, however the magnitude of the computations often prevent such models from being practical. For now, tradeoffs between computational complexity and the scope of the smart grid models are simply inevitable. Nonetheless, understanding details of the smart grid's dynamics in a reduced set of the time and space dimensions is a necessary first step, and integrating these smaller models with other models is critically important as modern life moves forward into the era of smart grids.

The focus of this dissertation is on how a single residence's hourly power profile might change via enabling technology's automated response to different pricing systems and local weather-dependent sources of electricity, such as rooftop wind turbines and/or solar panels. To test different concepts of 'enabling technology', the Energy Box simulation process as illustrated in figure 3-1 was developed. The full details of what each piece of the image represents will be presented throughout this chapter.

In figure 3-1, the cycle at the center of the image is the main driver of the Energy Box simulation process, with the top box entitled 'Energy Box Decision' representing the heart of the model - the decision-making process. Given the inherent uncertainty of the external influences (with weather in particular being extremely uncertain), dynamic programming (DP) is implemented in the Energy Box simulation process as the main method for making sequential decisions under uncertainty. Numerous other algorithms could also be used, and one of the Energy Box research goals is to develop a platform that can test any algorithm via this simulation process.

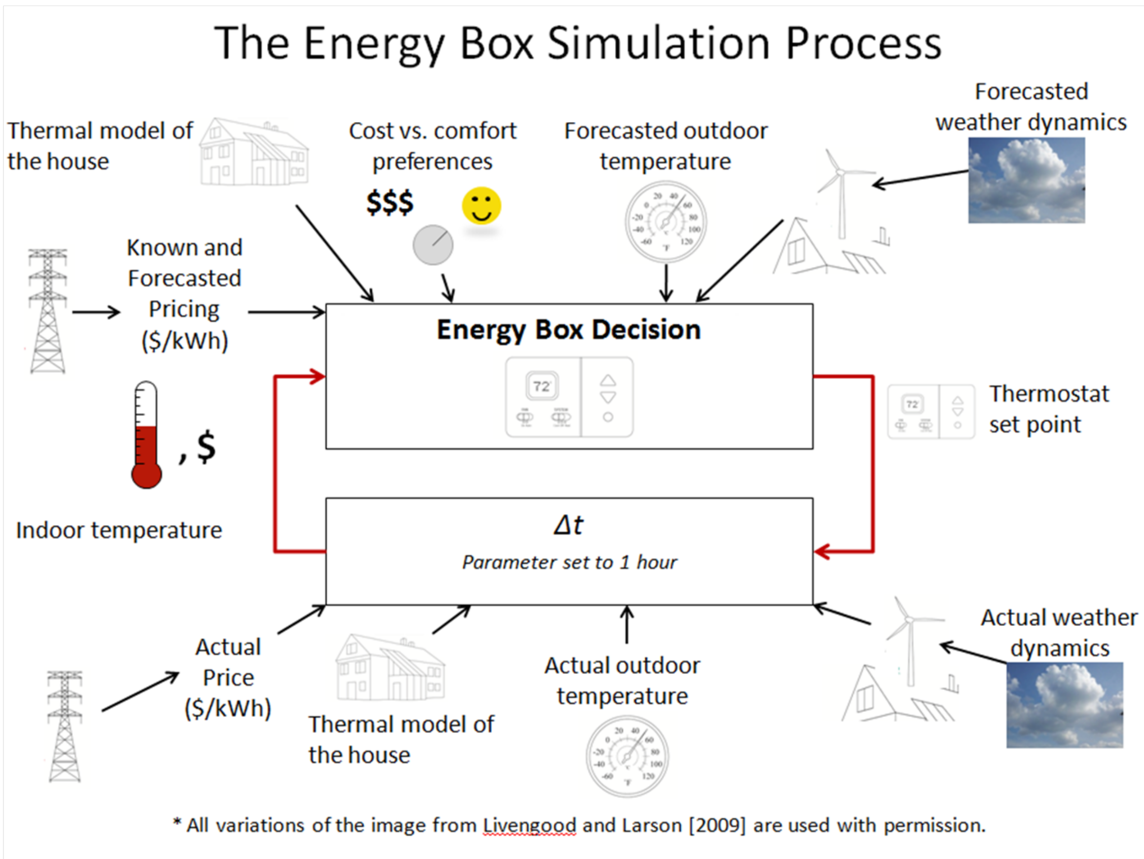

Figure 3-1: Generic view of the Energy Box Simulation Process

Dynamic programming is also chosen as the primary decision method used in this dissertation to address the research question of determining when **coordinated** decision making provides additional benefit over independent decision making. Two other decision methods are included to better illustrate the results of coordinated versus independent decision making. These methods are the 'Run Immediately' and 'Schedule for a Specific Starting

Time' decision methods. All three of these decision methods will be explained further in sections 3.3 and 3.4.

The Energy Box simulation process is a simple representation of a complex process. Although the Energy Box model is designed to look at a single electricity consumer, the model's structure supports simulating many variations of that particular consumer under the same external conditions (i.e. weather and electricity prices). The Energy Box simulation process iterates as many times as is necessary to collect the sequence of decisions the Energy Box decision methods make under each consumer variant. The key elements of each simulated consumer are

- which appliances does the consumer have,
- what flexibility does the consumer allow for each appliance,
- what is the consumer's typical occupancy pattern, and
- what decision method will be used by each appliance.

Once the Energy Box decisions have been made, those decisions are implemented in the simulation and the simulation then steps forward one time step, Δt. The time step Δt in the lower box of figure 3-1 is a parameter in the simulation that can technically take on any integer multiple of minutes. For simplicity, Δt was set to be one hour for the Energy Box implementation discussed throughout this dissertation. Once the Energy Box simulation process has updated all necessary values to simulate the passing of Δt minutes, the Energy Box Decision process uses these updated values to begin the cycle all over again. How often this cycle is repeated depends on a parameter establishing the total length of the simulation. For the rest of the discussion in this dissertation, this total length parameter was set to 50 simulated days.

The Energy Box simulation process is implemented in both Excel and Matlab, with Excel providing an interface for managing a wide range of parameters that Matlab ultimately reads for use in the simulation. The main elements of the Energy Box simulation process will be discussed in this chapter. Chapter 4 will present and discuss results pertaining to consumption-only consumers. Chapter 5 expands the Energy Box results to consumers that are called prosumers, i.e. consumers that also produce electricity, followed by some concluding remarks in Chapter 6.

3.1 Dynamic Programming Overview

Deciding when to use and store electricity requires a sequential decision-making process that balances the end-user's comfort, cost and lifestyle preferences in the face of uncertain conditions, such as the price of electricity, weather conditions, and electricity available from weather-dependent generation sources. As mentioned, the approach of choice for this dissertation for sequential decision-making under uncertainty is stochastic dynamic programming. With this decision-integrating algorithmic approach, the Energy Box uses the forecasted information of weather, price, and occupancy patterns to determine the best control signals given the available information at that time. The frequency with which these algorithms run and send new control signals depends 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. [1991] and Black [2005]. Similarly, Black and Larson have discussed some of the very general concepts described here in previous work as well [Black and Larson, 2007, Larson, 2008a,b].

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, 1957, Bellman and Dreyfus, 1962]. In the Energy Box context, **decisions** are the control options available to a resident. These decisions determine how much electricity will be used, how much will be stored in local storage devices, and how much will be sold back to the grid, when applicable. **States** refer to the current conditions at the home and on the grid – including the 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 that evolve over time. The weather and grid-level demand random variables use Markov chains for obtaining these stage-to-stage state transitions and will be discussed more in section 3.3.3. 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 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 decision rules for each preceding stage, culminating with the best decision given the available information at 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 the homeowner had the time and 'lifestyle bandwidth' to consider all of the use, store and sell options when presented with the same information.

This dynamic programming framework is implemented for event-based appliances (EBA) and thermostatically-controlled appliances (TCA) for this version of the Energy Box (appliance categories are explained further in section 3.3). Though storage devices are not included in this version of the Energy Box, modeling storage decisions could be structured in the same way as thermostatically-controlled appliances with a few adjustments. The variable names for the decision methods follow the structure used by Powell in his book *Approximate Dynamic Programming: Solving the curses of dimensionality* [Powell, 2007].

3.2 Categorizing Appliances and Devices

For reasons discussed in section 3.3.3, the time between stages (Δt) for this Energy Box model is one hour, hence the categorization of appliances is framed by the hourly dynamics of electricity-consuming appliances and devices. Other time dynamics, such as interrupting appliances for a few seconds or minutes at a time (like Grid Friendly Appliances^{TM} [Hammerstrom et al., 2007b]) are not in the scope of this model, though clearly they are also of interest. Ultimately, a commercial Energy Box might make decisions across at least these three times steps - seconds, minutes, and hours - with different goals to achieve at each time step. For the hourly time step dynamics, the home's appliances and devices are divided into 5 categories:

- Event-based appliances,
- Thermostatically-controlled appliances,
- Storage devices,
- Discretionary uses of electricity, and
- Distributed generation sources.

3.2.1 Event-based Appliances (EBAs)

The definition of an *event-based appliance (EBA)* for the Energy Box model is an appliance or electricity-consuming device that typically operates on the order of once or twice a day (if at all) with a cycle time of many minutes to many hours. The main control option for the Energy Box to control an event-based appliance is deciding when to begin the appliance's cycle, assuming that the appliance is ready to run its cycle. For this version of the Energy Box, the assumption is made that once a cycle is begun, it will continue running until the full cycle is completed. Though interruptions on the order of seconds or a few minutes may be technically feasible and may be of interest to the grid [Hammerstrom et al., 2007b], that option is not modeled in this version of the Energy Box, though such an option could be included in future versions.

Given this definition, the following appliances and electricity-consuming devices are placed in the event-based appliance category:

Event-based Appliances

- Dishwasher
- Clothes washing machine
- Clothes dryer
- A freezer's defrost cycle
- A programmable thermal carafe coffee maker
- Pool pumps

From this list, only the dishwasher (DW) and clothes washing machine (CWM) are modeled in full detail in this version of the Energy Box, though any of the event-based appliances could easily be modeled and included in the Energy Box. The reason for the decision to limit the model to only include the dishwasher and clothes washing machine is that two event-based appliances provide sufficient variety to study the research questions of interest for this dissertation.

3.2.2 Thermostatically-controlled Appliances

As its name suggests, a *thermostatically-controlled appliance* is any appliance that has a thermostat. Though the thermostat does not directly control the appliance, the thermostat's set point indirectly controls how often the appliance cycles on and off.

Appliances falling into this category are

Thermostatically-controlled appliances

- Air conditioner
- Electric space heater
- Electric hot water heater
- Refrigerator
- Freezer

From this list, only the air conditioner (AC) is modeled for this version of the Energy Box, although the structure used could easily be extended to all of the other appliances in this category. Among other reasons, one purpose of modeling air conditioning is that there is a tradeoff between the comfort that the air conditioner provides to the residents and the cost used to obtain that comfort. Ideally, a home would always be comfortable for no cost, though only a few locations around the world fall into this category. For the majority of the world, the outdoor temperature will either be too cold or too warm for a significant portion of the year, thus requiring heating and/or air conditioning to maintain desired levels of comfort. Managing the humidity level in the home is also a key factor affecting thermal comfort. Though only temperature is modeled and controlled in this version of the Energy Box, a commercial Energy Box would need to measure and control the humidity along with the temperature when managing the thermal comfort of the home's occupants.

For this version of the Energy Box, the thermal comfort preferences of the home's occupants are kept constant throughout the day, though the Energy Box model is designed to allow the thermal comfort preferences to vary across the four typical states of the home: (1) at home and awake, (2) at home and asleep, (3) away from home, and (4) away on vacation. Keeping the thermal preferences constant throughout the entire simulated day does not qualitatively affect the key results of interest for this dissertation.

The home's thermal characteristics are modeled via a simple first-order exponential model, as was used by Constantopoulos et al. [1991]. This model is introduced in detail in section 3.4.

3.2.3 Energy storage devices

A wide range of energy storage devices exist that could ultimately be included in the Energy Box model. The curious reader is referred to Dell and Rand [2001], Ibrahim et al. [2008], Hasnain [1998a] and Hasnain [1998b] for an overview of the possibilities of converting electricity into another form of energy via various storage systems. Ibrahim et al. [2008] in particular discusses many of the tradeoffs inherent in energy storage systems. As Brooks et al. [2010], Graves et al. [1999], McDowall [2001] and many others demonstrate, there are clearly benefits to using energy storage systems as part of the electric system. If time-varying pricing is included, clearly the best strategy for independently operating storage systems is to follow the stock market advice of buy low and sell high, that is to buy electricity for storage when the price is low and to sell it back (when possible) when the price is high. Some storage devices, such as laptop or mobile phone batteries, will not be able to sell electricity back to the grid. Nonetheless, these storage devices could adjust their charging pattern in response to time-varying pricing while ensuring that the end-user always has enough power to use the device at all times. The Energy Box could even explicitly schedule when these batteries should recharge, making them similar to event-based appliances in such a situation.

These and other strategies are being developed by researchers and companies for energy storage systems and certainly could be incorporated in future versions of the Energy Box model. However, for the Energy Box implementation in this dissertation, using only event-based appliances and thermostatically-controlled appliances was sufficient for addressing the research questions of interest. One other reason for not including energy storage devices in this version of the Energy Box is that modeling them requires careful consideration of the performance tradeoffs as discussed in Ibrahim et al. [2008]. For plug-in electric vehicles in particular, short-term operational decisions can affect the long-term life expectancy of the vehicle's battery, which is of critical importance to model and control correctly as a resident would want to ensure that her or his vehicle will be able to fulfill its primary purpose of mobility. Nonetheless, future Energy Box models will undoubtedly integrate energy storage decisions into the simulation process, especially as plug-in electric vehicles become more common.

3.2.4 Discretionary uses of electricity

Most any other use of electricity at a residence falls into a category called *discretionary uses of electricity*. Appliances and devices in this category often directly affect residents in ways that require more intelligent automation and feedback mechanisms than what is included in the Energy Box model at this time. Included in this category are

Discretionary uses of electricity

- Lighting
- Entertainment devices (e.g. televisions, sound systems)
- Computers
- Kitchen and cooking appliances

As will be discussed in Chapter 5, under the scenarios when coordinated control provides additional benefits over independent control, knowledge of the timing of these discretionary loads on a given day could prove useful. For this initial Energy Box model, this result will be demonstrated via the dishwasher, clothes washing machine and air conditioner, thus discretionary uses of electricity will not be modeled in this version of the Energy Box model.

3.2.5 Distributed generation

Last but not least are local sources of electricity generation, commonly called distributed generation or DG. A few examples are listed here:

Distributed generation

- Roof-mounted wind turbine
- Roof-mounted solar photovoltaics (PV)
- Solar thermal (particularly for hot water)
- Micro combined heat and power (microCHP or μCHP)

Some of these, namely the wind turbine, solar PV and solar thermal, are weather-dependent and uncontrollable, at least from a grid operations point of view.

Of the possible options in the *distributed generation* category, this dissertation will focus only on the weather-dependent wind turbine, as the uncontrollable and uncertain characteristics of the wind turbine helps provide a context for Chapter 5 to illustrate the scenarios of when coordinated control provides benefits over independent control.

Integrating controllable μCHP is certainly a topic of interest as well, particularly in colder climates. The curious reader is referred to Molderink et al. [2009], Kok et al. [2008], Pillai and Heussen [2009] and Tapia-Ahumada [2011] for related work on this topic.

3.3 Decision Methods for Event-based Appliances (EBA)

Using the categories defined in section 3.2, the decision algorithms used by this initial version of the Energy Box are defined in detail throughout the rest of this chapter.

For all of the decision methods, the mathematical representation of the main dynamic programming concepts will be used for consistency between the methods. Once again, the main dynamic programming concepts are: **decisions**, **states**, **stages**, **stage-to-stage state transition rules** and **rules for following an optimal policy** [Bellman, 1957, Bellman and Dreyfus, 1962].

Starting with *event-based appliances*, four states (S_t^{EBA}) are used by the Energy Box model for this type of appliance:

$$S_t^{EBA} = \begin{cases} \text{Not Ready to Run (NR2R)} \\ \text{Idle and Ready to Run (R2R)} \\ \text{Scheduled to Run} \\ \text{Running} \end{cases}$$

These four states are certainly not an exhaustive listing of the possible states of an event-based appliance (another state would be how much time is remaining on the appliance's cycle), however they will suffice for the purposes of this dissertation.

As modeled in this version, the Energy Box has no decisions to make when S_t^{EBA} = *Not Ready to Run* ($NR2R$), *Scheduled to Run*, or *Running*. When $S_t^{EBA} = NR2R$, it remains in $NR2R$ until the Energy Box simulation triggers the transition from S_t^{EBA} = *Not Ready to Run* ($NR2R$) to S_{t+1}^{EBA} = *Idle and Ready to Run* ($R2R$), simulating the loading of the appliance. If the event-based appliance is scheduled to start its load some time in the future, it will be in the state *Scheduled to Run* and will simply wait until the scheduled starting time arrives. Once S_t^{EBA} reaches the *Running* state, the event-based appliance will remain in that state until its cycle is complete, at which point the event-based appliance's state transitions back to $NR2R$.

Where the Energy Box is called into action is when S_t^{EBA} = *Ready to Run* ($R2R$). When in the $R2R$ state, the Energy Box calls the decision method that the current consumer is using to determine when the event-based appliance should transition into the *Running* state. The decision methods modeled for event-based appliances are:

- Run Immediately (RI),
- Schedule for a Specific Starting Time (ST), and
- Dynamic Programming (DP)

Each of these decision methods could be used by a consumer variant in the 'Energy Box Decision' box in figure 3-2 and will be described in detail in the following sections.

3.3.1 Event-based Appliance: Run Immediately (RI)

As the name suggests, if the event-based appliance's decision method is 'Run Immediately', then as soon as the event-based appliance enters the *R2R* state, it **immediately** transitions to the *Running* state. In other words, there is no decision to be made. The appliance simply starts as soon as it is loaded. This decision method is included for baselining purposes and simulates what the resident would do with no economic incentives nor information for changing the timing of her or his event-based electrical loads.

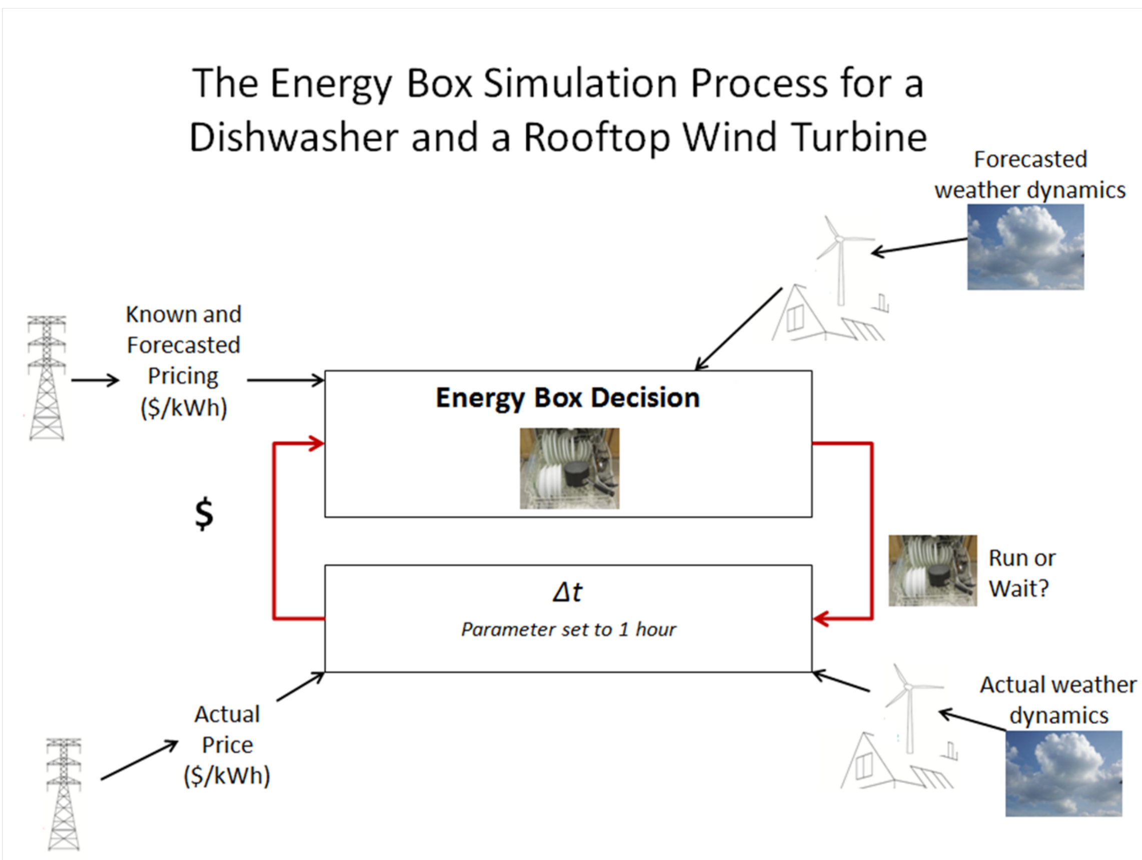

Figure 3-2: Illustration of the Energy Box Simulation Process for an Event-based Appliance (e.g. a Dishwasher) and a Rooftop Wind Turbine

3.3.2 Event-based Appliance: Schedule for a Specific Starting Time (ST)

Also for baselining purposes, the 'Schedule for a Specific Starting Time' decision method was developed to simulate when an event-based appliance's starting time could be set for a future moment in time. The output of the 'Schedule for a Specific Starting Time' algorithm is the future stage in which the event-based appliance will start its cycle. This decision is **not** changed at any point in this particular Energy Box implementation.

