Economic Welfare Gains from Demand Response and Real-Time Pricing for Industrial Processes

by

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(Under the direction of Scott Atkinson)

Abstract

Sustainable electricity supply has come to the forefront of current affairs in the U.S. The power grid of the future requires significant system-level upgrades to an outdated infrastructure. A combination of new technology and new energy management strategies will be necessary. An important topic of discussion is Demand Response (DR), and usually coupled with it is Real-Time Electricity Pricing (RTP). The former refers to electricity users' reducing their demand, often receiving some kind of benefit in exchange, which theoretically helps grid reliability during system stress and levels out market prices. The latter refers to the grid's pricing electricity based on current generation, which theoretically allows for more accurate price effects. Through analyzing a model of industrial load-shifting as a demand response method employed by a customer with day-ahead real-time pricing, this paper demonstrates the economic welfare benefits that can accrue from real-time pricing and demand response in modern power systems.

Index words: Energy Economics, Demand Response, Real-Time Pricing

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1 Introduction

1.1 The United States Power Grid

The United States power grid is a nationwide network that ultimately connects the producers and consumers of electricity. Energy is first generated (through burning fossil fuels, nuclear fission, or through renewable resources such as solar, wind, or hydroelectric generation), and then transmitted through power line infrastructure and transformer stations to ultimately arrive at a final consumption point, where total consumption is usually measured by a meter. The high voltage of the transmission lines allows for efficiently carrying large amounts of electricity over long distances, so generators can be larger to take advantages of economies of scale. These large central plants then serve as electricity sources for a wide area of users via the transmission network. The electricity voltage is reduced before being distributed to end-users [26].

In most areas in the current system, the high-voltage transmission lines are owned by entire grid "systems", allowing for further cost minimization by utility companies who can pool generation and distribution resources. There are now three large systems in the continental U.S; The Western Interconnection mostly serves the area west of the Rocky Mountains, the Electricity Reliability Council of Texas Interconnection supplies almost entirely Texas, and the Eastern Interconnection supplies everything else [26].

1.2 Major Problems Facing the Grid

The interconnected grid allows for greater cost savings for utilities and theoretically greater reliability, but the grid must consistently be improved to meet current challenges. Electrical energy must first be converted to another energy source to be stored, and this cannot be easily done at large enough scale to accommodate the needs of a grid [26]. Also, even high voltage power lines experience losses in power during transmission. These losses are a linear function of the length of the transmission line, and increase with the amount of power demanded [12] [18]. So, coordinating generation with demand (through one transmission network) is an increasingly daunting task. If not performed properly, there are significant safety risks as well as the possibilities of complete energy blackouts [26].

The Federal Electricity Regulatory Commission (FERC) creates reliability standards for the grid, to attempt to ensure minimal unplanned blackouts and safety hazards [26]. Reliability is threatened by the aging infrastructure, high demand spikes (i.e. huge air conditioning usage on exceedingly hot days) and variable supply on a regular basis. In addition to the political discussions necessary to finalize funding and planning for infrastructure upgrades, there is a goal of introducing digital "intelligent" technology into the grid to allow for more efficient use of the current resources via communication technology. Without this "smart grid", introducing renewable energy generation into the grid is difficult on a large scale, since something as fickle as changing weather can be responsible for large supply swings for wind and solar resources [6].

The smart grid would target multiple problems. One is transparency of electricity use by final customers. Power bills often arrive at month's end with only an aggregate usage number, which makes tracking energy usage difficult for consumers. Also, many people do not get information about the source of their energy, whether from fossil fuels or renewable resources. The information vacuum affects utility companies as well, as many utilities are not aware of issues (i.e. local power outages) until alerted by customers, which can extend blackout time tremendously [6].