This decision method is also used to mimic the electricity consumption at a home that is known in advance, thus allowing the usage of controllable appliances to be scheduled based on this known consumption. For example, an estimate of electricity consumption from discretionary uses could be simulated via the 'Schedule for a Specific Starting Time' algorithm if the daily patterns from a resident are known with sufficient certainty.

3.3.3 Event-based Appliance: Dynamic Programming (DP)

While the 'Run Immediately' and 'Schedule for a Specific Starting Time' decision methods are necessary for baselining purposes, the primary decision method in the Energy Box for event-based appliances is the dynamic programming algorithm. For event-based appliances, the dynamic programming algorithm essentially asks the question 'is now the best time to start the event-based appliance?' If so, the event-based appliance will start its cycle, and if not, it will wait. The stochastic dynamic programming framing for determining control decisions builds upon the work by Constantopoulos et al. [1991] that two decades ago considered an automated real-time response by space conditioning appliances with respect to spot pricing for electricity [Constantopoulos et al., 1991]. This structure provided the foundation for the dynamic programming model used by the Energy Box for thermostatically-controlled appliances, and straightforward extensions allow dynamic programming to be used for event-based appliances and storage devices, when applicable.

For the case when the event-based appliance's decision method is 'Dynamic Programming', the decision options (x_t^{EBA}) at each stage for this Energy Box model are

$$x_t^{EBA.DP}\,(R2R) = \begin{cases} \text{Start the event-based appliance} \\ \text{Wait} \end{cases}$$

Additional Energy Box variables and parameters influence which of these options is the best decision at the current stage. These variables and parameters will be introduced in the next subsection, followed by how they are incorporated into the event-based appliance's dynamic programming decision method processing.

Weather, Pricing and Other Energy Box Parameters Affecting the Dynamic Programming Decision

In order to examine how a single residence's hourly power profile might change in response to different pricing systems and local weather-dependent sources of electricity, the dynamics of these random variables must be simulated. These external variables (from the perspective of the home) are equivalent to 'Exogenous Information' in Powell [2007], where W denotes these types of variables. The same notation will be used here.

Forecasts of the price and weather variables are used by the decision methods in the 'Energy Box Decision' box in figure 3-2, and then the simulated 'actual' values of these variables are used in the Δt update step. Since weather dynamics and pricing systems depend on local and seasonal conditions, the data necessary for modeling these random variables were collected to simulate the conditions during a Boston summer. The choice of modeling summer weather for this implementation of the Energy Box model was to ensure that the use of an air conditioner was needed for a sufficient number of the simulated days. Different regions and seasons could easily be modeled instead of or along with a Boston summer, however a single region and season was adequate to demonstrate the results discussed in chapters 4 and 5.

Whenever a rooftop wind turbine is included in the Energy Box simulation process (such as the scenario illustrated in figure 3-2), a model of hourly wind speeds is necessary in order to calculate how much electricity will be generated by the wind turbine. Sahin and Sen [2001] and Brokish and Kirtley [2009] demonstrate that a first-order Markov chain is sufficient for simulating hourly wind speeds ($W_t^{wind.speed}$ or $W_t^{w.s.}$). A function can then convert the wind speed into an estimate of the electricity that would be generated by the rooftop wind turbine.

The wind speed Markov model uses 25 years of historical weather data from the National Oceanic and Atmospheric Administrations National Climatic Data Center (NCDC)[1]. To create the Markov chain transition matrices $P_{t,t+1}^{wind.speed}$, the summer months' wind data was separated by hour and discretized to integral wind speeds ranging from 0 meters per second to 30 meters per second (though the maximum wind speed in the data was significantly less than 30 meters per second). Transitions from one wind speed to the next were then counted, separated by the hour of the day, and normalized to create all of the $p_{i,j}$ values in

$$P_{t,t+1}^{wind.speed} = \begin{bmatrix} p_{0,0} & p_{0,1} & p_{0,2} & p_{0,3} & \cdot & \cdot & \cdot & p_{0,30} \\ p_{1,0} & p_{1,1} & p_{1,2} & p_{1,3} & \cdot & \cdot & \cdot & p_{1,30} \\ p_{2,0} & p_{2,1} & p_{2,2} & p_{2,3} & \cdot & \cdot & \cdot & p_{2,30} \\ p_{3,0} & p_{3,1} & p_{3,2} & p_{3,3} & \cdot & \cdot & \cdot & p_{3,30} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{30,0} & p_{30,1} & p_{30,2} & p_{30,3} & \cdot & \cdot & \cdot & p_{30,30} \end{bmatrix}$$

for each hour t. Normalizing across each row i ensures that $0 \leq p_{i,j} \leq 1$ and that

$$\sum_{j=1}^{n} p_{i,j} = 1 \quad \forall i.$$

Once the 24 hourly Markov transition matrices were set, a sequence of simulated wind

[1] http://cdo.ncdc.noaa.gov/cdo/info.html and http://www.ncdc.noaa.gov/oa/nndc/freeaccess.html

speeds could then be created via an initial condition for $w_0^{wind.speed}$ and the relationship

$$W_t^{wind.speed} = \left(\prod_{i=0}^{t-1} P_{i,i+1}^{wind.speed} \right) * w_0^{wind.speed}, \quad t > 0$$

for the range of hours included in that particular simulation. Further details of the weather models used for the Energy Box simulation process are included in Appendix B.

For each wind speed, the amount of electricity generated by the rooftop wind turbine is defined via the function

$$W_t^{wind.power} = k^{max.wind.power} * f^{wind.speed.to.wind.power}\left(W_t^{wind.speed}\right),$$

where $k^{max.wind.power}$ is a parameter reflecting the maximum power output the rooftop wind turbine can generate and where $f^{wind.speed.to.wind.power}\left(W_t^{wind.speed}\right)$ converts the wind speed into a percentage of the maximum power output. An example of such a function is shown in figure 3-3.

Whenever the indoor thermal comfort is included in the Energy Box simulation process (such as in the scenario described in section 3.4), a model of the outdoor temperature is needed in order to simulate the thermal characteristics of the home with sufficient accuracy. An hourly Markov chain was used to simulate the outdoor temperature just as it was used to simulate wind speed. The source of the temperature data was again from the NCDC and encompassed the same 25 year span. The outdoor temperatures were discretized to a set ranging from 50^{o}F to 110^{o}F, which captured all but a few hours out of the entire 25 years of data (the few hours that dipped slightly below 50^oF were counted as 50^oF in the model). Fixing the lower and upper temperature bounds in the model was necessary to keep the computational complexity of the outdoor temperature model in check, and clearly these bounds would need to change to whatever is appropriate for other seasons and regions.

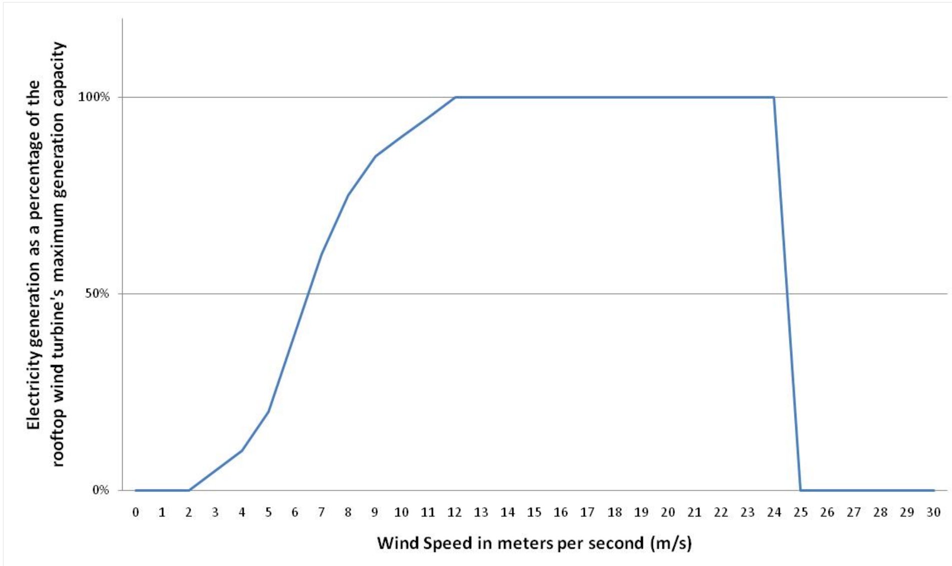

Figure 3-3: Illustration of the relationship ($f^{wind.speed.to.wind.power}$) between wind speed and the percentage of the maximum electricity generated by the rooftop wind turbine at each wind speed

Along with the weather external variables of wind speed and temperature, another external variable modeled for the Energy Box simulation process is electricity prices. Section 2.3 discussed the wide variety of elements that could be included in a retail electricity tariff. For this dissertation, only prices for electric energy (\$/kWh) were modeled. In particular, three of the common retail tariffs were modeled:

- the traditional flat rate tariff,
- the 'notched' time-of-use (TOU) tariff, and
- the hourly real-time pricing (RTP) tariff.

Figure 3-4 shows the flat tariff, time-of-use tariff, and the variability inherent in the hourly real-time pricing tariff via an example of an inexpensive day, an average day and an expensive day of the real-time pricing tariff in the Energy Box simulation.

Of the three, the most difficult tariff to establish is most certainly the hourly real-time pricing (RTP) tariff. In practice, a real-time tariff is influenced by many factors, including but not limited to the grid-level demand for electricity, unit commitment, the generation mix in the region, transmission costs, congestion, reliability charges, and the cost of

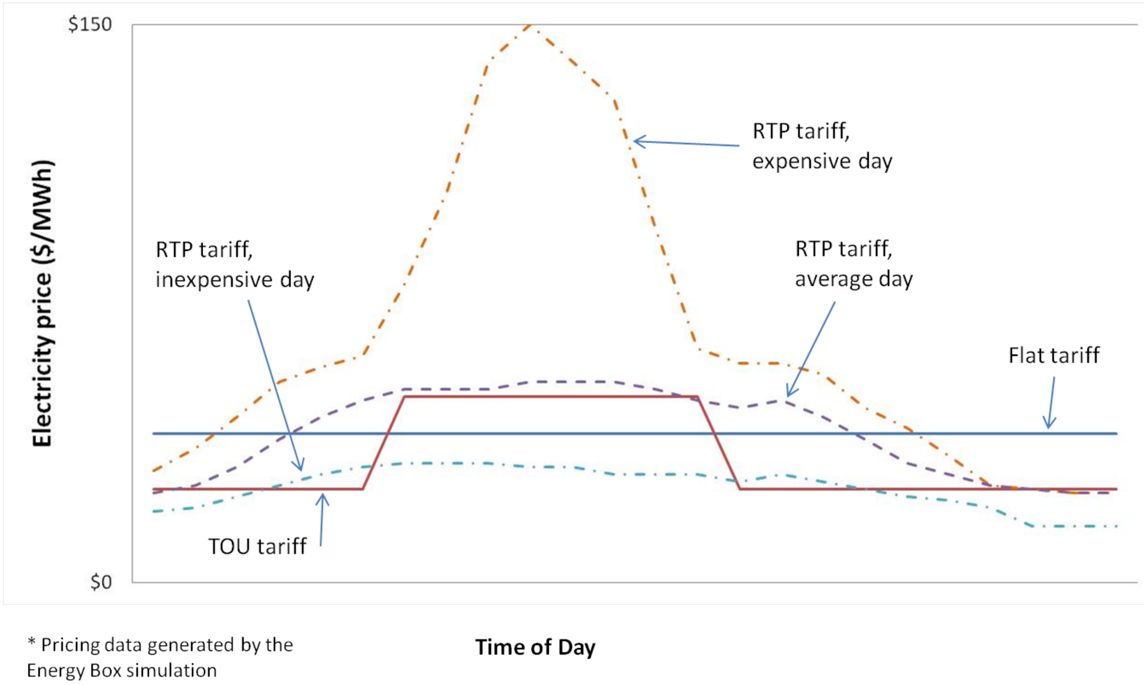

Figure 3-4: Illustration of the variability of the real-time pricing (RTP) tariff, for an example of an expensive day, average day, and inexpensive day from the Energy Box simulation

primary sources of energy. For this dissertation, the model for a retail real-time pricing rate was developed based on the dynamics of an hourly real-time wholesale electricity market in New England.

First, a 7-day 24-hour hourly Markov chain was created for modeling grid-level electricity demand, with the expansion to a 7-day model necessary as demand for electricity varies by the day of the week as well as the hour of the day. With the decision to focus on the Boston region, grid-level electricity demand information was collected from the Independent System Operator of New England (ISO-NE), which is the entity that oversees the operation of electricity markets in the New England area. From the ISO-NE website[2], hourly grid-level electricity demand information from 1993 to 2002 was collected and used to create this Markov model.

Since the exact values of electricity demand vary widely, discretizing these values is not as

[2]http://www.iso-ne.com/

straightforward as the process for modeling temperature and wind speeds. For each hour of each summer day, the grid-level electricity demand data was separated into seven ‘bins’, as described in detail in Appendix C. The end result was a Markov model that captured transitions from one bin to another throughout the week. For each set of data across the hours and days of the week, a representative value of grid-level electricity demand was then calculated to be used in the Energy Box’s pricing model. Just like the models for the weather dynamics, this model of grid-level electricity demand dynamics is a simplification of reality but is nonetheless sufficient for helping illustrate the key results of this version of the Energy Box.

With the model of grid-level electricity demand in place, the next step for creating the hourly real-time pricing model for the Energy Box simulation was to return to the ISO-NE website[3] and collect a year’s worth of hourly prices of electricity from the ISO-NE wholesale market for the year 2002 (which was the most recent year of data available on their website at the time of collection). In the ISO-NE wholesale market, some large demand users from the commercial and industrial sectors participate in the market and thus are free to adjust their electricity demand in response to these wholesale prices. For this reason, it was deemed acceptable for the Energy Box purposes to use this data to create the hourly real-time pricing tariff for the model by mapping grid-level demand (in MW) to price (in $/MW), as seen in Table C.5 in the Appendix. This table was created by stepping through the 2002 data and mapping multiples of 100 MW of grid-level electricity demand to multiples of $0.50/MW. For the purposes of this dissertation, this was sufficient to capture the general dynamics of hourly demand-sensitive pricing from a functioning electricity market. However, should the market share of home energy management systems such as the Energy Box increase to a significant collection of houses, a new model of the dynamics of the electricity market likely will need to be developed to capture the new dynamics induced by these automated home energy management systems.

The pricing model for the Energy Box simulation could then create a sequence of hourly

[3] http://www.iso-ne.com/

real-time prices by first simulating a sample sequence of grid-level demand ($W^{grid.level.demand}$ or $W^{g.d.}$) via the bin structure in the 7-day 24-hour Markov chain described previously. Then, using the representative value of grid-level electricity demand for each bin, the Energy Box simulation process locates the row in Table C.5 with the closest demand value greater than or equal to the representative grid-level demand value and sets the price for that hour to be the corresponding $/MW.

With prices in place for each hour of the simulation, a notional $Utility.Revenue$ value was calculated from the hourly grid-level demand and real-time prices as follows:

$$Utility.Revenue = \sum_t \left(w_t^{grid.level.demand} * w_t^{RTP.price} \right)$$

where t goes from 1 to the number of simulated hours in the simulation.

In order to keep the flat tariff and time-of-use (TOU) tariff consistent with the hourly real-time pricing (RTP) tariff, the following equations were used along with the now known $Utility.Revenue$ value to set the prices for those models:

$$Utility.Revenue = w^{flat.price} * \sum_t \left(w_t^{grid.level.demand} \right) \tag{3.1}$$

$$Utility.Revenue = \left[w^{peak.price} * \sum_{j \in \text{peak hours}} w_j^{g.d} \right] + \left[w^{off.peak.price} * \sum_{k \in \text{off-peak hours}} w_k^{g.d} \right] \tag{3.2}$$

The set of peak hours and off-peak hours is a parameter in the model's inputs, though for consistency the hours from 12:00 PM to 8:00 PM were fixed as the set of peak hours for this Energy Box model. In addition, the peak rate was defined as a scalar multiple of the off-peak rate,

$$w^{peak.price} = k^{TOU.peak.to.off-peak} * w^{off.peak.price}$$

where $k^{TOU.peak.to.off-peak}$ was set up as a parameter in the model. A range of values for $k^{TOU.peak.to.off-peak}$ was tested for this Energy Box simulation. Of note, for this Energy Box simulation, the affect of one home on the hourly electricity prices is assumed to be negligible. When thousands of Energy Boxes (or more) are connected, this assumption may no longer hold, though that is beyond the scope of this dissertation.

For each of the random variables introduced here, there is a parameter that establishes how their future uncertainty creates the simulated forecasts that will be used by the Energy Box decision methods. The three forecast structures used for this Energy Box simulation are

- perfect forecasts (PF),
- full distribution (FD), and
- median value of the distribution (MV).

The 'perfect forecast' (PF) is exactly as its name suggests and provides a bound of what the best decision would be if it was known a priori what would happen in the future. Of course, forecasts are not perfect, the reality of which is simulated by the other two forecast methods. Starting from the current values of the random variables, the Energy Box simulation steps through the Markov chain to calculate the distribution of possible states at any future stage. These distributions are what is used for the 'full distribution' (FD) forecasts. At each stage, the median value of the random variable's forecast is calculated and used in the 'median value of the distribution' (MV) forecast method. Using only the median value is the same as using the 'certainty equivalent control' method from Constantopoulos et al. [1991] discussed in section 2.3. Instead of using the full distribution, the expected value (in this case the median value) of the uncertainty distribution is used as though it were known with certainty. This 'certainty equivalent control' mimics what may occur if the forecasted information is collected from some weather forecast websites as the information available may only be the expected values of future weather conditions.

Using these three forecast methods, it is possible to compare how well the Energy Box decision methods perform in response to varying degrees of uncertainty introduced by these random variables.

Last but not least to be introduced in this section are a few parameters affecting the simulated consumer's electricity pricing tariff, as listed below:

- the number of stages of known, fixed prices (FP) and
- the policy for selling electricity back to the grid.

The 'fixed prices' (FP) parameter only affects the real-time pricing (RTP) tariff. The flat rate and time-of-use rates are assumed to be known and fixed for all hours of the simulation. For the real-time pricing tariff, the FP parameter establishes how many stages of prices are known at the time of the decision being made for the current stage. For all later stages, the real-time price is modeled as a random variable that is a function of the grid-level electricity demand ($W_t^{g.d.}$) and wind speed ($W_t^{w.s.}$) random variables. For the results in this dissertation, the hourly real-time electricity prices are set either an hour ahead or a day ahead (i.e. $FP = 1$ or $FP = 24$, respectively).

The next parameter affecting the consumer's electricity pricing tariff involves the policy for selling electricity back to the grid in cases where a consumer has storage devices or sources of distributed generation. To provide a reasonable range of variation for this dissertation, the function

$$W_t^{price.sell} = k^{buy.to.sell.scaling.factor} \cdot W_t^{price.buy} \tag{3.3}$$

was used. The variable $W_t^{price.buy}$ could reflect any of the flat, time-of-use, or hourly real-time pricing tariffs of electricity, and the scaling factor $k^{buy.to.sell.scaling.factor}$ is usually constrained so that $0 \leq k^{buy.to.sell.scaling.factor} \leq 1$. Of note is that $k^{buy.to.sell.scaling.factor} = 1$ is the same as having the traditional electromechanical meter run backwards whenever the local electricity generation exceeds the consumption at the home. This turns out to be a unique case and is examined in chapter 5. As discussed in Cory et al. [2009] and Klein et al.

[2007], some feed-in tariffs were implemented in the past where $k^{buy.to.sell.scaling.factor} > 1$, though this structure seems to be falling out of favor. Cory et al. [2009] and Klein et al. [2007] also discuss other feed-in tariff structures that would change some details of the chapter 5 results, however the overall results would remain the same and thus only the feed-in tariff structure from equation 3.3 is used for this version of the Energy Box simulation process.

Making the Dynamic Programming Decision for an Event-based Appliance

With all models for the Energy Box simulation process in place, all parameters can now be incorporated into the dynamic programming structure for an event-based appliance. As Powell illustrates quite clearly in his textbook *Approximate Dynamic Programming*, there are numerous ways to frame a dynamic programming problem, and the reader interested in learning more details about the wide range of dynamic programming problem formulations is encouraged to read at least the first three chapters of Powell's textbook [Powell, 2007]. The characteristics of the Energy Box decisions as framed allow for a finite horizon dynamic programming method to be used. To proceed, the key elements to be defined in the context of this problem are

- the terminal stage,
- the contribution function(s) for each stage, and
- the overall objective function.

In the context of an event-based appliance, the terminal stage of the dynamic programming decision method is either the stage by which the consumer specifies the event-based appliance must complete its cycle or the final stage of the decision horizon (DH), whichever comes first. The decision horizon parameter (DH) is included to establish a final stage for the forecasts that are created via the Markov chains introduced in section 3.3.3 since the Markov chains could technically provide forecasts over an infinite time horizon, clearly an unrealistic option. The other parameter that could set the terminal stage is called the flexibility constraint (FC), which is the stage by which the consumer wants the event-based appliance to be completed. For this implementation of the Energy Box model, the decision horizon (DH) is fixed at 24 hours, though the sensitivity of the DH parameter was tested and ultimately did not yield any unexpected results. For shorter decision horizons, the chance to take advantage of opportunities beyond the decision horizon were missed. For longer decision horizons, the additional forecasted information of the weather and grid-level electricity demand random variables did not noticeably alter the decisions made when the decision horizon was set at 24 hours. Since this implementation of the Energy Box ensures that an event-based appliance will complete its load within a day, the consumer's flexibility constraint (FC) will always determine the terminal stage for the event-based appliance's dynamic programming decision method (i.e. $FC \leq DH$). The sensitivity of this modeling choice could certainly be revisited in future implementations.

At the terminal stage of the event-based appliance's dynamic programming process, the Energy Box is forced to choose $Start$ to meet the resident's deadline if the appliance has not yet started its cycle. For all stages prior to the terminal stage, the Energy Box will continue to calculate whether it is best to $Start$ the event-based appliance or $Wait$. The details of this calculation will be expanded upon mathematically in the following paragraphs. To make these calculations, the dynamic programming model needs a defined **rule for following an optimal policy**. Following Powell's convention, one or more **contribution functions** and an **objective function** will be used to jointly define the **rule for following an optimal policy**. In general, the **contribution functions** are defined in the context of each dynamic programming model. The minimization or maximization of one or more of these **contribution functions** is what ultimately becomes the **objective function**. For event-based appliances, the **contribution function** is the expected cost of running the event-based appliance at a given stage t, represented by C_t^{cost}. The event-based appliance's **objective function** is thus to minimize the contribution function C_t^{cost} between the current moment in time and the terminal stage FC.

One last assumption for this section is that **the event-based appliance's cycle is short enough to start and finish in the time between stages. As a reminder,**

the time between stages is currently set at one hour. This assumption is included to clarify the discussion about the dynamic programming process. In the Energy Box simulation, the coding supports event-based appliance cycle times that last longer than the time between stages, and with a straightforward extension, the dynamic programming process described here operates successfully in those cases as well.

Everything is now set for the mathematical representation of the dynamic programming decision method for an event-based appliance:

$$\min_{\left(x_t^{EBA}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA}, x_t^{EBA}, W_{t+1}\right)\right]. \tag{3.4}$$

Solving this equation for the event-based appliance depends on some of the parameters discussed earlier:

- Uncertainty parameter: PF (perfect forecasts), MV (median value), FD (full distribution)
- Electricity pricing tariff: Flat, TOU (time-of-use), RTP (real-time pricing)
  - If RTP, then set the FP parameter to fix the hourly prices either one hour ahead or one day ahead (i.e. $FP = 1$ or $FP = 24$)
- Wind turbine: Yes or no
  - If yes, then set $k^{buy.to.sell.scaling.factor} \in [0, 1]$

The influence of these parameters on the event-based appliance dynamic programming algorithm is demonstrated in Appendix D by stepping through the details of how Equation 3.4 is solved via a backward dynamic programming algorithm for two of the combinations of parameters. The reason it is a 'backward' algorithm is that the process begins at the terminal stage of the dynamic programming formulation and traverses from the terminal stage back to the current moment in time, again as illustrated in Appendix D. Ultimately, the dynamic programming algorithm determines the best decision for the current moment in time, which is then implemented in the Energy Box simulation process.

One note: though it may seem counterintuitive initially, there is no typo in Equation 3.4 regarding the time indices of states (S_t^{EBA}), decisions (x_t^{EBA}), and exogenous information (W_{t+1}). The discrepancy is that decisions x_t^{EBA} made at stage t while in state S_t^{EBA} are affected by information such as weather forecasts that are not known precisely until stage $t+1$. This distinction is subtle but important, and it will arise frequently in the backward dynamic programming algorithm in Appendix D.

3.4 Decision Methods for Thermostatically-controlled Appliances

Unlike event-based appliances, the exact amount of electricity consumed by thermostatically-controlled appliances often depends on external states, such as the outdoor temperature. As such, the exact electricity consumption is impossible to know in advance and cannot be scheduled in the same way as event-based appliances. Thus, the only algorithms implemented for thermostatically-controlled appliances are the Run Immediately (RI) and Dynamic Programming (DP) algorithms. These two algorithms will be introduced in the context of an air conditioner (AC).

3.4.1 Thermostatically-controlled Appliance: Run Immediately (RI)

The thermostatically-controlled appliance's Run Immediately (RI) algorithm is again used for baselining purposes, just like the event-based appliance's Run Immediately algorithm. In the case of Run Immediately, a fixed value is maintained as the thermostat's set point for the entire simulation. However, this does **not** mean that the indoor temperature, $S_t^{TCA.indoor.temperature}$, is constant for the entire simulation. In many hours of the simulation, the outdoor temperature is lower than the Run Immediately thermostat set point, causing the indoor temperature to drop below the set point since a heater is not implemented in this version of the Energy Box. Clearly this would be a problem if the temperature was too cold, though the decision to limit the weather to the summertime in Boston means that foregoing a heater in the Energy Box model is not be a problem at this time.

3.4.2 Thermostatically-controlled Appliance: Dynamic Programming (DP)

For the thermostatically-controlled appliance's dynamic programming decision method, the mathematical representation is

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH-1}} \sum_{t=0}^{DH} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{TCA}, x_t^{TCA}, W_{t+1}\right) + \hat{C}_{t+1}^{Comfort}\left(S_t^{TCA}, x_t^{TCA}, W_{t+1}\right)\right] \tag{3.5}$$

Though the details of the thermostatically-controlled appliance's dynamic programming algorithm are discussed here in the context of an air conditioner (AC) and thermal comfort inside the home, the same structure could be used by all thermostatically-controlled appliances. The **state** for the air conditioner's dynamic programming algorithm is the set of all possible temperatures inside the home ($S_t^{TCA.indoor.temperature}$ or $S_t^{TCA.i.t.}$) and is illustrated by the bulb thermometer in figures 3-5 and 3-6. Technically the range of indoor temperatures could include all possible outdoor temperatures (illustrated by the circular thermometer in figures 3-5 and 3-6), so the set of possible indoor temperatures in the model are the integral values on the Fahrenheit scale in the same range as the outdoor temperature of 50^oF to 110^oF.

The **decision** values for the air conditioner's thermostat, $x_t^{TCA.AC.thermostat}$ (illustrated by the square thermostat in figures 3-5 and 3-6), include all acceptable set points for the thermostat, discretized to integral values on the Fahrenheit scale. The range of acceptable set points is established as an input parameter for each consumer simulated and will be discussed further at the end of this section.

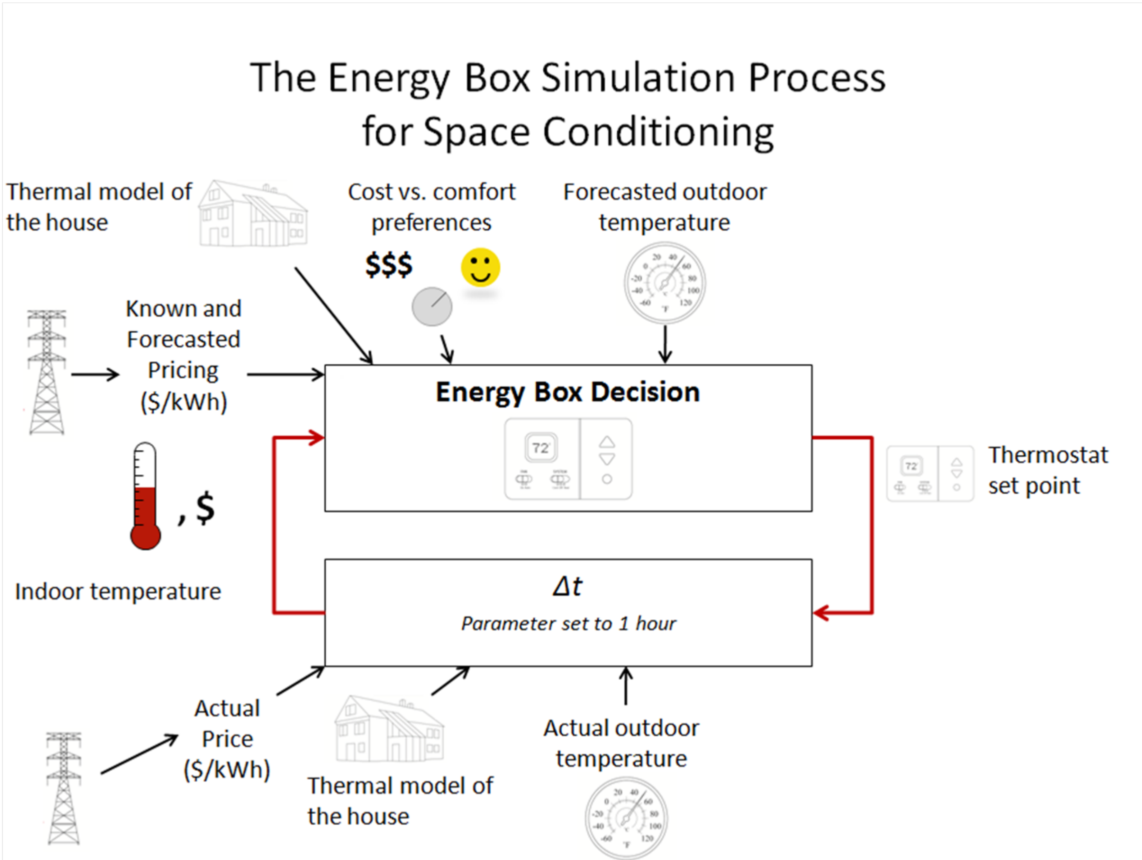

Figure 3-5: Illustration of the Energy Box Simulation Process for a Thermostatically-controlled Appliance (e.g. Space Conditioning)

The **stage-to-stage state transition rule** for the home's indoor temperature is influenced by a number of factors, as illustrated in figure 3-6 and listed here:

- the current temperature inside the home ($S_t^{TCA.indoor.temperature}$ or $S_t^{TCA.i.t.}$),
- the thermostat's set point ($x_t^{TCA.AC.thermostat}$ or $x_t^{TCA.AC.}$),
- the outdoor temperature ($W_{t+1}^{outdoor.temperature}$ or $W_{t+1}^{o.t.}$),
- the thermal time constant of the building (ϵ), and
- the efficiency of the air conditioning unit when cooling the air in the home, which is captured as part of the function $f^{AC.cooling.output}\left(S_t^{TCA.i.t.}, x_t^{TCA.AC}, W_{t+1}^{o.t.}\right)$.

Each of these is included as part of the image from figure 3-6, which illustrates the dynamic programming process. As a reminder, in the finite horizon dynamic programming process implemented for the Energy Box, the first calculation is the terminal stage. All contributions of comfort and cost (illustrated by the smiling face and $$$, respectively) beyond this terminal stage are modeled to be zero. The dynamic programming process commences at the terminal stage and steps backwards in time as illustrated via the $-\Delta t$ box in figure 3-6. As mentioned previously in this chapter, the time step for the dynamic programming process is a parameter that is set to one hour for the discussion in this dissertation. After stepping backwards through the dynamic programing process, the best decision at the current moment in time is determined and implemented via the Energy Box simulation. Once all decisions from all controllable appliances have been set, the Energy Box simulation process illustrated in figure 3-5 steps forward in time one time step Δt (again one hour), and the decisions are recalculated given any updated information from the new weather and price forecasts.

Returning to the focus of air conditioning in this section, the relationship between the thermal model of the home, the outdoor temperature and the temperature inside the home at the next time step, $S_{t+1}^{TCA.indoor.temperature}$, is found via the equation

$$S_{t+1}^{TCA.i.t.} = \epsilon \cdot S_t^{TCA.i.t.} + (1-\epsilon) \cdot \left(W_{t+1}^{o.t.} - f^{AC.cooling.output} \left(S_t^{TCA.i.t.}, x_t^{TCA.AC}, W_{t+1}^{o.t.} \right) \right), \quad (3.6)$$

which is essentially the same exponential decay building thermal model[4] used by Constantopoulos et al. [1991].

Intuitively, one might assume that the temperature in the home at stage $t+1$ would reach

[4]This is clearly a simplified building thermal model, as it treats the entire home as a single zone with a single thermal parameter. Other more elaborate building thermal models could be used, though this first-order approximation is sufficient for this dissertation. A future version of the Energy Box under development by MIT Ph.D. candidate Woei Ling Leow will include a more detailed learning thermal model for buildings with zonal controls (i.e. multiple thermostats), so there will be a significant advancement in this element of the next Energy Box model.

the thermostat set point established at stage t, i.e. $S_{t+1}^{TCA.i.t.} = x_t^{TCA.AC.thermostat}$. However, this is not always the case, as the amount of cooling needed ($f^{AC.cooling.output}$) to reach the thermostat set point from one stage to the next may exceed the maximum amount of cooling available from the air conditioning unit ($k^{max.AC}$). Or, as was introduced in section 3.4.1, the indoor temperature may already be below the thermostat set point and the outdoor temperature may be low enough that the indoor temperature will remain below the thermostat set point between stage t and $t+1$. In these cases, $S_{t+1}^{TCA.i.t.} \neq x_t^{TCA.AC}$, and the reachable indoor temperature $S_{t+1}^{TCA.i.t.}$ will need to be calculated either using the maximum cooling output from the air conditioner or with the cooling output set to 0 for $w^{AC.cooling.output}$ in equation 3.6, depending on which situation has occurred.

In other words, after some algebraic manipulation,

$$S_{t+1}^{TCA.i.t.} = \begin{cases} \epsilon \cdot S_t^{TCA.i.t.} + (1-\epsilon) \cdot \left(w_{t+1}^{o.t.} - k^{max.AC}\right), & w_{t+1}^{o.t.} - \frac{x_t^{TCA.AC} - \epsilon \cdot S_t^{TCA.i.t.}}{(1-\epsilon)} > k^{max.AC}, \\ \epsilon \cdot S_t^{TCA.i.t.} + (1-\epsilon) \cdot w_{t+1}^{o.t.}, & w_{t+1}^{o.t.} - \frac{x_t^{TCA.AC} - \epsilon \cdot S_t^{TCA.i.t.}}{(1-\epsilon)} < 0 \\ x_t^{TCA.AC} & o.w. \end{cases} \tag{3.7}$$

Last but not least to discuss for the air conditioner's dynamic programming algorithm are the **contribution functions** and **objective function** used to define the **rule for following an optimal policy**.

As shown in equation 3.5, there are two contribution functions for the air conditioner's dynamic programming algorithm: C_t^{Cost} and $C_t^{Comfort}$. The purpose of these contribution functions is to calculate a numerical value of cost and thermal comfort that matches the preferences of the home's occupants. These values are then balanced via a tuning parameter in the **objective function**. Essentially, the objective function's purpose is to balance the minimization of cost with the maximization of comfort (or equivalently the minimization of discomfort).

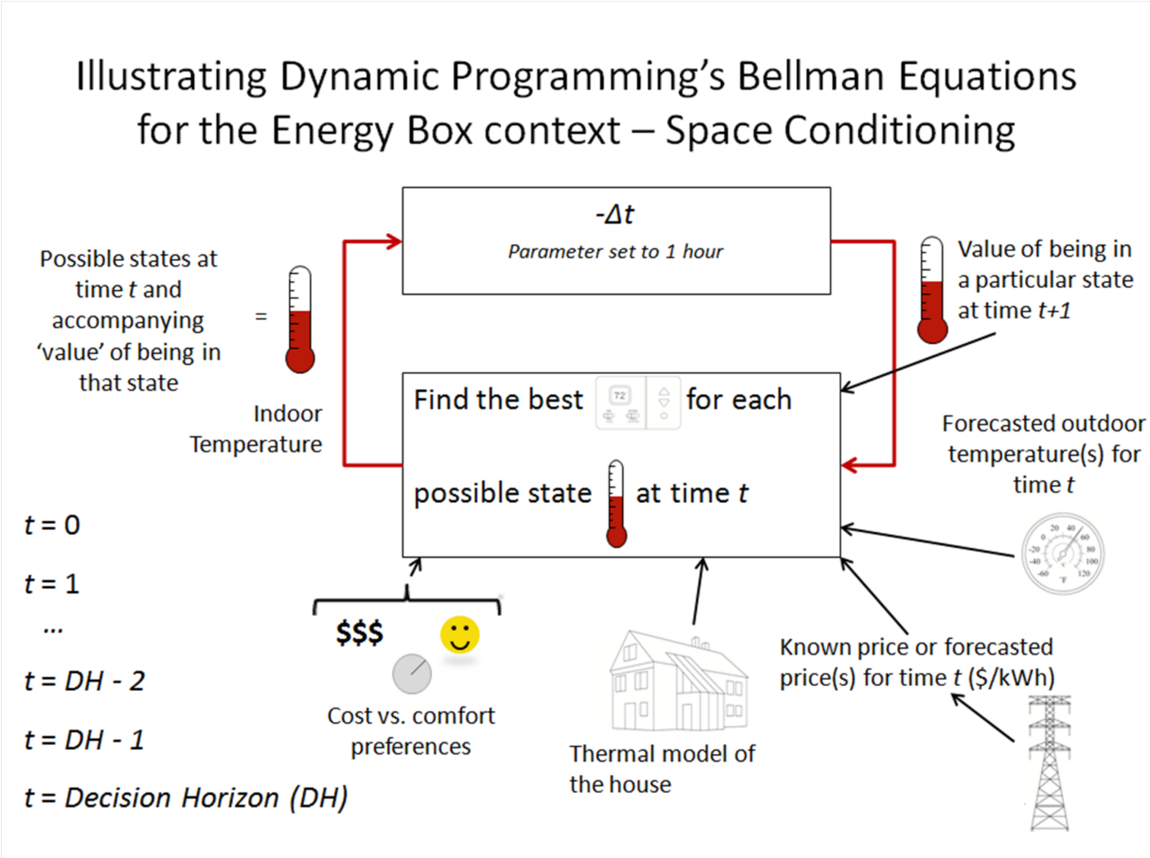

Figure 3-6: Illustrating Dynamic Programming's Bellman Equations in the Energy Box context for Space Conditioning

The calculation of C_t^{Cost} is straightforward. The calculation of $C_t^{Comfort}$, on the other hand, is what ultimately balances the tradeoff between cost and comfort in this particular implementation. Structurally, the comfort contribution function is as follows:

$$C_t^{Comfort}\left(S_t^{TCA.i.t.}\right) =$$

$$k^{warm} \cdot \left(max\left[\left(S_t^{TCA.i.t.} - k^{max.comfortable}\right), 0\right]\right)^{m^{warm}} +$$

$$k^{cool} \cdot \left(min\left[0, \left(k^{min.comfortable} - S_t^{TCA.i.t.}\right)\right]\right)^{m^{cool}}$$

For the comfort function, it is necessary to use $S_t^{TCA.i.t.}$ instead of $x_t^{TCA.AC}$ since it is possible that the indoor temperature will not be the same as the desired thermostat set point, as shown by equation 3.7. The parameters k^{warm}, m^{warm}, k^{cool}, m^{cool}, $k^{max.comfortable}$, and $k^{min.comfortable}$ would be set by the resident(s) and could vary by the occupancy state introduced in section 3.2.2. For clarity in the results discussion, most of the above parameters are fixed to specific values. In particular, $k^{cool} = 0$ and $m^{warm} = 2$ for all of the Energy Box simulation runs discussed in chapter 4 and 5. Of note is that with $k^{cool} = 0$, this means that m^{cool} and $k^{min.comfortable}$ are unused in this scenario. This leaves k^{warm} and $k^{max.comfortable}$ as the two parameters for this contribution function that can be adjusted. Figures 3-7 and 3-8 illustrate the adjustments available for k^{warm} and $k^{max.comfortable}$.

In the example case illustrated by figure 3-7, $k^{max.comfortable}$ is 72^oF. In other words, 72^{o}F is the warmest indoor temperature that is still comfortable for this particular resident. Continuing with this example, figure 3-7 shows that 73^oF and 74^oF are tolerable but less than comfortable, and any indoor temperature $\geq 75^oF$ is considered uncomfortable.

Recalling the distinction made earlier between the indoor temperature and the thermostat set point, figure 3-7 also illustrates the limitations imposed on the thermostat set point $x_t^{TCA.AC.thermostat}$. In the Energy Box model, the warmest set point allowable on the thermostat is a parameter $k^{max.tolerable}$, which is equivalent to the warmest temperature that is not in the resident's range of uncomfortable temperatures. For the example illustrated in figure 3-7,

$$x_t^{TCA.AC.thermostat} \leq k^{max.tolerable} = 74^oF.$$

Although the thermostat can never be set in the resident's uncomfortable range, it is possible that the outdoor temperature is so hot that the air conditioner is physically unable to keep the house cool enough given the resident's preferences. Nonetheless, knowing these preferences it is possible that the Energy Box could pre-cool the home to minimize the amount of time the indoor temperature reaches the uncomfortable range. The point is simply that the Energy Box never actively sets the thermostat to an uncomfortable temperature set point, however it may be inevitable, given the weather outside, that an uncomfortable temperature is reached. An equivalent lower limit would be included for $x_t^{TCA.AC.thermostat}$ if electric heating was also included in the simulation.

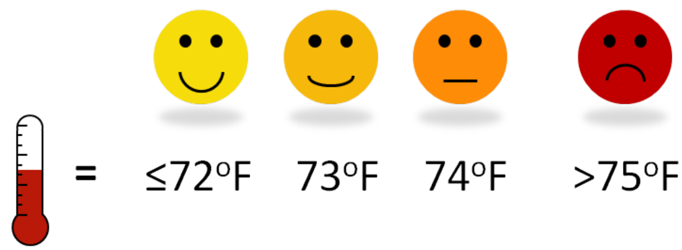

Figure 3-7: Illustrating one example of comfort preferences where $k^{max.comfortable} = 72^o F$ and $k^{max.tolerable} = 74^o F$

The balance between tolerable indoor temperatures and cost savings is managed via k^{warm}, which is essentially a dial as illustrated by figure 3-8. Maximum comfort incurs the highest cost ($$$) whereas the minimum cost ($) provides only tolerable comfort. Different settings on the dial shift the resident's preference between comfort and cost, ultimately affecting the sequence of thermostat set points implemented by the air conditioner's dynamic programming decision method. Examples of how this performs will be presented in chapter 4.

Figure 3-8: Illustrating k^{warm} as a dial that determines the tradeoff preference between comfort and cost

One closing note for this section is that the k^{warm}, $k^{max.comfortable}$ and $k^{max.tolerable}$ parameters could be time-varying. For the results discussion in this dissertation, these parameters were kept as time-invariant for each simulated consumer because allowing these parameters to vary with time did not qualitatively affect the main results for this dissertation's objectives.