1.2.1 Incorporating Renewables

There is another big risk to power grid reliability: the variability of renewable energy generation. Electricity supply from renewables is highly variable, and having systems in place which are flexible with respect to generation will be necessary to incorporate the energy properly [10]. There are even cases of over-generation from exceedingly cooperative weather conditions; in June 2013 in Germany, solar and wind generation peaked at 51GW, on a grid that cannot handle more than 45GW without reliability risks. The wholesale electricity price actually became negative, dropping to - €100 / MWh [13]. Reducing load is easy for the solar and wind plants, but the nuclear and other fossil fuel generators incurred huge costs as a result of the lags associated with decreasing load from such plants and the inefficiency of running at reduced capacity [13]. Large electricity producers who were actively paying the grid to take their energy and had already reduced generation to prevent further costs were even forced to shut down in some cases.

The current U.S. power grid infrastructure was not built to accommodate renewable energy, either. Transmission lines do not already go to places that are sunny or windy, there are not bad-weather contingency plans in place such as fast-starting generators or efficient large-scale storage, and multiple paths are not always in place for electricity to skirt around malfunctioning areas to prevent blackouts [10]. It is estimated that $1 trillion will be spent by 2030 to upgrade the U.S. grid to handle renewables [10].

1.3 Electricity Wholesale Markets, Regulation, and Regional Transmission Operators

A fundamental shift in the way utility companies, customers, and the grid itself share information could lead to huge efficiency gains. Market participants could all be more responsive to price changes and unplanned events. As consumers become more aware of daily price fluctuations and more able to respond through curbing their usage or shifting it to non-peak times (i.e. doing laundry at night), the utility companies will also have lower, more constant demand to meet with their relatively fixed supply, which can reduce system pressure and increase overall reliability.

Through a combination of new smart technology, more readily available pricing information, and grid policies promoting responsive consumer behavior, it seems likely there is surplus welfare that can be captured by the grid system as a whole. The economic analysis depends on the arrangement of electricity markets, which also varies across different portions of the grid.

The actual workings of the market depend on how it is regulated. There was large, sweeping deregulation of energy markets in the U.S. during the 1990s that affected the grid's management. In the few remaining regulated markets, utilities are vertically integrated. They control the electricity from generation through the transmission and distribution infrastructure all the way to the customer's meter. In the most common model of deregulated markets, utilities typically do not own the generation or transmission capital, and only manage distribution and maintenance of portions of the grid and the financial transactions of final customers [8]. As Christensen and Greene [7] found in 1976, the greater competition in the market which allows for multiple, smaller generator firms as opposed to fewer, larger ones does not impact their economies of scale [7]. So, supply-side efficiency is not sacrificed in deregulated markets with multiple generators, which intuitively provides greater reliability as there are more failure points.

Deregulated markets typically have an organization that operates the grid [8]. The Federal Electrical Regulatory Commission (FERC) established these organizations, called either Independent System Operators (ISOs) or Regional Transmission Organizations (RTOs), via various pieces of legislation in the late 1990s. Since the RTOs and ISOs are financially independent from the market participants, they can provide non-discriminatory access to transmission infrastructure, foster competition among generators, prioritize reliability (which utilities would otherwise not be likely to undertake individually due to a free rider problem), and separate administrative duties from utility companies [17]. They also oversee the wholesale electricity market, wherein electricity is sold from generators to

Load Serving Entities, often utility companies, who then resell the electricity to final customers [14] [1].

2 Real-Time Pricing and Demand Response

The multitude of firms constantly buying from and selling into the market creates a huge amount of data, all of which increases final electricity prices. Although there are computational limitations on the speed at which firms and consumers can publish and process pricing data, intuitively there is value in more accurate, timely prices, to allow price-responsive behavior. Users could choose to consume less during "peak" (high-price and high-stress) periods through a variety of methods, saving money for themselves and reducing stress on the overall grid. Thus, it can theoretically benefit the organizations overseeing the grid (hereby referred to as RTOs for simplicity, though this is not strictly accurate in all grid systems) to incentivize or develop faster and better ways of determining, displaying, and distributing price information.