3.5 Coordinated Decision Methods

One of the key research questions of this dissertation is determining when **coordinated** decision algorithms provide additional benefits when compared to the independent decision algorithms, and this section describes the varieties of coordination tested in this dissertation. Figure 3-9 illustrates the coordinated decision options implemented for two controllable appliances. Figure 3-11 then highlights how coordination differs slightly in the case when an uncontrollable local source of electricity generation like a wind turbine is added to the Energy Box simulation.

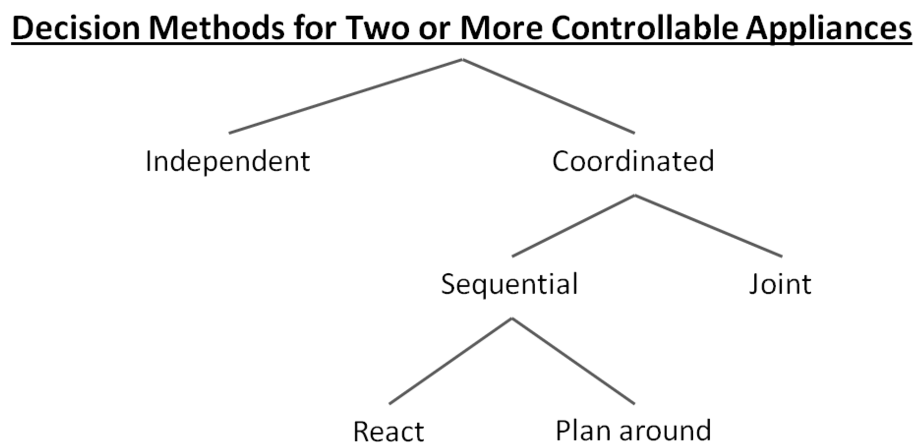

Figure 3-9: High-level Illustration of the Independent and Coordinated Decision Methods

To begin with, figure 3-5 from section 3.4 is the baseline illustration of the Energy Box simulation process for **independent** decision methods. Though the focus of that figure is the air conditioner, any other appliance could be the focus instead. For the air conditioner's independent decision method illustrated in figure 3-5, notice that the dishwasher decision is not included as part of the 'Energy Box Decision' inputs.

By comparison, figure 3-10 shows that for **sequential** decision methods, the decision made for the dishwasher is now included as part of the air conditioner's 'Energy Box Decision' inputs. There are two variations of sequential decision methods as shown in figure 3-9, and those are **react** and **plan around**. In some cases, the dishwasher's starting time is unknown until the moment its cycle is started. That new knowledge is sent to the air conditioner's decision method and the Energy Box may then **react** to the new information that the dishwasher will be consuming electricity over the next hour or two. On the other hand, if the dishwasher is scheduled for a particular future time and that information is sent to the air conditioner's decision method, then the Energy Box can **plan around** the dishwasher's upcoming electricity consumption.

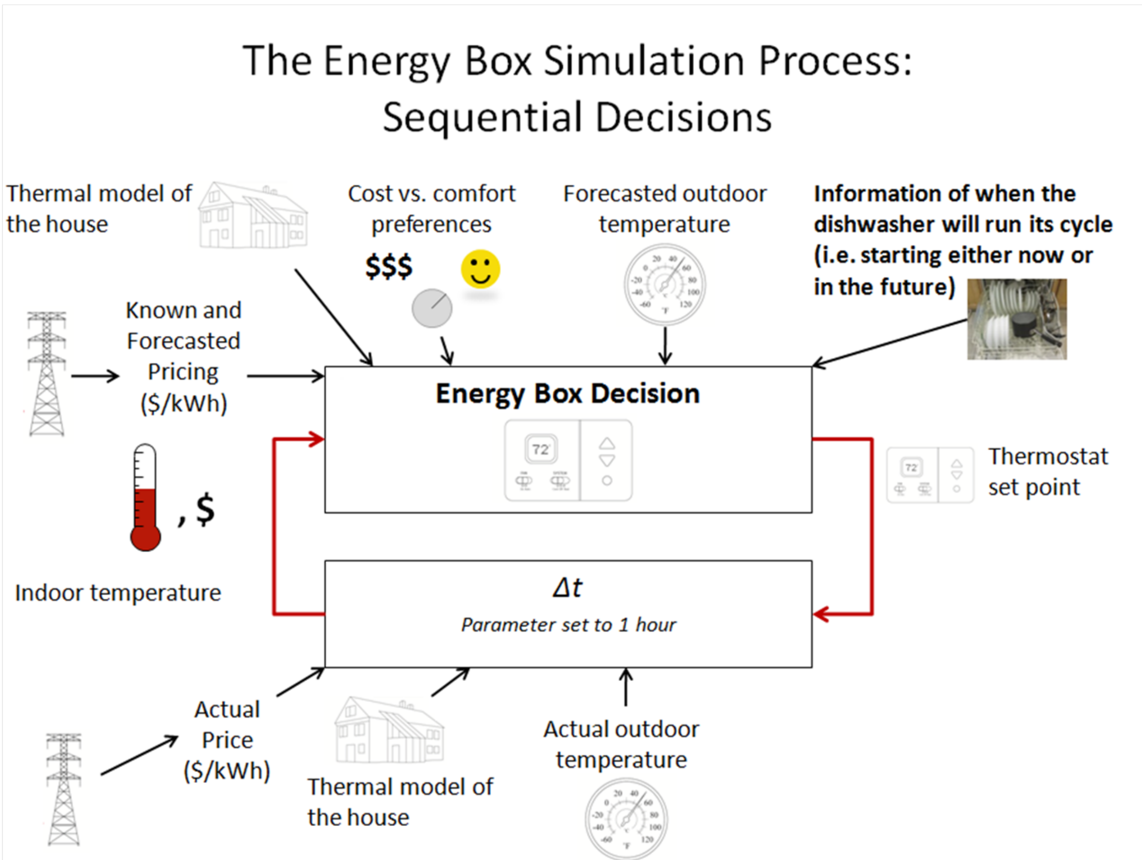

Figure 3-10: The Energy Box Simulation Process for Sequential Decisions

The most complex of the coordinated decision methods for two controllable appliances is the **joint** decision method. Though figure 3-11 shows a thermostatically-controlled appliance (the air conditioner) and an event-based appliance (the dishwasher), this joint process can also be implemented for two thermostatically-controlled appliances or for two event-based appliances.

To illustrate, consider a joint dynamic programming algorithm for two event-based appliances. The processing is essentially the same as the independent dynamic programming algorithms except for the key difference that the states are an ordered pair and that a joint decision occurs when both event-based appliances are in the *Ready to Run* ($R2R$) state. In the state combination of ($R2R$, $R2R$), there are ultimately four combinations of decisions at each stage: ($Start$, $Start$), ($Start$, $Wait$), ($Wait$, $Start$) and ($Wait$, $Wait$). From there, the decision combination with the best expected value at stage 0 is what is implemented in the simulation. If only one event-based appliance starts its cycle, then the Energy Box reverts back to the independent dynamic programming algorithm for the other event-based appliance in the next stage. If both event-based appliances start their cycle, then they will both return to their idle *Not Ready to Run* ($NR2R$) states in the next stage. Last but not least, if neither event-based appliance starts its cycle, then the Energy Box runs the joint dynamic programming algorithm again at the next stage.

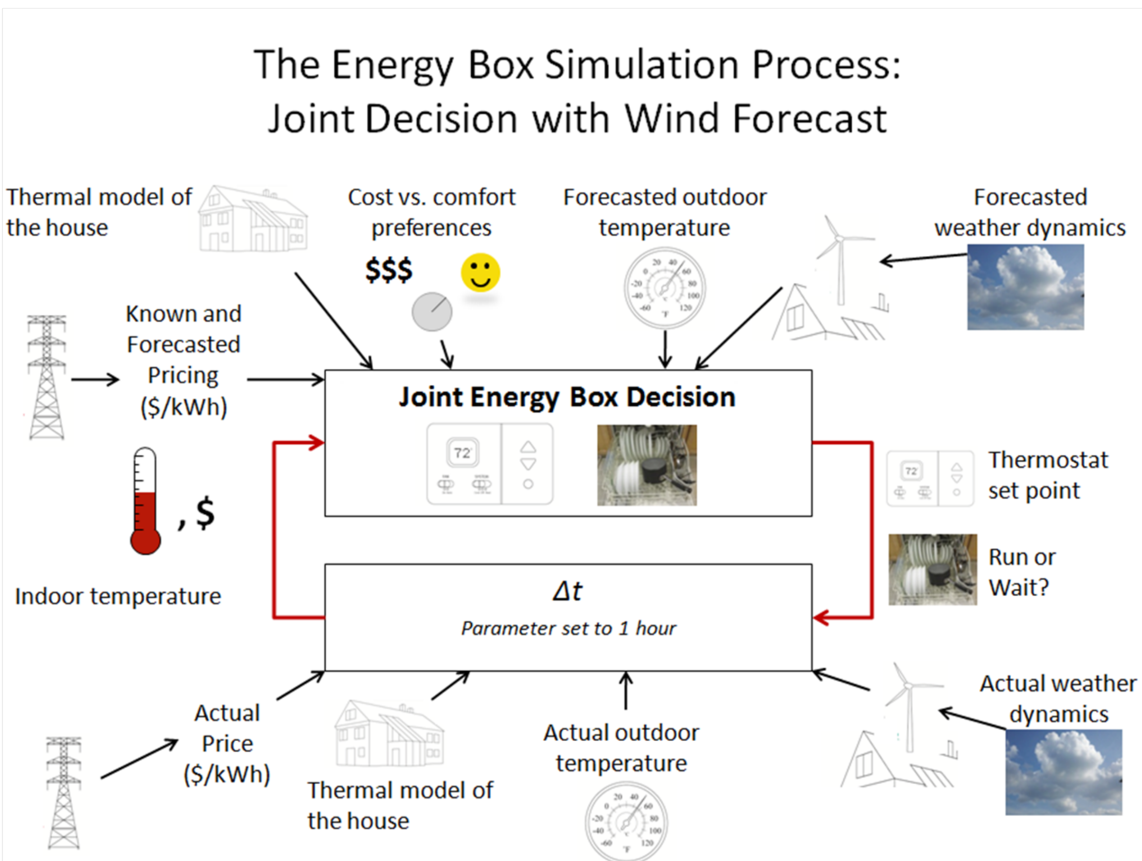

Figure 3-11: The Energy Box Simulation Process for a Joint Decision with a Wind Forecast

The joint dynamic programming algorithm for a thermostatically-controlled appliance and event-based appliance is again essentially processed in the same way as the independent dynamic programming algorithm. Anytime the event-based appliance is in its *Ready to Run* (*R2R*) state, the joint thermostatically-controlled appliance and event-based appliance dynamic programming algorithm will be called using an ordered pair of states and decisions for the thermostatically-controlled appliance and event-based appliance in the dynamic programming processing. As soon as the joint dynamic programming algorithm returns a decision to *Start* the event-based appliance, the thermostatically-controlled appliance reverts back to its independent dynamic programming algorithm. The thermostatically-controlled appliance then continues running its own dynamic programming algorithm until the next time the event-based appliance is loaded in the simulation.

Once again, the **sequential** and **joint** variations of coordinated decision methods apply only for two (or more) *controllable* appliances. Each of these coordinated decision options can also have an uncontrollable weather-dependent local source of electricity generation added to the simulation. Figure 3-11 illustrates this for the joint air conditioner and dishwasher scenario by adding a wind turbine to the simulation. When adding the wind turbine, there are two new cases to consider in that the Energy Box can make the decisions *without* or *with* a wind forecast. Adding a wind turbine *without* a wind forecast simply means the Energy Box has no knowledge of when electricity will be supplied by the wind turbine. On the other hand, adding a wind turbine *with* a wind forecast means the Energy Box can coordinate electricity consumption to coincide with windier hours if it is beneficial to do so. Determining when the Energy Box should incorporate these variations of coordination into the decision methods will be discussed throughout the next two chapters.

Chapter 4

Energy Box Results for Consumers

Although discussion abounds about smart grid technologies, few of these technologies are installed in residences today. Notable examples of these technologies are distributed generation (DG) and/or storage systems, such as plug-in electric vehicles that are able to discharge electricity to the grid. Residents using these technologies are prosumers, both producers and consumers of electricity, and are the focus of Chapter 5. This chapter focuses on results specific to the vast majority of electricity customers, those who do not utilize distributed generation nor storage systems and thus are not able to sell electricity to the grid. In other words, this chapter focuses on electricity consumers.

4.1 Benefits of Coordination to Electricity Consumers

Electricity consumers face two main external factors that drive decisions of how and when to use electricity: the electricity tariff and system constraints. As discussed in section 2.3, a variety of retail electricity tariffs exist. Along with a tariff for electric energy ($/kWh), some consumers may experience a 'demand charge' or 'power limit', each of which was discussed in section 2.3. Flohr [2010] and Morganti et al. [2009b] show how coordination within a home is beneficial when facing 'demand charges' or 'power limits', respectively, even when the price per kWh for electric energy is constant. With these results already well established in the literature, demand charges and power limits were not included in this research implementation of the Energy Box model, though certainly a commercial version of the Energy Box would need to accommodate all types of electricity tariff elements and system constraints.

In some locations, a consumer's electricity tariff only involves a cost of electric energy ($/kWh), with no additional demand charge and no power limit. If this cost of electric energy is an hourly real-time pricing tariff where prices are fixed less than an hour in advance ($FP = 1$ from the terminology in chapter 3), will benefits arise from coordinated control relative to independent control **within** a home?

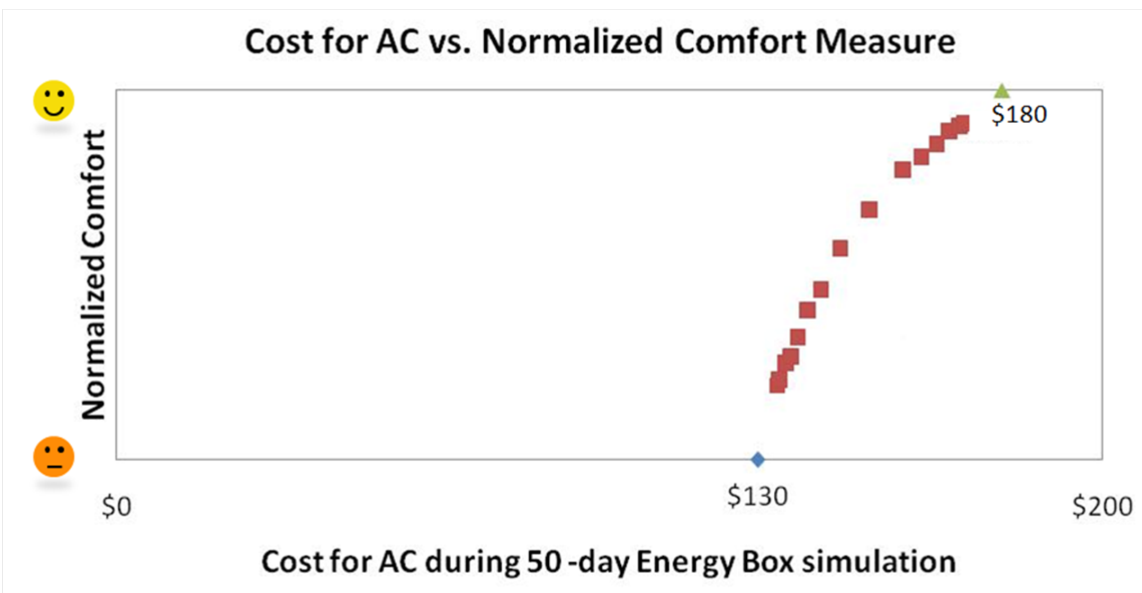

Figure 4-1: Comparison of the cost and comfort outputs for fixed thermostat set points and a range of settings on the comfort versus cost dial described in section 3.4.2

To test this, consider first the independent control of the air conditioner and the dishwasher when facing hourly real-time pricing. Figure 4-1 presents the results from the air conditioner's dynamic programming algorithm for a range of settings on the comfort versus cost dial described in section 3.4.2 and illustrated in figure 3-8. This provides the baseline of comfort versus cost tradeoffs when the air conditioner is controlled independently of the dishwasher.

All coordinated decision methods for two controllable appliances from section 3.5 were then tested with the same set of simulated consumers and the same range of settings on the comfort versus cost dial, again with hourly real-time pricing. As illustrated in figure 4-2, it was found that the comfort and cost results from the coordinated control simulations were always exactly the same as the comfort and cost results from the independent control simulations.

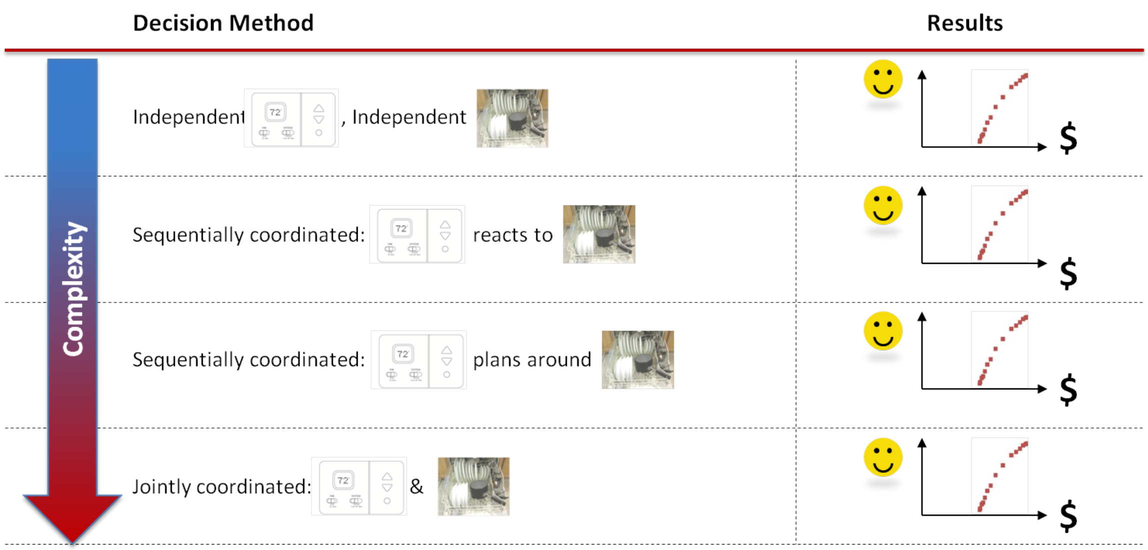

Figure 4-2: Illustration of equivalent cost and comfort outputs from Independent, Sequential and Joint decision methods for Consumers

From these simulations, it was observed that for appliances and storage devices providing independent services, **there are no benefits to coordinated control over independent control for consumers facing time-varying pricing of electric energy if there are no accompanying demand charges, power limits or inclining block rates as part of the electricity pricing tariff**. Proposition 1 and its accompanying proof at the end of this chapter in section 4.3 presents the full mathematical arguments needed to validate this observation for those interested. The rest of this section discusses the same result with a minimal amount of mathematical detail.

Consider the dynamic programming mathematical formulation for an event-based appliance, presented originally as equation 3.4 from section 3.3.3 and copied here for convenience:

$$\min_{\left(x_t^{EBA}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA}, x_t^{EBA}, W_{t+1}\right)\right].$$

.

The dynamic programming mathematical formulation for coordinated decision making between two event-based appliances would be

$$\min_{\left(x_t^{EBA_1}\right)_{t=0}^{FC}, \left(x_t^{EBA_2}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_1}, x_t^{EBA_1}, S_t^{EBA_2}, x_t^{EBA_2}, W_{t+1}\right)\right]. \tag{4.1}$$

.

If the contribution function

$$E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_1}, x_t^{EBA_1}, S_t^{EBA_2}, x_t^{EBA_2}, W_{t+1}\right)\right]$$

can be mathematically separated into

$$E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_1}, x_t^{EBA_1}, W_{t+1}\right)\right] + E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_2}, x_t^{EBA_2}, W_{t+1}\right)\right],$$

then there are no benefits of coordinated decision making relative to independent decision making as is illustrated in the proof of Proposition 1 in section 4.3.

On the other hand, if C^{cost} cannot be mathematically separated, then there could be some benefits from coordinated decision making relative to independent decision making. For instance, if the electricity tariff includes a demand charge (i.e. a price for electric power alongside the time-varying price for electric energy) or if the system imposes a power limit, then C^{cost} is indeed mathematically inseparable, hence the realization of coordination benefits via Flohr [2010] and Morganti et al. [2009a].

Similarly, Mohsenian-Rad and Leon-Garcia [2010] show that if the electricity tariff charges a piecewise linear or non-linear rate for electric energy ($/kWh) in each (hourly) time step (often called 'inclining block rates'), then coordinated decision making could provide benefits over independent decision making, again because C^{cost} is not mathematically separable.

A related observation also holds for the $C^{comfort}$ contribution function that is in the thermostatically-controlled appliance's dynamic programming mathematical formulation (equation 3.5) from section 3.4.2. Thermal comfort can be obtained via HVAC systems (Heating, Ventilation and Air Conditioning), dehumidifiers and/or thermal storage systems controlling the indoor temperature and/or humidity level. If more than one of these appliances are controllable, then $C^{comfort}$ may not be mathematically separable, in which case coordinated decision making between the HVAC system, dehumidifier and thermal storage system may (though may not) produce benefits over independent decision making.

Nonetheless, the key result observed in this particular scenario is that for appliances and storage devices providing independent services, if the electricity tariff is hourly real-time pricing for electric energy with no demand charges, power limits or inclining block rates, then there is no benefit to coordinated decision making over independent decision making.

4.2 Potential System Problems with Locally-focused 'Enabling Technology'

As discussed in section 2.3, time-varying pricing of electricity in electricity markets has long been proposed as a method that would let the electric grid reach a state of homeostasis, automatically adjusting to variations of supply and demand and thus maintaining a balanced equilibrium [Schweppe et al., 1980, Chao et al., 1986, Chao and Wilson, 1987, Borenstein et al., 2002, Borenstein, 2005]. For a system with large, centralized power plants, time-varying pricing is in theory supposed to smooth out the aggregate demand curve to let these large power plants operate most efficiently, thus bringing down costs for everyone.

Numerous pilot programs (collected and summarized by the Brattle group [Faruqui et al., 2007, Faruqui and Sergici, 2008]) produced encouraging results that peak electricity demand would indeed decrease in response to time-varying pricing tariffs. Faruqui et al. [2007] and Faruqui and Sergici [2008] discuss further that 'enabling technology' clearly increased residents' peak load reductions by automating the responses to these time-varying pricing policies. The exact implementation of the 'enabling technology' varied by pilot, but generally included (a) smart thermostats that 'automatically raise the temperature setting on the thermostat by two or four degrees' Fahrenheit and (b) 'always-on gateway systems' that would automatically shed electric load whenever the price of electricity surpassed a pre-set threshold [Faruqui et al., 2007].

Adhering to this dissertation's notation, the threshold-controlled smart thermostat's decisions are simply

$$x^{TCA.AC} = \begin{cases} k^{max.comfortable} + 2 & w^{price.buy} > k^{threshold.price} \\ k^{max.comfortable} & w^{price.buy} \leq k^{threshold.price} \end{cases} \tag{4.2}$$

Considering that the only control option designed into this particular 'enabling technology' implementation is the reduction of electricity demand during high-priced hours via this threshold control structure, it was essentially guaranteed that the peak load reduction would increase with the inclusion of more elements of 'enabling technology'. This threshold control process was recreated in the Energy Box simulation and yielded the same observed results as the pilot programs from Faruqui et al. [2007] and Faruqui and Sergici [2008].

However, what if the objective of the 'enabling technology' was explicitly designed to minimize the cost paid by the consumer while maintaining a sufficient level of thermal comfort? This is precisely the objective of the Energy Box's dynamic programming decision method. Ultimately, the open research question is: *Will the aggregate peak electricity demand on the grid be lowered when automated home energy management systems control the thermostat in response to hourly real-time pricing?* Though it is impossible to reach a conclusion to this particular question given the scale and scope of the current Energy Box model, drilling down briefly into the detailed output provides an interesting observation.

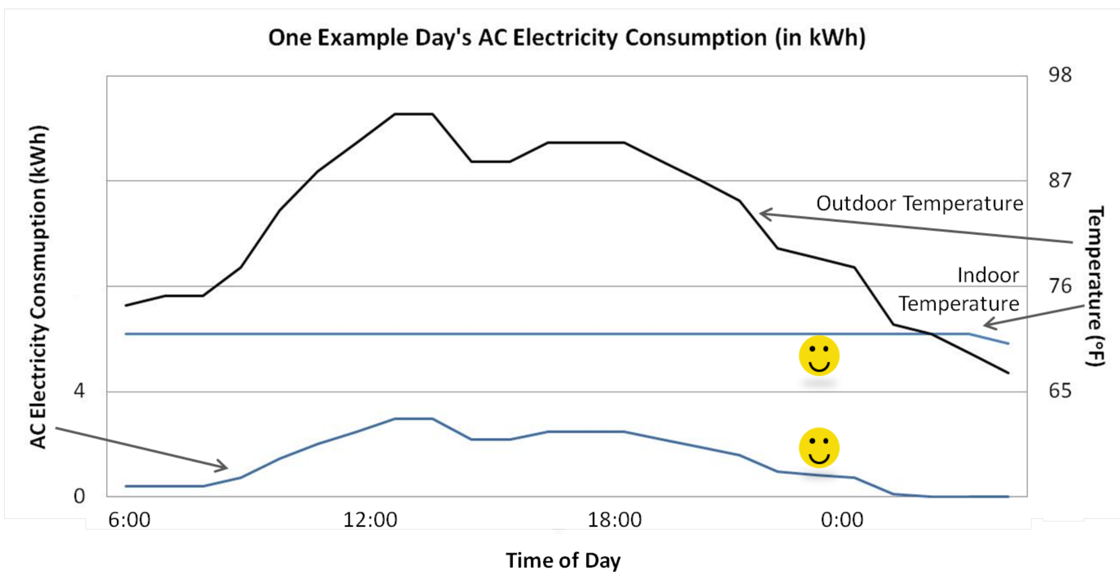

Figure 4-3: Illustration of the correlation between outdoor temperature and electricity consumption (kWh) for air conditioning when the thermostat is fixed at the consumer's preferred set point

To provide a point of reference, first consider the electricity consumption from the air conditioner when the thermostat is fixed to a specific set point. Figure 4-3 shows how the electricity consumption for air conditioning on an example day nicely matches the shape of the outdoor temperature in order to maintain this particular resident's comfortable set point. Figure 4-4 then shows how changing the set point for the entire day to be the resident's tolerable set point decreases the electricity consumption but maintains the same shape.

For the final scenario, consider the Energy Box's dynamic programming algorithm for the air conditioner where the thermostat set point can take on the range of values

$$x^{TCA.AC} \in \left[k^{max.comfortable} - 2, k^{max.comfortable} + 2\right]$$

at each hour with an objective function of minimizing cost while maximizing comfort via the tradeoffs described in section 3.4.2.

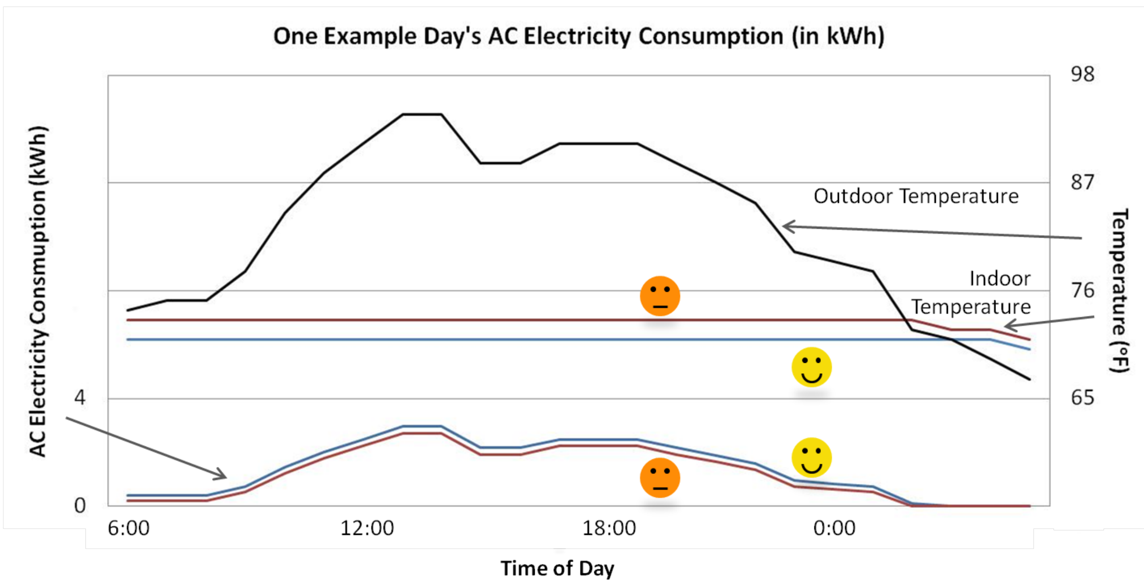

Figure 4-4: Illustration of the correlation between outdoor temperature and electricity consumption (kWh) for air conditioning when the thermostat is fixed at both the consumer's preferred and tolerably comfortable set points

As shown in figure 4-1, there are cost savings that can be obtained by trading away some thermal comfort. But how are these savings obtained? Figure 4-5 shows a typical day using the air conditioner's dynamic programming algorithm under hourly real-time pricing rates with prices known both a day ahead ($FP = 24$) and less than an hour ahead ($FP = 1$), and clearly (a) the peak electricity demand from this individual home has increased instead of decreased, and (b) the air conditioner's electricity consumption is no longer smooth. Instead, it oscillates wildly as the dynamic programming algorithm takes advantage of even the slightest variations in electricity prices. What is happening is that the automated 'enabling technology' with the competing objectives of minimizing cost while maximizing comfort is capturing any and every penny of savings available due to the hourly real-time pricing tariff's price differences. The sensitivity of this oscillatory behavior to the hourly time step will need to be tested in future research, however it is expected that this 'enabling technology'-induced oscillatory behavior will hold for most sub-hourly, hourly and multiple hour time steps.

As mentioned earlier, the traditional objective of time-varying electricity pricing tariffs is to smooth out the aggregate load curve as traditional centralized electricity generation is most efficient when operated at a constant output. Clearly if the behavior from figure 4-5 coincides across a large number of residential customers, then the hourly real-time pricing tariff will have in fact made the aggregate demand curve less smooth than it was before hourly real-time pricing was introduced.

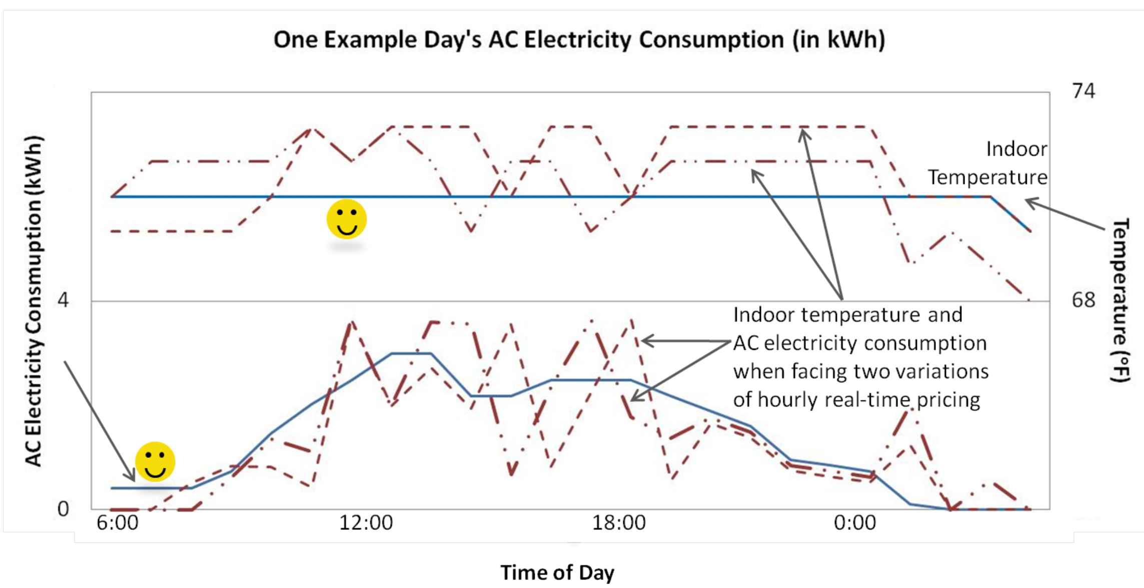

Figure 4-5: Electricity consumption (kWh) from the air conditioner for the fixed, comfortable thermostat set point and for two instances of the dynamic programming output under hourly real-time pricing tariffs

In an independently developed model, Ramchurn et al. [2011a] found exactly this same result with their model of 500 customers. In addition to the oscillations induced during the day, the model by Ramchurn et al. [2011a] shows another behavior induced by hourly real-time prices set a day in advance: all event-based appliances with sufficient flexibility in their starting time congregated at the lowest priced hour, creating the largest peak of all from these 500 customers at a traditionally off-peak hour. With 'enabling technology' automating responses, this is what could happen if appropriate feedback or learning mechanisms (like the one proposed later in the paper by Ramchurn et al. [2011a]) are not included in the tariff and system design.

Implementation of the real-time pricing (RTP) tariff is clearly important as well. Schweppe et al. [1980] and others call for the real-time pricing tariff to have hourly prices set less than an hour in advance, and the behavior induced by this system may indeed lead to a state of homeostasis. However, the desire for certainty in prices has caused some programs to adopt a day-ahead hourly real-time pricing tariff (i.e. RTP with $FP = 24$ instead of RTP with $FP = 1$) [Spees and Lave, 2007, Energy, 2011]. This tariff structure deviates significantly from the real-time pricing economic theory [Schweppe et al., 1980, Borenstein et al., 2002, Borenstein, 2005] as these hourly prices are fixed a day in advance based on expected costs and consumption. There is no apparent feedback mechanism to update the prices should residents change their behavior significantly from what was expected. As such, something like the behavior seen in figure 4-5 may (though may not) pose a problem to the grid when automated home energy management systems like the Energy Box scale up to a large number of consumers. In that case, hourly real-time pricing with prices fixed a day in advance could induce an aggregate load curve that is less smooth than when it started, which is exactly the opposite of the goal of time-varying pricing.

This is most certainly **not** saying that time-varying electricity pricing tariffs should be discarded. It's certainly possible that the oscillatory behavior induced locally will not coincide with each other across many homes, and thus from the grid's perspective, no instabilities or inefficiencies would emerge. In addition, other system designs could be implemented that better integrate time-varying pricing into retail electricity markets. For instance, time-varying pricing might work well with an appropriate bidding structure, feedback mechanism and/or learning mechanism, though the cost of implementing and monitoring such a system certainly needs to be considered [Hammerstrom et al., 2007a, Kok et al., 2008, Wang, 2009]. Similarly, aggregators could help coordinate electricity consumption across a large number of clients, managing the behavior of the thermostat and other controllable appliances to meet comfort objectives while ensuring a desirable aggregate demand curve for the grid, whatever that shape may be [Medina et al., 2010, Brooks et al., 2010, Chao, 2010].

Again, numerous system designs could smartly integrate responsive demand into grid operations either via time-varying pricing or other real-time signals. Ultimately, regional details likely will influence what system design is best for that region [Chao et al., 2006], and as discussed in section 2.4, these system designs should be simulated and tested at large scale to better understand the 'smart grid' dynamics that emerge under each system design [Podmore and Robinson, 2010].

4.3 Mathematical Details for Proving When Coordination Provides No Additional Benefits for a Consumer

Proposition 1. *For appliances and storage devices providing independent services, if the electricity tariff is hourly real-time pricing for electric energy with no demand charges, power limits or inclining block rates, then there is no benefit to coordinated decision making over independent decision making.*

Proof. The following proof will use two event-based appliances, named EBA_1 and EBA_2 for differentiation, to illustrate the arguments. With proper modifications, the result holds for an event-based appliance and thermostatically-controlled appliance, two thermostatically-controlled appliances or any other combination of controllable appliances that provide independent services. A well-defined terminal stage (FC) is also assumed for this proof, though the result will still hold even without this assumption.

The objective of this proof is to show that the result of the coordinated decision process is equivalent to the sum of the results from the two independent decision processes. Using the mathematical formulations from section 4.1, the mathematical equivalent of this objective is

$$\min_{\left(x_t^{EBA_1}\right)_{t=0}^{FC},\left(x_t^{EBA_2}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_1}, x_t^{EBA_1}, S_t^{EBA_2}, x_t^{EBA_2}, W_{t+1}\right)\right] =$$

$$\min_{\left(x_t^{EBA_1}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_1}, x_t^{EBA_1}, W_{t+1}\right)\right] +$$

$$\min_{\left(x_t^{EBA_2}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_2}, x_t^{EBA_2}, W_{t+1}\right)\right].$$

Base Case: As discussed in section 3.3.3, the only possible state for an event-based appliance (EBA) at the terminal stage (FC) is *Not Ready to Run* ($NR2R$) since the Energy Box simulation process guarantees that the event-based appliance will complete its cycle by a consumer-specified flexibility constraint (FC). The value of being in the state $NR2R$ at the terminal stage FC is defined to be 0:

$$V_{FC}^{EBA_1}\left(NR2R_1\right) = 0$$
$$V_{FC}^{EBA_2}\left(NR2R_2\right) = 0$$
$$V_{FC}\left(NR2R_1, NR2R_2\right) = 0.$$

From the terminal stage definitions above, it follows that

$$V_{FC}\left(NR2R_1, NR2R_2\right) = V_{FC}^{EBA_1}\left(NR2R_1\right) + V_{FC}^{EBA_2}\left(NR2R_2\right) = 0,$$

which means that in the base case at the terminal stage, the coordinated decision process of the two event-based appliances is separable into their independent decision processes.

Iterative Case: Assume that the coordinated decision process of two event-based appliances is separable into their independent decision processes at stage $i+1$, i.e.

$$V_{i+1}\left(S_{i+1}^{EBA_1}, S_{i+1}^{EBA_2}\right) = V_{i+1}^{EBA_1}\left(S_{i+1}^{EBA_1}\right) + V_{i+1}^{EBA_2}\left(S_{i+1}^{EBA_2}\right)$$

for all state combinations $\left(S_{i+1}^{EBA_1}, S_{i+1}^{EBA_2}\right)$.

At stage i, there are numerous state combinations of $\left(S_i^{EBA_1}, S_i^{EBA_2}\right)$. However, for any state combination in which either $S_i^{EBA_1}$ or $S_i^{EBA_2}$ is in the state *Not Ready to Run* (*NR2R*) or *Running*, then as discussed in section 3.3.3, there is no decision to make for that particular event-based appliance. For these state combinations, the coordinated decision making process is equivalent to the independent decision process for the event-based appliance that is in the *Idle and Ready to Run* (*R2R*) state, meaning that the coordinated decision process of two event-based appliances is separable into their independent decision processes at stage i for all of these state combinations.

This leaves only the case where both event-based appliances are in the *Idle and Ready to Run* (*R2R*) state, i.e. whenever $\left(S_i^{EBA_1}, S_i^{EBA_2}\right) = (R2R_1, R2R_2)$. In this case, both event-based appliances have the choice of deciding whether to *Start* or to *Wait*. For space constraints in the equations that follow, $St = Start$ and $Wa = Wait$. In order to show that the coordinated decision process is separable into the independent decision processes, consider first the value of being in state $(R2R_1, R2R_2)$:

$$V_i\left(S_i^{EBA_1} = R2R_1, S_i^{EBA_2} = R2R_2\right) = \tag{4.3}$$

$$= min \begin{cases} E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, St_1, R2R_2, St_2, W_{i+1}\right)\right] + V_{i+1}\left(NR2R_1, NR2R_2\right) \\ E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, St_1, R2R_2, Wa_2, W_{i+1}\right)\right] + V_{i+1}\left(NR2R_1, R2R_2\right) \\ E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, Wa_1, R2R_2, St_2, W_{i+1}\right)\right] + V_{i+1}\left(R2R_1, NR2R_2\right) \\ E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, Wa_1, R2R_2, Wa_2, W_{i+1}\right)\right] + V_{i+1}\left(R2R_1, R2R_2\right). \end{cases}$$

With the assumption that

$$V_{i+1}\left(S_{i+1}^{EBA_1}, S_{i+1}^{EBA_2}\right) = V_{i+1}^{EBA_1}\left(S_{i+1}^{EBA_1}\right) + V_{i+1}^{EBA_2}\left(S_{i+1}^{EBA_2}\right)$$

for all state combinations $\left(S_{i+1}^{EBA_1}, S_{i+1}^{EBA_2}\right)$, equation 4.3 becomes

$$V_i\left(S_i^{EBA_1} = R2R_1, S_i^{EBA_2} = R2R_2\right) = \tag{4.4}$$

$$= min \begin{cases} E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, St_1, R2R_2, St_2\right)\right] + V_{i+1}^{EBA_1}\left(NR2R_1\right) + V_{i+1}^{EBA_2}\left(NR2R_2\right) \\ E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, St_1, R2R_2, Wa_2\right)\right] + V_{i+1}^{EBA_1}\left(NR2R_1\right) + V_{i+1}^{EBA_2}\left(R2R_2\right) \\ E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, Wa_1, R2R_2, St_2\right)\right] + V_{i+1}^{EBA_1}\left(R2R_1\right) + V_{i+1}^{EBA_2}\left(NR2R_2\right) \\ E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, Wa_1, R2R_2, Wa_2\right)\right] + V_{i+1}^{EBA_1}\left(R2R_1\right) + V_{i+1}^{EBA_2}\left(R2R_2\right), \end{cases}$$

with the dependence on W_{i+1} dropped from $\hat{C}_{i+1}^{cost}$ for space reasons.

Consider the first element of the minimization portion of equation 4.4 as an example. Under a real-time pricing (RTP) tariff with prices fixed one hour in advance ($FP = 1$), it follows that

$$E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1, St_1, R2R_2, St_2\right)\right] = \tag{4.5}$$

$$= \sum_{grid.demand} \left[\mathbb{P} \left[W_{i+1}^{g.d.} = w_{i+1}^{g.d.} \right] \cdot w_{i+1}^{RTP.price.buy} \left(w_{i+1}^{g.d.} \right) \cdot \left(w^{demand.EBA_1} + w^{demand.EBA_2} \right) \right].$$

Because the summation and discrete probability mass function are all linear functions with respect to stage i, equation 4.5 is separable, and thus

$$E \left[\hat{C}_{i+1}^{Cost} \left(R2R_1, St_1, R2R_2, St_2 \right) \right] = E \left[\hat{C}_{i+1}^{Cost} \left(R2R_1, St_1 \right) \right] + E \left[\hat{C}_{i+1}^{Cost} \left(R2R_2, St_2 \right) \right] \quad (4.6)$$

The same arguments hold for the other three elements of the minimization, and with this observation, equation 4.4 becomes

$$V_i \left(S_i^{EBA_1} = R2R_1, S_i^{EBA_2} = R2R_2 \right) = \quad (4.7)$$

$$= min \begin{cases} E \left[\hat{C}_{i+1}^{Cost} \left(R2R_1, St_1 \right) \right] + E \left[\hat{C}_{i+1}^{Cost} \left(R2R_2, St_2 \right) \right] + V_{i+1}^{EBA_1} \left(NR2R_1 \right) + \\ V_{i+1}^{EBA_2} \left(NR2R_2 \right) \\ E \left[\hat{C}_{i+1}^{Cost} \left(R2R_1, St_1 \right) \right] + E \left[\hat{C}_{i+1}^{Cost} \left(R2R_2, Wa_2 \right) \right] + V_{i+1}^{EBA_1} \left(NR2R_1 \right) + \\ V_{i+1}^{EBA_2} \left(R2R_2 \right) \\ E \left[\hat{C}_{i+1}^{Cost} \left(R2R_1, Wa_1 \right) \right] + E \left[\hat{C}_{i+1}^{Cost} \left(R2R_2, St_2 \right) \right] + V_{i+1}^{EBA_1} \left(R2R_1 \right) + \\ V_{i+1}^{EBA_2} \left(NR2R_2 \right) \\ E \left[\hat{C}_{i+1}^{Cost} \left(R2R_1, Wa_1 \right) \right] + E \left[\hat{C}_{i+1}^{Cost} \left(R2R_2, Wa_2 \right) \right] + V_{i+1}^{EBA_1} \left(R2R_1 \right) + \\ V_{i+1}^{EBA_2} \left(R2R_2 \right) \end{cases}$$

A quick aside will prove a result that will finish the separation of equation 4.7 to prove the original proposition.