Coupled with this additional price data are any policies taken by RTOs which incentivize users to curb demand during peak periods. The RTOs have a primary goal of meeting demand with available supply, which becomes much easier as overall system demand fluctuations are minimized. A more predictable system demand allows for more timely and efficient use of the existing generation infrastructure, which often has lag times for scaling generation upward or downward rapidly [2].

By causing end-users to smooth out their consumption, RTOs can maintain system reliability. This can ultimately prevent a grid failure in cases where capacity is constrained but the marginal price of electricity cannot be set high enough to deter over-consumption by individuals. These various policies fall under the umbrella name of demand response, defined by Albadi and El-Saadany [2] as *"the changes in electricity usage by end-use* *customers from their normal consumption patterns in response to changes in the price of electricity over time"*. In some of these DR systems, incentive payments are paid to customers to incentivize their load reduction at peak use times, and these payments are also referred to as demand response [2]. These incentives can take many different forms, such as energy or dollar credits, subsidy payments, price reductions, etc., and the specifics are discussed below under Section 2.1. However the grid should incentivize this demand change, there are three major ways in which end-users actually respond:

1. Customers can simply reduce their electricity use during peak periods. They consider the loss in utility they receive as a result to be less costly than the utility of the incentive is beneficial to them. An easy example would be reducing their air conditioning and tolerating the resulting higher temperature [2].

2. Customers can load-shift. They use less energy during peak periods and more energy during off-peak periods. This is really a manner of scheduling, such as by running a dishwasher or laundry machine in the evening. However, industrial customers and residential customers who incur costs for scheduling will not necessarily benefit from doing so without an additional DR incentive from their RTO [2].

3. Customers can use their own distributed generation — onsite generation independent of the grid, such as rooftop solar panels on a residential home — as their source of power during these peak periods. These customers may not change their electricity use at all in this case, but the grid will benefit from reduced demand as their customers' power needs are met through external generation [2]. There are obviously up-front costs associated with building distributed generation infrastructure, as well as possible costs for both the utility companies/RTOs and consumers in setting up the system which allows for switching the source of generation.

2.1 Types of Demand Response

There is a large amount of variation on the system-side of DR. Figure 1, a recreation of Figure 1 from [2] , organizes the programs under their two main classifications, Incentive-Based-Programs (IBP) and Price-Based Programs (PBP). In IBP, customers receive some kind of payment (direct money, an energy credit, or a rate reduction) for reducing load. In PBP, customers respond to price signals, as they would in any other market, though the natures of these prices differ among the various programs.

For the purpose of this paper, the Real-Time Pricing (RTP) systems are important, and worth summarizing quickly. In RTP systems, the customers pay prices that reflect the wholesale markets' electricity costs at a given time [2]. The time period of interest depends on the system; hourly is typical, but something like half-hour or quarter-hour time blocks for calculating electricity prices is not necessarily infeasible with given computational strength. Often, customers receive this price information as a projected price for a future time. The difference between receiving the price information and curtailing demand changes among systems, but customers commonly receive price information either one hour or one day (twenty-four hours) before the price goes into effect [2].

Intuitively, many economists find RTP to be the most effective DR strategy [2]. It reduces the situation to a price response, which is theoretically beneficial to all parties involved, despite possibly being difficult to calculate and monitor for many individuals in a large grid system.

2.2 Demand Response Case Studies

Various cases worldwide are already experimenting with DR, to see if practical applications of the theoretical solutions are possible. Kiwi Power in London, for example, has had moderate success paying users to switch off equipment that is non-essential, such as stopping a freezer once the interior is "cold enough". The utility then sells this extra energy back to the RTO to put into the grid. They have even combined this service with other useful infrastructure, such as using the emergency generators in hospitals to add energy into the grid when needed, which dually eliminates the need to test the generators for functionality [20]. There are obvious engineering costs to set up such a system, and intangible costs such as consumers' feelings regarding the utilities' control of their equipment. There are also concerns of separating the computer algorithms from the big machines. A DR firm can calculate energy needs much more rapidly than a power station can switch on and off, and this needs to be taken into account.