Lemma 2.

$$min\left[c_1+c_3,c_1+c_4,c_2+c_3,c_2+c_4\right]=min\left[c_1,c_2\right]+min\left[c_3,c_4\right] \tag{4.8}$$

Proof.

$$\begin{aligned}
min\left[c_1+c_3,c_1+c_4,c_2+c_3,c_2+c_4\right] &= min\left[min\left[c_1+c_3,c_1+c_4,c_2+c_3,c_2+c_4\right]\right]\\
&= min\left[min\left[c_1+c_3,c_1+c_4\right],min\left[c_2+c_3,c_2+c_4\right]\right]\\
&= min\left[c_1+min\left[c_3,c_4\right],c_2+min\left[c_3,c_4\right]\right]\\
&= min\left[c_1,c_2\right]+min\left[c_3,c_4\right]
\end{aligned}$$

□

Replacing the variables in the Lemma as follows

$$\begin{aligned}
c_1 &= E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1,St_1\right)\right]+V_{i+1}\left(NR2R_1\right)\\
c_2 &= E\left[\hat{C}_{i+1}^{Cost}\left(R2R_1,Wa_1\right)\right]+V_{i+1}\left(R2R_1\right)\\
c_3 &= E\left[\hat{C}_{i+1}^{Cost}\left(R2R_2,St_2\right)\right]+V_{i+1}\left(NR2R_2\right)\\
c_4 &= E\left[\hat{C}_{i+1}^{Cost}\left(R2R_2,Wa_2\right)\right]+V_{i+1}\left(R2R_2\right)
\end{aligned}$$

provides the final step necessary to complete the proof:

$$V_i\left(S_i^{EBA_1}=R2R_1,S_i^{EBA_2}=R2R_2\right)= \tag{4.9}$$

$$= min \begin{cases} E\left[\hat{C}^{Cost}_{i+1}\left(R2R_1, St_1\right)\right] + E\left[\hat{C}^{Cost}_{i+1}\left(R2R_2, St_2\right)\right] + V^{EBA_1}_{i+1}\left(NR2R_1\right) + \\ V^{EBA_2}_{i+1}\left(NR2R_2\right) \\ E\left[\hat{C}^{Cost}_{i+1}\left(R2R_1, St_1\right)\right] + E\left[\hat{C}^{Cost}_{i+1}\left(R2R_2, Wa_2\right)\right] + V^{EBA_1}_{i+1}\left(NR2R_1\right) + \\ V^{EBA_2}_{i+1}\left(R2R_2\right) \\ E\left[\hat{C}^{Cost}_{i+1}\left(R2R_1, Wa_1\right)\right] + E\left[\hat{C}^{Cost}_{i+1}\left(R2R_2, St_2\right)\right] + V^{EBA_1}_{i+1}\left(R2R_1\right) + \\ V^{EBA_2}_{i+1}\left(NR2R_2\right) \\ E\left[\hat{C}^{Cost}_{i+1}\left(R2R_1, Wa_1\right)\right] + E\left[\hat{C}^{Cost}_{i+1}\left(R2R_2, Wa_2\right)\right] + V^{EBA_1}_{i+1}\left(R2R_1\right) + \\ V^{EBA_2}_{i+1}\left(R2R_2\right) \end{cases}$$

$$= min \begin{cases} E\left[\hat{C}^{Cost}_{i+1}\left(R2R_1, St_1\right)\right] + V^{EBA_1}_{i+1}\left(NR2R_1\right) \\ E\left[\hat{C}^{Cost}_{i+1}\left(R2R_1, Wa_1\right)\right] + V^{EBA_1}_{i+1}\left(R2R_1\right) \end{cases}$$

$$+ min \begin{cases} E\left[\hat{C}^{Cost}_{i+1}\left(R2R_2, St_2\right)\right] + V^{EBA_2}_{i+1}\left(NR2R_2\right) \\ E\left[\hat{C}^{Cost}_{i+1}\left(R2R_2, Wa_2\right)\right] + V^{EBA_2}_{i+1}\left(R2R_2\right) \end{cases}$$

$$= V_i\left(S^{EBA_1}_i = R2R_1\right) + V_i\left(S^{EBA_2}_i = R2R_2\right).$$

By showing that $V_i\left(S^{EBA_1}_i, S^{EBA_2}_i\right)$ and $V_i\left(S^{EBA_1}_i\right) + V_i\left(S^{EBA_2}_i\right)$ are equivalent for the base case (terminal stage FC) and for the iterative case, this means that

$$\min_{\left(x^{EBA_1}_t\right)^{FC}_{t=0}, \left(x^{EBA_2}_t\right)^{FC}_{t=0}} \sum_{t=0}^{FC} E\left[\hat{C}^{Cost}_{t+1}\left(S^{EBA_1}_t, x^{EBA_1}_t, S^{EBA_2}_t, x^{EBA_2}_t, W_{t+1}\right)\right] =$$

$$\min_{\left(x^{EBA_1}_t\right)^{FC}_{t=0}} \sum_{t=0}^{FC} E\left[\hat{C}^{Cost}_{t+1}\left(S^{EBA_1}_t, x^{EBA_1}_t, W_{t+1}\right)\right] +$$

$$\min_{\left(x_t^{EBA_2}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA_2}, x_t^{EBA_2}, W_{t+1}\right)\right].$$

Therefore, it has been proven that there is no benefit to coordinated decision making over independent decision making for appliances and storage devices providing independent services when the electricity tariff is hourly real-time pricing for electric energy with no demand charges, power limits or inclining block rates.

$\square$

Chapter 5

Energy Box Results for Prosumers

In the future, a majority of electricity customers may no longer be just consumers but instead would be prosumers of electricity, i.e. customers who both produce and consume electricity. Even though residential sources of electricity generation, energy storage systems and plug-in electric vehicles are not common in today's residential settings, the clear interest in integrating these elements into the smart grid led to their inclusion in the Energy Box simulation. This chapter examines whether coordinated decision making between distributed generation (particularly uncontrollable, weather-dependent generation sources) and electricity consumption provides additional benefits over independent decision making. The results discussed in this chapter focus on benefits of coordinating electricity consumption with forecasted electricity generation from a rooftop wind turbine, though the general results certainly would extend to other uncontrollable, weather-dependent sources of electricity generation (like solar photovoltaics).

5.1 Coordinating the Air Conditioner and the Rooftop Wind Turbine

Fgure 5-1 presents some of the results obtained when integrating the air conditioner's dynamic programming algorithm with and without wind forecasts under varying values of $k^{buy.to.sell.scaling.factor}$. Throughout this chapter, the electricity pricing tariff is hourly real-time pricing with prices fixed a day in advance ($FP = 24$) so that the primary driver of uncertainty comes only from the wind forecast. Similar results were obtained for hourly real-time pricing with prices fixed an hour in advance ($FP = 1$).

The first comfort versus savings tradeoff curve in figure 5-1 provides a reference case when no rooftop wind turbine is included in the simulation. This curve is equivalent to the comfort versus cost tradeoff curve in figure 4-1 from chapter 4 except for the shift in focus from cost to savings.

Returning to figure 5-1, the next two comfort versus savings tradeoff curves (moving from left to right) are when $W^{price.sell} = 0$ and are the results without and with the wind forecast. In this scenario, any unused electricity generated by the rooftop wind turbine is effectively 'lost'. Nonetheless, adding a rooftop wind turbine even without a wind forecast dominates the case with no wind turbine as the savings essentially double. Having a reasonable forecast of expected wind speeds further improves the realized savings. The relative savings observed across the three forecast structures - perfect forecasts (PF), full distribution (FD), and median value of the distribution (MV) - originally presented in section 3.3.3 were quite similar, so only the results from the simulations using perfect forecasts (PF) are presented throughout this chapter.

Proceeding to the next two comfort versus savings tradeoff curves (again moving from left to right in figure 5-1), the results for without and with the PF wind forecast when $W^{price.sell} = 0.5 \cdot W^{price.buy}$ are shown. Additional realized savings from having the forecasted wind speeds relative to not having the forecasted wind speeds is noticeably smaller for $W^{price.sell} = 0.5 \cdot W^{price.buy}$ than when $W^{price.sell} = 0$. Overall, benefits of coordinating

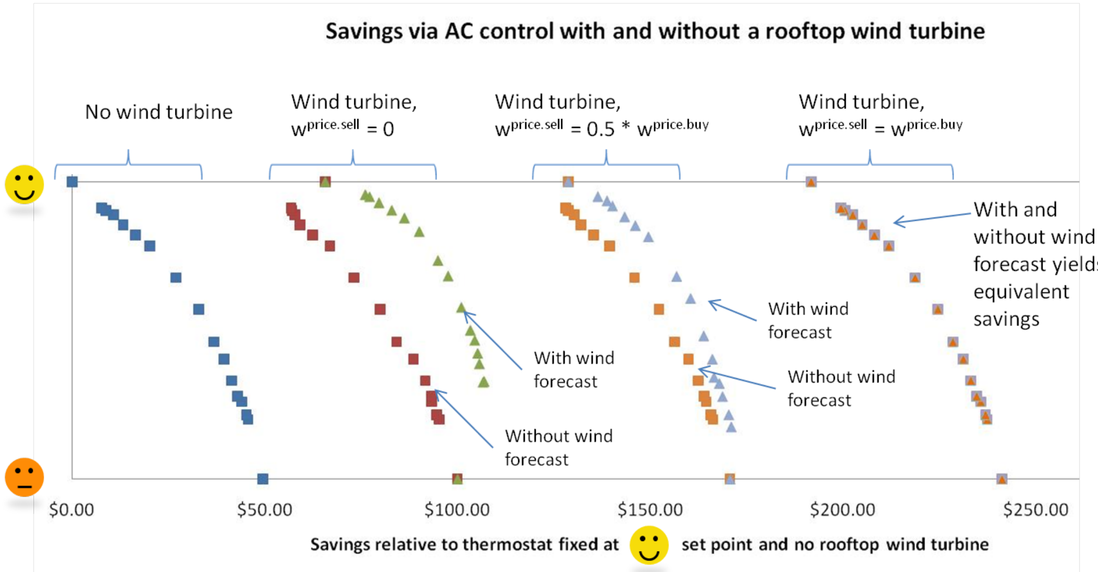

Figure 5-1: Coordinated response of the air conditioner with a rooftop wind turbine: includes results from three relationships between $W^{price.sell}$ and $W^{price.buy}$

air conditioning consumption with forecasted generation from the wind turbine decreases as $k^{buy.to.sell.scaling.factor}$ increases from 0 to 1.

The final comfort versus savings tradeoff curve is actually two equivalent curves and captures what happens in the linear price case of $W^{price.sell} = W^{price.buy}$, i.e. when $k^{buy.to.sell.scaling.factor} = 1$. In this case, there is **no benefit** to having a forecast of the wind speed. The thermostat set point decisions made by the air conditioner's dynamic programming algorithm when $W^{price.sell} = W^{price.buy}$ are exactly the same as the decisions made by the air conditioner's dynamic programming algorithm when no rooftop wind turbine is included in the simulation. In other words, the air conditioner's dynamic programming algorithm would decide to do exactly what it did without a wind turbine included in the decision process. Thus, there is **no benefit** to coordinating electricity usage with forecasted weather-dependent distributed generation when $W^{price.sell} = W^{price.buy}$.

The proof discussed in section 5.3 illustrates the theory behind the simulation results from figure 5-1. These results hold for all of the appliances and decision structures discussed in chapter 3, and many simulation runs numerically support these results as well.

Recent related research from Pedrasa et al. [2010] with an independently developed model found similar numerical results using Particle Swarm Optimization, suggesting that these results hold for other optimization methods, as one would expect. One note is that the structure of a feed-in tariff for distributed generation may differ from the $W^{price.sell} = k^{buy.to.sell.scaling.factor} \cdot W^{price.buy}$ structure used here, and the exact results given those feed-in tariffs would depend on the relationship between $W^{price.sell}$ and $W^{price.buy}$.

Similarly, these results would need to be revisited if other contribution functions beyond C^{cost} and $C^{comfort}$ (defined in sections 3.3.3 and 3.4.2) were included in the objective function. For instance, a competing contribution function with a goal of maximizing the electricity used from the local wind turbine would potentially benefit from coordinated control of appliances at the home. This Energy Box model did not include a contribution function for maximizing the electricity used from the local wind turbine, though this would be a straightforward addition if desired in a future Energy Box implementation.

5.2 Coordinating the Controllable Appliances with the Rooftop Wind Turbine

Adding a dishwasher to the mix, consider only the case where $W^{price.sell} = 0$. The comfort and savings results from coordination between the dishwasher, air conditioner and wind forecasts for various values of k^{warm} are shown in figure 5-2.

The comfort versus savings tradeoff curve with red square markers captures the results from independent decision making without wind forecasts (note: this is the same curve from figure 5-1 with red square markers).

The comfort versus savings tradeoff curve with green triangle markers captures the results for independent decision making with wind forecasts (note: this is the same curve from figure 5-1 with green triangle markers).

The tails extending out to the right with circle markers are the results from coordinated

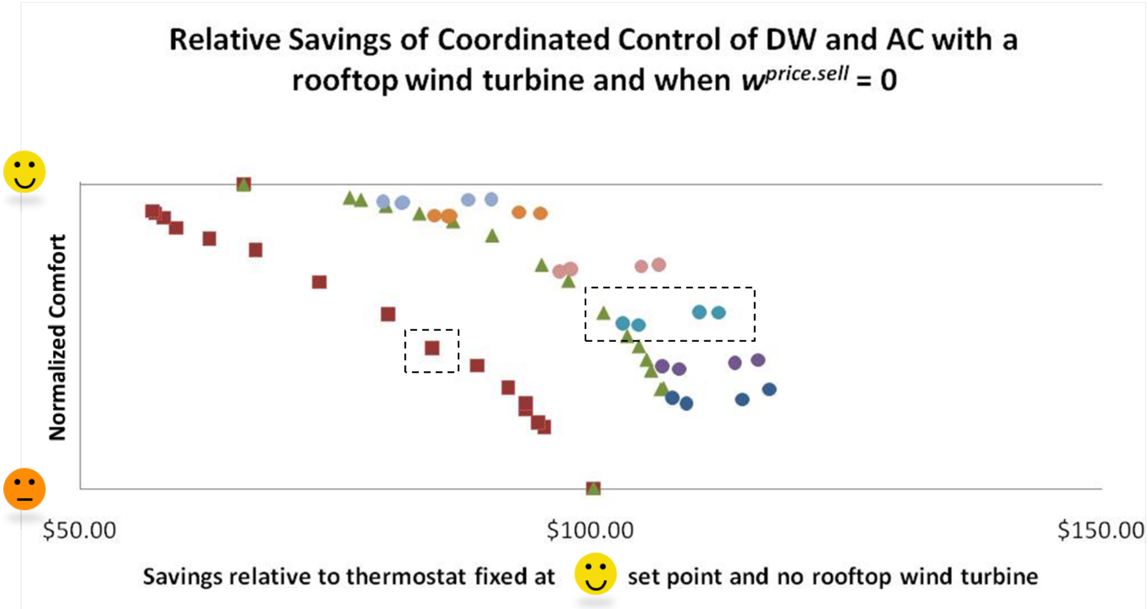

Figure 5-2: Coordinated response of the dishwasher and air conditioner with a rooftop wind turbine: an overview of many values of the parameter k^{warm} controlling the comfort versus cost tradeoff

decisions between the dishwasher and air conditioner with the wind forecast for a subset of values of the cost versus comfort tradeoff parameter k^{warm}.

The variation of coordination benefits is easier to see in figure 5-3. As is labeled in the figure, the method of coordination has a clear affect on the amount of additional benefits realized from coordinated decision making, with a ranking of most additional benefits to least additional benefits being:

1. **Joint** dishwasher & air conditioner dynamic programming algorithm

2. The air conditioner's dynamic programming algorithm **plans around** known electricity consumption for dishwashing

3. The air conditioner's dynamic programming **reacts** to previously unknown electricity consumption for dishwashing

Just as benefits diminished as $k^{sell.to.buy.scaling.factor}$ increases from 0 to 1 in figure 5-1, the magnitude of the benefit from coordinated decision making decreases in the same way for the dishwasher and air conditioner as $k^{sell.to.buy.scaling.factor}$ increases from 0 to 1.

The results illustrated for two controllable appliances and a wind turbine in figure 5-3 also hold for three controllable appliances and a wind turbine, and thus it is reasonable to assume that the same qualitative results hold for any number of controllable appliances, though there will likely be diminishing returns for each additional appliance added into the coordinated decision methods. Computation requirements and the complexity of the joint decision method in particular increases exponentially as more appliances are added. A sensitivity analysis in future research will identify the right balance of implementing coordinated decision methods given the expected additional benefits in terms of comfort and cost.

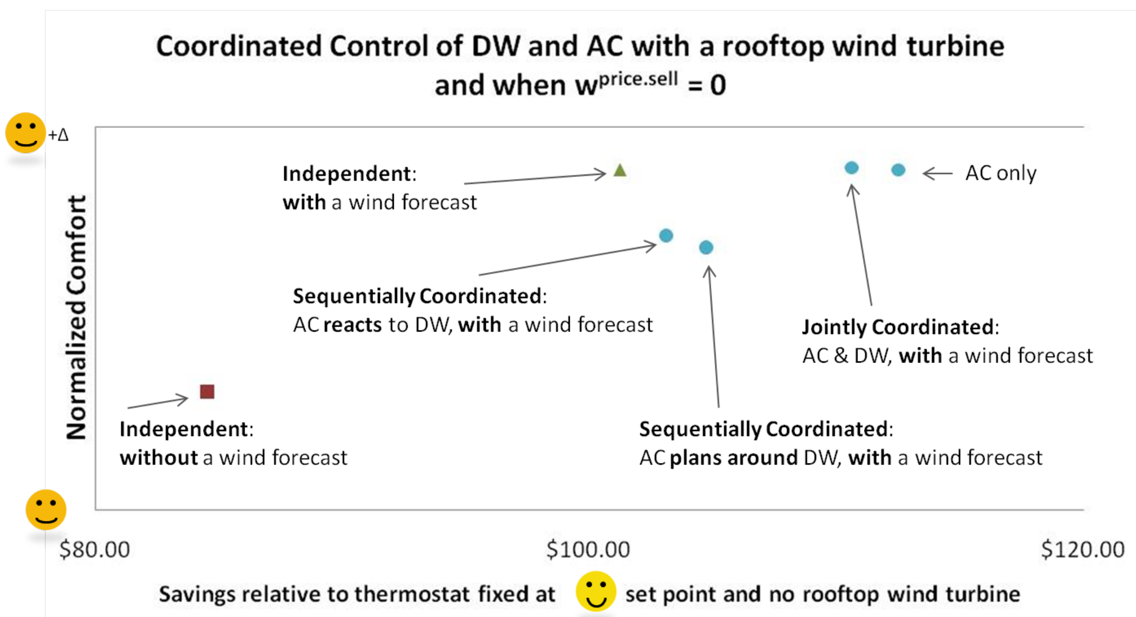

Figure 5-3: Coordinated response of the dishwasher and air conditioner with a rooftop wind turbine: details from one value of the parameter k^{warm} controlling the comfort versus cost tradeoff

5.3 Mathematical Details for Proving When Coordination Provides No Additional Benefits for a Prosumer

Proposition 3. *There is **no benefit** to coordinating electricity usage with forecasted weather-dependent distributed generation (DG) when* $W^{price.sell} = W^{price.buy}$.

Proof. This proposition holds for all types of appliances and is illustrated here for a thermostatically-controlled appliance. Consider the mathematical representation of the dynamic programming algorithm for a thermostatically-controlled appliance:

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{\hat{C}_{t+1}^{Cost}\left(S_t^{TCA}, x_t^{TCA}, W_{t+1}\right)\right\}.$$

Including a wind turbine's locally generated electricity into this algorithm is equivalent to calculating the value of the $\hat{C}_{t+1}^{Cost}\left(S_t^{TCA}, x_t^{TCA}, W_{t+1}\right)$ contribution function at each stage t in the following way:

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot \max\left[W_t^{net.demand}, 0\right] + W_t^{price.sell} \cdot \max\left[W_t^{net.generation}, 0\right]\right\}$$

where

$$W_t^{net.demand} = -W_t^{net.generation}$$

and

$$W_t^{net.demand} = W_t^{demand.TCA}\left(S_t^{TCA}, x_t^{TCA}\right) - W_t^{generation.DG.wind}\left(W_t^{wind.speed}\right).$$

Using $W_t^{net.demand} = -W_t^{net.generation}$, we obtain the next two steps:

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot \max\left[W_t^{net.demand}, 0\right] + W_t^{price.sell} \cdot \max\left[-W_t^{net.demand}, 0\right]\right\}$$

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot \max\left[W_t^{net.demand}, 0\right] + W_t^{price.sell} \cdot \min\left[W_t^{net.demand}, 0\right]\right\}.$$

Since $W_t^{price.buy} = W_t^{price.sell}$ is assumed in this case, we then have

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot \max\left[W_t^{net.demand}, 0\right] + W_t^{price.buy} \cdot \min\left[W_t^{net.demand}, 0\right]\right\}$$

which is the same as

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot \left(W_t^{net.demand} + 0\right)\right\}.$$

Substituting in for $W_t^{net.demand}$ (and leaving out the dependencies due to space constraints) yields

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot \left(W_t^{demand.TCA} - W_t^{generation.DG.wind}\right)\right\},$$

which expands to

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot W_t^{demand.TCA} - W_t^{price.buy} \cdot W_t^{generation.DG.wind}\right\}.$$

Since $W_t^{price.buy} \cdot W_t^{generation.DG.wind}$ does not depend on x_t^{TCA}, the right-hand term can be pulled out of the minimization process:

$$\min_{\left(x_t^{TCA}\right)_{t=0}^{DH}} \left[\sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot W_t^{demand.TCA}\right\}\right] - \sum_{t=0}^{DH} E\left\{W_t^{price.buy} \cdot W_t^{generation.DG.wind}\right\}.$$

Hence, in the end we have the thermostatically-controlled appliance's dynamic programming process separated from the expected revenue from the local wind turbine, which means that there is no benefit to coordinating electricity usage with forecasted weather-dependent distributed generation (DG) when $W^{price.sell} = W^{price.buy}$.

$\square$

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Chapter 6

Energy Box Conclusions and Future Work

6.1 Summary of Key Results

As discussed in chapter 1, the main motivation of the Energy Box research was to design, construct and test a prototype software architecture that can accommodate a wide variety of local energy management environments and user preferences. Hopefully it will serve as a platform for continued research into local energy management algorithms. A few extension ideas are discussed in section 6.2.

One of the specific research questions studied in depth for this dissertation was determining when **coordinated** control of appliances and devices at a single residence or business provides additional benefits to the consumer relative to independent control of appliances and devices. This focus evolved during examination of the dissertation results. A summarization of these results are illustrated in figure 6-1.

It is well established in the literature that there are benefits to coordination between appliances at a single home when the electricity pricing tariff includes a demand charge (i.e. a price for power (\$/kW)) or involves inclining block rates (i.e. where the price

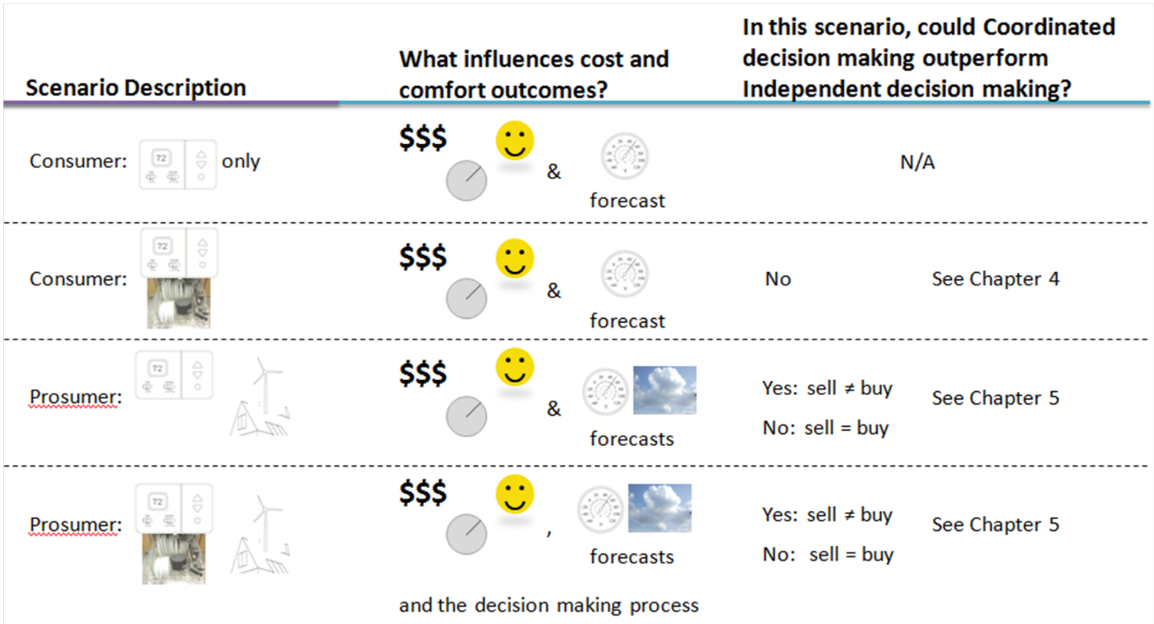

Figure 6-1: Summary of Energy Box Results

for electric energy (\$/kWh) increases as the total amount of electric energy consumed increases). Similarly, the literature establishes a clear benefit to coordinating between appliances at a single home whenever the electricity system includes technical constraints such as power limits (i.e. a limit on electric power consumption that, if exceeded for too long, causes the house to be blacked out).

With these results well established, this dissertation focused on scenarios where only the price for electric energy (\$/kWh) is included in the electricity pricing tariff. It is assumed that the price for electric energy could be time-varying. Under this type of electricity pricing tariff, whenever residents are only consumers of electricity (i.e. the resident does not have local sources of electricity generation nor storage devices that could sell electricity back to the grid), then there are no additional benefits from coordinating decisions across appliances and devices within a home, as was discussed in Chapter 4. In other words, for electric consumers under certain time-varying pricing scenarios, appliances can be optimally controlled one at a time, independent of each other. To be clear, the optimal decisions will most likely shift electricity consumption in response to the time-varying prices, such as shifting schedulable loads to the cheapest-priced hour of the day. However, the optimal decision made for one appliance in no way affects the optimal decision for another appliance.

On the other hand, coordinating decisions between appliances at a home could provide additional benefits relative to independent control of appliances and devices if a resident both consumes and produces electricity. These benefits are realized, as discussed in Chapter 5, when the price for selling electric energy is not equivalent to the price for buying electric energy. However, when the selling price and the buying price for electricity are equal, the benefits of coordination evaporate.

Returning to the case when the price for selling electric energy is not equivalent to the price for buying electric energy, then the results from Chapter 5 again demonstrate that coordination arguably provides additional benefits over independent decision making. Summarizing the results illustrated in figure 5-3 from Chapter 5 for the case of a dishwasher, an air conditioner and a rooftop wind turbine, the ranking of most to least improvement realized from coordination over independent decision methods is

1. the **joint** dynamic programming decision method of the air conditioner's thermostat and the dishwasher with a wind forecast,
2. the air conditioner's dynamic programming decision method with a wind forecast **plans around** known dishwasher starting times
3. the air conditioner's dynamic programming decision method with a wind forecast **reacts** to dishwasher starting times, and
4. the air conditioner's dynamic programming decision method makes its decisions using a wind forecast but with no knowledge of when the dishwasher runs

6.2 Further Energy Box-related Research

Stemming from this initial Energy Box research, three broad categories for further research have been identified. The first is expanding the capabilities of the single-home Energy

Box model. Some of the potential areas for expansion are listed here.

- Implement and compare other decision making methods under uncertainty with the results from dynamic programming.
- Implement and integrate decision making methods for all appliances, storage devices and sources of distributed electricity generation.
- Develop joint decision making algorithms for three or more appliances at a time.
- Use non-intrusive load monitoring and/or other similar methods to detect when uncontrollable loads start up so that, when beneficial, the Energy Box can update its decisions for controllable appliances to **react** to the knowledge that an uncontrollable load will now be consuming electricity [Leeb et al., 1995, Norford and Leeb, 1996].
- Collect and identify patterns in daily consumption to allow the Energy Box to **plan around** expected consumption using this historical information [Abreu et al., 2010].
- Integrate real-time occupancy and location data (e.g. via GPS information from mobile phones) into the algorithms so that the Energy Box can adapt to the inherent variability in most people's daily activities [Gupta et al., 2009].

The second research direction would be to integrate the dynamics of thousands (or more) of Energy Boxes into smart grid simulations to determine the best way to coordinate electricity demand **across** homes and businesses. The uncertain aggregate dynamics of automated responses from many individual residents' 'enabling technology' in response to time-varying pricing tariffs and/or other new control structures for the smart grid leads Podmore and Robinson [2010] and others to call for the need to develop large-scale smart grid simulators to test these options at scale before rolling them out to the physical system [Podmore and Robinson, 2010, Kok et al., 2008, 2005, Chassin et al., 2008, Burke and Auslander, 2008]. With these simulators, researchers will be able to estimate the aggregate effect of large penetrations of Energy Boxes and other home energy management systems on the smart grid and the accompanying market structures.

Still other research questions remain to be addressed.

Will hourly time-varying pricing tariffs elicit the desired shape of aggregate electricity demand when prices are fixed a day in advance? Results from Ramchurn et al. [2011a] suggest that there is significant potential for unintended consequences under such a tariff.

What if the hourly time-varying prices were fixed less than an hour in advance? This could alleviate some of the problems stemming from fixing hourly prices of electricity a day in advance, but will residents and businesses be willing to deal with such price uncertainty from one hour to the next?

Alternatively, could strategies that are not based on time-varying pricing be developed for coordinating electricity demand across homes and businesses? For example, what if a sufficiently large number of residents were willing to participate in a program that coordinated the running of dishwashers overnight? Upon loading the dishwasher, the resident could hit a 'run overnight' button that would select a starting time at random during the overnight hours. The distribution from which this starting time is chosen could be shaped each night by the program coordinator to induce whatever shape is desired in aggregate from all of the dishwashers. For participating in this program, each resident could receive a rebate for each time (s)he uses the 'run overnight' feature.

A properly designed smart grid simulator would be able to test and compare the aggregate effect of 'enabling technologies' like the Energy Box when responding to time-varying electricity pricing tariffs and/or other electricity service structures like the ones listed above and in section 2.4. The estimated benefits of these smart grid designs would also need to be compared with the expected costs of implementing that system when determining the best approaches for coordinating electricity demand across many homes.

Whether testing methods for coordinating electricity demand **within** a home or **across** many homes, models and simulators are paramount to a better understanding of what might happen throughout the ongoing smart grid evolution.

However, what is arguably the most important research direction will involve implementing and testing these automated decision making methods in homes of volunteers to determine if the automated responses made by the Energy Box or other 'enabling technologies' meet the residents' expectations of comfort and cost while allowing the residents to maintain (or improve) their lifestyle. The best ideas from a technical and grid management perspective may never realize their full potential at scale if residents and businesses feel that the energy management service provided is undesirable. For this reason along with the others discussed above, further research is necessary to continue investigating the technical, management and social challenges of the smart grid evolution.

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Appendix A

Energy Box Computer Code

The Energy Box model developed for this dissertation is implemented in Matlab and Excel, with the data processing in Matlab and data visualization in Excel. For anyone interested in the code and data sets, please contact the author at dlivengo 'at' alum 'dot' mit 'dot' edu.

Included in the files is a copy of the sequence of random numbers used in the model to generate the 50 example days used in creating the figures from chapters 4 and 5. An example of that data is presented here in Table A.1. The Markov matrices used for modeling the weather and demand random variables are also included in Appendices B and C.

Table A.1: Energy Box simulated Random Numbers

Simulated Day Number	Simulated Hour	Grid-level Demand Simulated Value	Simulated Price of Electric Energy ($/kWh)	Simulated Outdoor Temp. (^oF)	Sim. Wind Speed (m/s)	Grid-level Demand Random Number Sample Sequence	Outdoor Temperature Random Number Sample Sequence	Wind Speed Random Number Sample Sequence
1	6:00	13891	26.00	75	4	0.640558837	0.814723686	0.92274457
1	7:00	16099	34.00	76	4	0.658774142	0.905791937	0.800372092
1	8:00	17715	41.50	75	3	0.675330331	0.126986816	0.285946856
1	9:00	18593	44.50	76	3	0.744557714	0.913375856	0.543663233
1	10:00	19697	49.00	77	6	0.842177573	0.632359246	0.984776237
1	11:00	20571	54.00	78	7	0.516657168	0.097540405	0.715678067
1	12:00	21018	56.00	79	8	0.151868701	0.278498219	0.838969597
1	13:00	21172	56.00	82	8	0.380664274	0.546881519	0.433260561
1	14:00	21199	56.00	86	8	0.821019401	0.957506835	0.470624716
1	15:00	21256	56.00	90	8	0.171364379	0.964888535	0.560713411
1	16:00	21290	56.00	90	7	0.329975281	0.157613082	0.269091544
1	17:00	21783	58.00	92	8	0.966471987	0.970592782	0.749018468
1	18:00	21295	56.00	94	8	0.806292597	0.957166948	0.503887773
1	19:00	20703	54.00	94	8	0.22218793	0.485375649	0.646809666
1	20:00	21289	56.00	94	7	0.999773123	0.800280469	0.307745582
1	21:00	20089	52.00	87	5	0.063738697	0.141886339	0.138724636
1	22:00	18147	43.00	84	5	0.425483118	0.421761283	0.475572934
1	23:00	16138	34.00	83	4	0.404338152	0.915735525	0.362459281
1	0:00	14655	29.00	82	5	0.400292884	0.79220733	0.788113428
1	1:00	13766	26.00	82	6	0.111922644	0.959492426	0.780295821
1	2:00	13255	25.00	81	6	0.424310773	0.655740699	0.668512214
1	3:00	12988	24.00	77	4	0.613545883	0.035711679	0.13350386
1	4:00	13329	25.00	77	2	0.988061286	0.849129306	0.021555887
1	5:00	13996	26.00	78	2	0.219900779	0.933993248	0.559840706
2	6:00	15622	32.00	78	2	0.354081078	0.678735155	0.300819018
2	7:00	17545	41.50	78	4	0.266241879	0.757740131	0.939409714
2	8:00	18907	44.50	78	6	0.291498034	0.743132468	0.980903636
2	9:00	19858	49.00	77	5	0.188389542	0.39222702	0.286620389
2	10:00	19470	47.00	78	6	0.022859624	0.65547789	0.800820287
2	11:00	20063	52.00	79	7	0.449404182	0.171186688	0.896111351
2	12:00	20396	52.00	82	7	0.243640193	0.706046088	0.597526577
2	13:00	20723	54.00	82	8	0.868726545	0.031832846	0.884016736
2	14:00	20766	54.00	84	9	0.528610767	0.276922985	0.943731541
2	15:00	20675	54.00	80	9	0.914135168	0.046171391	0.549158087
2	16:00	22165	59.00	78	10	0.973930177	0.097131781	0.728386825
2	17:00	21842	58.00	80	9	0.585425959	0.823457828	0.576758298
2	18:00	19635	49.00	81	5	0.118975383	0.694828623	0.025857471
...	...	...	...	...	...	...	...	...

Appendix B

Weather Modeling Details

A few examples of the wind speed Markov chain matrices introduced in section 3.3.3 are introduced here. In particular, the transition matrix from midnight to 1:00 AM ($P_{0h,1h}^{wind.speed}$) and the transition matrix from 1:00 AM to 2:00 AM ($P_{1h,2h}^{wind.speed}$) are shown in Tables B.1 and B.2, respectively. The other 22 hourly Markov chain matrices are available as part of the Energy Box computer code as discussed in Appendix A. The outdoor temperature Markov chain matrices are also included in the Energy Box computer code, which are too large to present here.

For both wind speeds and outdoor temperatures, the weather forecast is generated in the following process, illustrated here using wind speeds. Say for instance that the current time is 6:00 AM. The simulated wind speed for the hour from 5:00 AM to 6:00 AM is used as the initial condition $w_0^{wind.speed}$, where the 0 in this case represents the current moment in time, as opposed to $0h$, which represents the midnight hour.

The forecasted distribution of wind speeds for all future hours in the model are then calculated as follows:

$$W_1^{wind.speed} = P_{6h,7h}^{wind.speed} * w_0^{wind.speed}$$

$$
\begin{aligned}
W_2^{wind.speed} &= P_{7h,8h}^{wind.speed} * W_1^{wind.speed} \\
&= P_{7h,8h}^{wind.speed} * P_{6h,7h}^{wind.speed} * w_0^{wind.speed} \\
&= \left(\prod_{i=6h}^{7h} P_{i,i+1}^{wind.speed} \right) * w_0^{wind.speed}
\end{aligned}
$$

For any future hour t, $W_t^{wind.speed}$ is calculated via

$$
W_t^{wind.speed} = \left(\prod_{i=6h}^{t-1} P_{i,i+1}^{wind.speed} \right) * w_0^{wind.speed}
$$

Continuing with this example, when the Energy Box simulation process steps forward in time one time step (an hour in this case), the simulated 'actual' wind speed for the 6:00 AM to 7:00 AM hour is chosen via $W_1^{wind.speed}$ from above and the random number generated for that hour from the extended version of Table A.1. After the Energy Box simulation process steps forward in time one hour to 7:00 AM, the same process from before is used with $w_0^{wind.speed}$ now reflecting the simulated wind speed for the 6:00 AM to 7:00 AM hour:

$$
W_1^{wind.speed} = P_{7h,8h}^{wind.speed} * w_0^{wind.speed}
$$

$$
\begin{aligned}
W_2^{wind.speed} &= P_{8h,9h}^{wind.speed} * W_1^{wind.speed} \\
&= P_{8h,9h}^{wind.speed} * P_{7h,8h}^{wind.speed} * w_0^{wind.speed} \\
&= \left(\prod_{i=7h}^{8h} P_{i,i+1}^{wind.speed} \right) * w_0^{wind.speed}
\end{aligned}
$$

$$
W_t^{wind.speed} = \left(\prod_{i=7h}^{t-1} P_{i,i+1}^{wind.speed} \right) * w_0^{wind.speed}
$$

This process is repeated throughout the Energy Box simulation process for each hour of each simulated day to determine the wind speed forecasts used by the decision methods.

Again, the same process is used for modeling outdoor temperatures and their forecasts, with all necessary Markov chain matrices included in the Energy Box computer code upon request.

Table B.1: Example Wind Speed Markov Chain Matrix: Midnight to 1AM

0:00 to 1:00	0 m/s	1 m/s	2 m/s	3 m/s	4 m/s	5 m/s	6 m/s	7 m/s	8 m/s	9 m/s	10 m/s	11 m/s	12 m/s	13 m/s	14 m/s	15 m/s	... ...
0 m/s	0.17	0.00	0.50	0.25	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
1 m/s	0.00	0.50	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
2 m/s	0.06	0.04	0.31	0.45	0.10	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
3 m/s	0.03	0.00	0.27	0.49	0.13	0.05	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
4 m/s	0.01	0.00	0.06	0.27	0.38	0.22	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
5 m/s	0.01	0.00	0.01	0.10	0.30	0.39	0.16	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
6 m/s	0.00	0.00	0.02	0.04	0.09	0.35	0.36	0.10	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	...
7 m/s	0.00	0.00	0.00	0.01	0.03	0.18	0.39	0.27	0.11	0.02	0.00	0.00	0.00	0.00	0.00	0.00	...
8 m/s	0.00	0.00	0.00	0.04	0.04	0.04	0.21	0.31	0.29	0.06	0.02	0.00	0.00	0.00	0.00	0.00	...
9 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.18	0.32	0.23	0.14	0.00	0.00	0.00	0.00	0.00	...
10 m/s	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.20	0.40	0.00	0.20	0.00	0.00	0.00	0.00	0.00	...
11 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.25	0.00	0.25	0.00	0.25	0.00	0.00	0.00	0.00	...
12 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	...
13 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.50	0.00	0.00	...
14 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	...
15 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Table B.2: Example Wind Speed Markov Chain Matrix: 1AM to 2AM

1:00 to 2:00	0 m/s	1 m/s	2 m/s	3 m/s	4 m/s	5 m/s	6 m/s	7 m/s	8 m/s	9 m/s	10 m/s	11 m/s	12 m/s	13 m/s	14 m/s	15 m/s	... ...
0 m/s	0.27	0.00	0.55	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
1 m/s	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
2 m/s	0.09	0.03	0.47	0.31	0.04	0.03	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
3 m/s	0.03	0.00	0.19	0.40	0.28	0.08	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	...
4 m/s	0.01	0.00	0.05	0.28	0.44	0.14	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
5 m/s	0.00	0.00	0.01	0.10	0.29	0.37	0.17	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	...
6 m/s	0.00	0.00	0.00	0.01	0.10	0.34	0.37	0.12	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	...
7 m/s	0.00	0.00	0.00	0.03	0.04	0.18	0.35	0.32	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.00	...
8 m/s	0.00	0.00	0.00	0.02	0.02	0.07	0.14	0.39	0.27	0.05	0.05	0.00	0.00	0.00	0.00	0.00	...
9 m/s	0.00	0.00	0.08	0.00	0.08	0.17	0.08	0.17	0.33	0.08	0.00	0.00	0.00	0.00	0.00	0.00	...
10 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.50	0.00	0.17	0.17	0.00	0.00	0.00	0.00	...
11 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	...
12 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	...
13 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	...
14 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	...
15 m/s	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Appendix C

Time-Varying Pricing Model Details

As mentioned in section 3.3.3, modeling the electricity demand required some approximations as the exact values of electricity demand varied widely each hour of each day. As a reminder, grid-level electricity demand information was collected from the Independent System Operator of New England (ISO-NE), which is the entity that oversees the operation of electricity markets in the New England area. From the ISO-NE website[1], hourly grid-level electricity demand information from 1993 to 2002 was collected and used to create this Markov model.

For each hour of each summer day, the grid-level electricity demand data was separated into seven 'bins' as defined here. First, the minimum, median (or expected value (EV)) and maximum values were found for each hour of each day of the week. For each hour of each day, the 'bins' were defined using the minimum, EV and maximum values for that hour as follows:

$$\Delta_l = \frac{2 * (EV - minimum)}{7}$$

[1] http://www.iso-ne.com/

$$\Delta_h = \frac{2 * (maximum - EV)}{7}$$

$$\text{Bins} = \begin{cases} \left[minimum, EV - \frac{5\Delta_l}{2}\right) \\ \left[EV - \frac{5\Delta_l}{2}, EV - \frac{3\Delta_l}{2}\right) \\ \left[EV - \frac{3\Delta_l}{2}, EV - \frac{\Delta_l}{2}\right) \\ \left[EV - \frac{\Delta_l}{2}, EV + \frac{\Delta_h}{2}\right) \\ \left[EV + \frac{\Delta_h}{2}, EV + \frac{3\Delta_h}{2}\right) \\ \left[EV + \frac{3\Delta_l}{2}, EV + \frac{5\Delta_h}{2}\right) \\ \left[EV + \frac{5\Delta_l}{2}, maximum\right] \end{cases}$$

The corresponding representative values used for each bin (and used as the bin labels from here onward) are

$$\text{Representative values (and bin labels)} = \begin{cases} EV - 3\Delta_l \\ EV - 2\Delta_l \\ EV - \Delta_l \\ EV \\ EV + \Delta_h \\ EV + 2\Delta_h \\ EV + 3\Delta_h \end{cases}$$

From the ten years of grid-level demand data collected from ISO-NE, the resulting distribution of data in each bin is shown in Table C.1. The balance of data in each bin was deemed sufficient, with a slight emphasis on the median bin.

The representative values for each hour of each day were then calculated, with two exam-

Table C.1: Demand Bin Distribution for ISO-NE Demand data from 1993-2002

Year	Percentage of data points in each bin for each year of data						
	EV - $3\Delta_l$	EV - $2\Delta_l$	EV - Δ_l	EV	EV + Δ_h	EV + $2\Delta_h$	EV + $3\Delta_h$
1993	12%	10%	18%	24%	15%	9%	12%
1994	19%	9%	13%	22%	12%	12%	14%
1995	14%	13%	13%	22%	10%	13%	15%
1996	13%	10%	14%	24%	11%	12%	15%
1997	12%	11%	16%	23%	15%	10%	12%
1998	12%	14%	15%	19%	12%	11%	18%
1999	22%	9%	10%	20%	12%	11%	15%
2000	15%	11%	14%	25%	15%	8%	12%
2001	16%	16%	10%	21%	17%	8%	13%
2002	17%	12%	12%	23%	11%	8%	18%
Cumulative 1993-2002	15%	12%	14%	22%	13%	10%	14%

ples shown in Tables C.2 and C.3 for Sunday and Monday. As can be seen, the grid-level demand on Monday is significantly higher than the grid-level demand on Sunday, which is consistent across all weekdays versus weekend days. The representative values for the other five days are included in the Energy Box computer code upon request.

Once the bins were set, the Markov transition matrices were calculated by counting the transitions from one bin to another from one hour to the next from the ISO-NE data. Ultimately, 168 ($7 \cdot 24$) Markov matrices were created to reflect each hour's transition to the next across the entire week. Two examples of these Markov chain matrices are illustrated in Table C.4, with the other 166 included in the Energy Box computer code upon request.

Last but not least, with the model of grid-level electricity demand in place, the final step for creating the hourly real-time pricing model for the Energy Box was to return to ISO-NE's website[2] and collect a year's worth of hourly prices of electricity from the ISO-NE wholesale market for the year 2002 (which was the most recent year of data available on their website at the time of collection). This data was then used to create the hourly real-time pricing tariff for the model by mapping grid-level demand (in MW) to price (in \$/MW), as seen in Table C.5. This table was created by stepping through the 2002

[2]http://www.iso-ne.com/

Table C.2: Representative Demand Values for Each Hour on Sundays

Sunday	EV - $3\Delta_l$	EV - $2\Delta_l$	EV - Δ_l	EV	EV + Δ_h	EV + $2\Delta_h$	EV + $3\Delta_h$
0:00 - 0:59	10264	10687	11111	11534	12551	13568	14585
1:00 - 1:59	9651	10036	10422	10807	11793	12779	13765
2:00 - 2:59	9310	9676	10041	10407	11340	12274	13207
3:00 - 3:59	9136	9479	9823	10166	11059	11952	12845
4:00 - 4:59	9096	9427	9757	10088	10954	11820	12686
5:00 - 5:59	9048	9405	9762	10119	10992	11866	12739
6:00 - 6:59	9378	9714	10050	10386	11231	12077	12922
7:00 - 7:59	10237	10560	10883	11206	12049	12891	13734
8:00 - 8:59	11432	11767	12101	12436	13335	14233	15132
9:00 - 9:59	12428	12815	13203	13590	14609	15629	16648
10:00 - 10:59	13040	13521	14002	14483	15665	16848	18030
11:00 - 11:59	13476	14043	14610	15177	16489	17802	19114
12:00 - 12:59	13501	14184	14866	15549	16977	18404	19832
13:00 - 13:59	13316	14102	14888	15674	17167	18661	20154
14:00 - 14:59	13153	14014	14875	15736	17257	18778	20299
15:00 - 15:59	13126	14057	14988	15919	17427	18936	20444
16:00 - 16:59	13334	14295	15257	16218	17693	19168	20643
17:00 - 17:59	13579	14532	15485	16438	17871	19303	20736
18:00 - 18:59	13675	14572	15469	16366	17728	19089	20451
19:00 - 19:59	13619	14462	15306	16149	17508	18867	20226
20:00 - 20:59	13946	14782	15617	16453	17854	19255	20656
21:00 - 21:59	13832	14630	15429	16227	17433	18639	19845
22:00 - 22:59	12500	13301	14103	14904	16003	17102	18201
23:00 - 23:59	11140	11934	12728	13522	14531	15540	16549

data and mapping multiples of 100 MW of grid-level electricity demand to multiples of \$0.50/MW. For the purposes of this dissertation, this was sufficient to capture the general dynamics of hourly demand-sensitive pricing from a functioning electricity market.

The pricing model for the Energy Box simulation could then create the sequence of hourly real-time prices by first simulating a sample sequence of grid-level demand ($W^{grid.level.demand}$) via the random number sequence from Table A.1 and the bin structure in the 7-day, 24-hour Markov chain described here. Then, using the representative value of grid-level electricity demand for each bin illustrated for Sunday and Monday in Tables C.2 and C.3, the Energy Box model looked up the row in Table C.5 with the closest demand value greater than or equal to the representative grid-level demand value and set the price for that hour to be the corresponding \$/MW.

Table C.3: Representative Demand Values for Each Hour on Mondays

Monday	EV - $3\Delta_l$	EV - $2\Delta_l$	EV - Δ_l	EV	EV + Δ_h	EV + $2\Delta_h$	EV + $3\Delta_h$
0:00 - 0:59	10200	10933	11666	12399	13369	14338	15308
1:00 - 1:59	9722	10410	11097	11785	12701	13617	14533
2:00 - 2:59	9523	10170	10818	11465	12331	13196	14062
3:00 - 3:59	9472	10099	10725	11352	12161	12971	13780
4:00 - 4:59	9695	10318	10940	11563	12317	13071	13825
5:00 - 5:59	10461	11048	11634	12221	12964	13706	14449
6:00 - 6:59	12460	12937	13414	13891	14613	15334	16056
7:00 - 7:59	14385	14956	15528	16099	16765	17432	18098
8:00 - 8:59	15308	16110	16913	17715	18335	18955	19575
9:00 - 9:59	15794	16727	17660	18593	19269	19944	20620
10:00 - 10:59	16233	17388	18542	19697	20330	20964	21597
11:00 - 11:59	16480	17844	19207	20571	21152	21733	22314
12:00 - 12:59	16533	18028	19523	21018	21611	22204	22797
13:00 - 13:59	16607	18129	19650	21172	21867	22563	23258
14:00 - 14:59	16546	18097	19648	21199	21936	22672	23409
15:00 - 15:59	16483	18074	19665	21256	21978	22701	23423
16:00 - 16:59	16501	18097	19694	21290	21998	22705	23413
17:00 - 17:59	16325	17916	19507	21098	21783	22468	23153
18:00 - 18:59	15925	17499	19074	20648	21295	21943	22590
19:00 - 19:59	15584	17082	18581	20079	20703	21326	21950
20:00 - 20:59	15862	17263	18663	20064	20676	21289	21901
21:00 - 21:59	15414	16800	18186	19572	20089	20606	21123
22:00 - 22:59	13668	15015	16362	17709	18147	18584	19022
23:00 - 23:59	11977	13241	14504	15768	16138	16508	16878

Table C.4: Example Hourly Demand Markov Matrices: Monday from Midnight to 1AM and Monday at 11PM to Tuesday at Midnight

Monday 0:00 to 1:00	EV - $3\Delta_l$	EV - $2\Delta_l$	EV - Δ_l	EV	EV + Δ_h	EV + $2\Delta_h$	EV + $3\Delta_h$
EV - $3\Delta_l$	0.9485	0.0515	0.0000	0.0000	0.0000	0.0000	0.0000
EV - $2\Delta_l$	0.0459	0.9083	0.0459	0.0000	0.0000	0.0000	0.0000
EV - Δ_l	0.0000	0.0547	0.8750	0.0703	0.0000	0.0000	0.0000
EV	0.0000	0.0000	0.0254	0.9391	0.0355	0.0000	0.0000
EV + Δ_h	0.0000	0.0000	0.0000	0.0738	0.8934	0.0328	0.0000
EV + $2\Delta_h$	0.0000	0.0000	0.0000	0.0000	0.0842	0.8526	0.0632
EV + $3\Delta_h$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0244	0.9756
...	...	...	...	...	...	...	...
Monday to Tuesday 23:00 to 0:00	EV - $3\Delta_l$	EV - $2\Delta_l$	EV - Δ_l	EV	EV + Δ_h	EV + $2\Delta_h$	EV + $3\Delta_h$
EV - $3\Delta_l$	0.8777	0.1079	0.0144	0.0000	0.0000	0.0000	0.0000
EV - $2\Delta_l$	0.0755	0.7642	0.1604	0.0000	0.0000	0.0000	0.0000
EV - Δ_l	0.0000	0.1066	0.7869	0.1066	0.0000	0.0000	0.0000
EV	0.0049	0.0000	0.0680	0.8447	0.0825	0.0000	0.0000
EV + Δ_h	0.0000	0.0000	0.0000	0.0957	0.8696	0.0348	0.0000
EV + $2\Delta_h$	0.0000	0.0000	0.0000	0.0000	0.0707	0.8889	0.0404
EV + $3\Delta_h$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0325	0.9675
...	...	...	...	...	...	...	...

Table C.5: Energy Box simulated Electricity Pricing

Capacity Available for Electricity Generation (in MW)	Simulated Cost of Electricity (in $/MW)	Capacity Available for Electricity Generation (in MW)	Simulated Cost of Electricity (in $/MW)
9,000	0	22,500	59
10,000	10	22,700	60
10,500	15	22,900	61
11,500	20	23,000	63
12,000	22	23,100	66
12,500	23	23,200	70
13,000	24	23,300	75
13,500	25	23,400	80
14,000	26	23,500	85
14,500	27	23,600	90
15,000	29	23,700	95
15,500	31	23,800	100
16,000	32	23,900	105
16,500	34	24,000	110
17,000	36	24,100	120
17,500	38.5	24,200	130
18,000	41.5	24,300	140
18,500	43	24,400	150
19,000	44.5	24,500	200
19,500	47	24,600	300
20,000	49	24,700	400
20,500	52	24,800	600
21,000	54	24,900	800
21,500	56	25,000	1,000
22,000	58		

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Appendix D

Dynamic Programming Process Details

Originally introduced in Chapter 3, this Appendix provides a detailed overview of the dynamic programming decision method that is implemented in the Energy Box model. Though the discussion in this Appendix focuses on the dynamic programming algorithm for an event-based appliance, the process would be essentially equivalent for thermostatically-controlled appliances and storage devices.

As a reminder, the mathematical representation of the dynamic programming decision method for an event-based appliance is

$$\min_{\left(x_t^{EBA}\right)_{t=0}^{FC}} \sum_{t=0}^{FC} E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA}, x_t^{EBA}, W_{t+1}\right)\right]. \tag{D.1}$$

As discussed in Chapter 3, equation D.1 is solved via a backward dynamic programming algorithm. The reason it is a ‘backward’ algorithm is that the process begins at the terminal stage of the dynamic programming formulation and traverses from the terminal stage back to the current moment in time. Ultimately, the dynamic programming algorithm determines the best decision for the current moment in time, which is then implemented in the Energy Box simulation process.

Solving equation D.1 for the event-based appliance depends on some of the parameters discussed in Chapter 3:

- Uncertainty parameter: PF (perfect forecasts), MV (median value), FD (full distribution)
- Electricity pricing tariff: Flat, TOU (time-of-use), RTP (real-time pricing)
  - If RTP, then set the FP parameter to fix the hourly prices either one hour ahead or one day ahead (i.e. $FP = 1$ or $FP = 24$)
- Wind turbine: Yes or no
  - If yes, then set $k^{buy.to.sell.scaling.factor} \in [0, 1]$

For the first illustration of the event-based appliance dynamic programming algorithm, consider the following scenario:

- Uncertainty parameter: FD (full distribution)
- Electricity pricing tariff: RTP (real-time pricing), $FP = 1$ (i.e. prices fixed one hour ahead)
- Wind turbine: No

At the terminal stage of the consumer's flexibility constraint (FC), the only possible state is *Not Ready to Run* ($NR2R$) because the event-based appliance must be completed by this stage. In this case, $C_{FC}^{Cost}\left(S_{FC}^{EBA}, x_{FC}^{EBA}\right) = 0$ because there is no electricity used. Hence,

$$V_{FC}\left(NR2R\right) = 0.$$

Of note is that the *Not Ready to Run* ($NR2R$) state is also used in this process to reflect when the event-based appliance has completed its cycle and has not yet been loaded again by the Energy Box simulation.

The variable $V_t\left(S_t^{EBA}\right)$ for all stages t stores the value of being in state S_t^{EBA} at stage t, which allows the backward dynamic programming algorithm to use the **principle of optimality** to capture the optimal path from state S_t^{EBA} at stage t in a single value that will be used in the backward dynamic programming algorithm's recursive process. The role that $V_t\left(S_t^{EBA}\right)$ plays will become clearer during the next steps of the event-based appliance's backward dynamic programming process.

Continuing backward to stage $FC-1$, if $S_{FC-1}^{EBA} = NR2R$, no action occurs because the event-based appliance's cycle has already been completed. In this case,

$$V_{FC-1}\left(NR2R\right) = 0 + V_{FC}\left(NR2R\right) = 0.$$

On the other hand, if $S_{FC-1}^{EBA} = \mathit{Idle\ and\ Ready\ to\ Run}\ (R2R)$, the decision x_{FC-1}^{EBA} must be to $Start$ in order for the event-based appliance to complete its cycle by the consumer's deadline. In this case, the calculation of $E\left[\hat{C}_{FC}^{Cost}\left(S_{FC-1}^{EBA}, x_{FC-1}^{EBA}, W_{FC}\right)\right]$ will be influenced by the set of possible prices at this stage, which is a function of grid-level demand:

$$\begin{gathered} E\left[\hat{C}_{FC}^{Cost}\left(R2R, Start, W_{FC}\right)\right] = \\ \sum_{grid.demand}\left(\mathbb{P}\left[W_{FC}^{g.d.} = w_{FC}^{g.d.}\right] \cdot w_{FC}^{RTP.price.buy}\left(w_{FC}^{g.d.}\right) \cdot w^{demand.EBA}\right). \end{gathered}$$

The variable $w^{demand.EBA}$ is the number of kWh consumed by the event-based appliance during its cycle, which again is assumed will complete in the time between stages. For this case,

$$\begin{aligned} V_{FC-1}\left(R2R\right) &= E\left[\hat{C}_{FC}^{Cost}\left(R2R, Start, W_{FC}\right)\right] + V_{FC}\left(NR2R\right) \\ &= E\left[\hat{C}_{FC}^{Cost}\left(R2R, Start, W_{FC}\right)\right]. \end{aligned}$$

For stages 1 to $FC-2$, if the state is $NR2R$, once again there is no action because the event-based appliance's cycle has already been completed. Using stage 1 as an example, we have

$$V_1\left(NR2R\right) = 0 + V_2\left(NR2R\right) = 0.$$

However, if the state is $R2R$ (again using stage 1 as an example), then the decision options are either to $Start$ the event-based appliance or $Wait$. The decision providing the minimum value for $V_1\left(R2R\right)$ is now one of the following options:

$$V_1\left(R2R\right) = \min \begin{cases} E\left[\hat{C}_2^{Cost}\left(R2R, Start, W_2\right)\right] + V_2\left(NR2R\right) \\ E\left[\hat{C}_2^{Cost}\left(R2R, Wait, W_2\right)\right] + V_2\left(R2R\right) \end{cases}$$

The calculation of $E\left[\hat{C}_2^{Cost}\left(R2R, Start, W_2\right)\right]$ follows the same process as that described for stage $FC-1$. On the other hand, $E\left[\hat{C}_2^{Cost}\left(R2R, Wait, W_2\right)\right] = 0$ because no electricity is consumed by the event-based appliance between stages 1 and 2 if $x_1^{EBA(R2R)} = Wait$.

The backwards dynamic programming process has now reached the current moment in time, stage 0. In this stage, the state of the event-based appliance is guaranteed to be *Idle and Ready to Run* ($R2R$), and once again the decision options are either to $Start$ the event-based appliance or $Wait$.

$$V_0\left(R2R\right) = \min \begin{cases} E\left[\hat{C}_1^{Cost}\left(R2R, Start, W_1\right)\right] + V_1\left(NR2R\right) \\ E\left[\hat{C}_1^{Cost}\left(R2R, Wait, W_1\right)\right] + V_1\left(R2R\right) \end{cases}$$

For stage 0 and prices fixed an hour in advance ($FP = 1$), the price of electricity is now fixed to a specific value, which simplifies the calculation of $E\left[\hat{C}_1^{Cost}\left(R2R, Start, W_1\right)\right]$, yielding a final decision of

$$V_0\left(R2R\right) = \min \begin{cases} w_0^{RTP.price.buy} \cdot w^{demand.EBA} + V_1\left(NR2R\right) \\ 0 + V_1\left(R2R\right) \end{cases}$$

This is ultimately the decision that matters in the Energy Box simulation. If the decision at stage 0 is to $Wait$, then the event-based appliance remains in the $R2R$ state until the next stage, at which point the backwards dynamic programming process repeats itself at the start of the next hour with the updated states of the weather and grid-level demand information. If the decision is to $Start$ the event-based appliance at stage 0, then the event-based appliance will transition to $NR2R$ and there is no longer any decision to make until the simulation simulates the next loading of the appliance.

Continuing for a moment with simulations that do not include a wind turbine at the residence, a few of the scenarios yield obvious decisions, regardless of some of the other parameters' settings. For instance, with a flat rate pricing tariff and no wind turbine, the event-based appliance will simply start as soon as it is loaded. Under time-of-use rates and with no wind turbine, any of the off-peak hours would be considered the 'best' hour to run the appliance, so the first available off-peak stage will be the stage at which the event-based appliance begins its cycle. Similarly, if the hourly RTP rate has fixed prices a day in advance (i.e. $FP = 24$ and again no wind turbine), then the event-based appliance will wait to run at the stage with the lowest price.

The situation becomes more interesting when local generation from a wind turbine is included. With a wind turbine on the roof, even a pricing policy of a flat rate for electric energy means this decision is not trivial.

To demonstrate the details of one of these cases, consider the following scenario:

- Uncertainty parameter: MV (median value)
- Electricity pricing tariff: Flat
- Wind turbine: Yes

– $k^{buy.to.sell.scaling.factor}$ left as a parameter initially

Just as in the previous case, $V_{FC}(NR2R) = 0$ for the terminal stage.

The difference begins at stage FC-1. Once again, if $S_{FC-1}^{EBA} =$ *Idle and Ready to Run* ($R2R$), the decision x_{FC-1}^{EBA} must be to *Start* the event-based appliance in order for it to complete its cycle by the consumer's deadline. However, the new scenario causes a change in the calculation of $E\left[\hat{C}_{FC}^{Cost}\left(S_{FC-1}^{EBA}, x_{FC-1}^{EBA}, W_{FC}\right)\right]$. With a wind turbine on the roof, a flat rate electricity tariff and MV forecasts, we now have

$$E\left[\hat{C}_{FC}^{Cost}\left(R2R, Start, W_{FC}\right)\right] =$$

$$w_{FC}^{flat.price.buy} \cdot \max\left(w_{FC}^{net.demand}, 0\right) + w_{FC}^{flat.price.sell} \cdot \max\left(w_{FC}^{net.generation}, 0\right)$$

where

$$w_{FC}^{net.demand} = -w_{FC}^{net.generation},$$

and

$$w_{FC}^{net.demand} = w^{demand.EBA} - w_{FC}^{generation.DG.wind}\left(w_{FC}^{wind.speed}\right).$$

At this point, the policy for selling electricity back to the grid comes into play as

$$w_{FC}^{flat.price.sell} = k^{buy.to.sell.scaling.factor} * w_{FC}^{flat.price.buy}.$$

The backwards dynamic programming algorithm's processing is adjusted to incorporate this new structure when calculating $E\left[\hat{C}_{t+1}^{Cost}\left(S_t^{EBA}, x_t^{EBA}, W_{t+1}\right)\right]$ at all stages. The effect that $k^{buy.to.sell.scaling.factor}$ has on the decision algorithms is illustrated in full detail in chapter 5.