Another UK case-study is looking at altering prices to encourage DR participation. A tariff additionally increases the price of electricity during peak demand to account for the negative externality that high individual demand levies on grid reliability. The high price then encourages demand reduction, which can be done automatically through digital technology such as smart meters. This technology can allow users to set break-prices — price limits that merit demand changes once the limits are breached — and adjust throughout the day with the real prices, minimizing their direct involvement in the load reduction and making it more accessible [23]. However, there are upfront costs for this technology, and the tariffs themselves can be confusing for users to understand the best way to get involved. And, poor families who cannot as easily adjust their energy use due to financial and time constraints may bear a larger share of the costs as a result [23]. The volunteer trials of these tariffs have had mixed results, and have further been complicated by a selection bias wherein energy-conscious volunteers are the majority of the sample [23].

The U.S. has plenty of examples of DR use. As of 2013, roughly 95% of global DR programs were offered in North America [11]. The studies of interest to the model in this paper are cases of large consumers rescheduling industrial processes as a demand response strategy, such as the universities outlined in Section 2.5.

2.3 Economic Perspectives: Short- and Long-Run Considerations

Determining the overall welfare of DR systems requires isolating all the economic costs and benefits. There are the obvious direct benefits where participants save on energy costs (either through lower prices or receiving some incentive payment). In some cases, participants could even use more energy and still spend less money, depending on the price differentials and sizes of the incentive payments. There are also positive externalities from individuals' participation in DR that benefit everyone involved in the grid. The first is grid reliability, which benefits everyone who values easy access to electricity and a reduction in blackouts. In general, peak prices are lower for all consumers and operating costs are lower for generators, as the reduced demand allows for more efficient use of generation capital which translates to lower prices. This is especially helpful near peak demand, as costs increase dramatically near maximum output for a given generator. On a similar note, infrastructure upgrades can be delayed, as current capital is being used more efficiently instead of simply expanding overall capacity. And lastly, DR can help wholesale electricity markets. By providing more choices for consumption and giving consumers the ability to act directly in the market, prices can be kept in check as firms' market power is limited [2].

There are upfront costs to both participants and providers of DR services. Consumers need to pay for smart technology, such as smart thermostats for their homes or distributed generation resources, i.e. rooftop solar panels. Also, consumers need to take time to prepare a response strategy, such as reducing the AC when prices breach a certain point, which is hard to quantify on a large scale but is certainly incorporated into each consumer's participation decision. The system has to also pay for technology, including smart meters to monitor supply and demand in real time and databases and management software to analyze and react to all the new data. They also have to introduce new billing systems and educate potential consumers about the DR program, which can be a constant marketing and communication cost [2]. While the program is running, the participants' costs are mostly intangible — lost comfort due to demand reduction, such as a hotter home temperature during the summer, or costs associated with rescheduling demand-intensive activities, which can be exceedingly costly for an industrial customer. There may also be operating and maintenance costs associated with distributed generation, where applicable. Beyond continuous marketing and communication, the system providers must pay any incentive payments (if applicable) as well as administration and program evaluation costs incurred during the program. As DR is a very data-heavy ordeal, constantly assessing and improving the program based on real-data is crucial to success, and can become quite costly as the program continues [2].

The complicated nature of DR systems begs the question of their necessity. Could producers not simply be incentivized by a governing body to invest in additional generation capital, and constantly have additional capacity? Besides the fact that energy demand would likely eventually grow to overcome the installed overcapacity, Lijesen [16] found that the relatively low elasticity of electricity demand could lead to even a small amount of market power for individual firms creating large welfare transfers from consumers to producers [16]. These welfare transfers come typically when peak prices rise dramatically with minimal demand reduction, and this effect may incentivize firms to make their own investment in additional capacity to capture their share of the welfare. Thus, any incentives from an outside third party could simply create a free-rider problem. If the governing body somehow subsidized investments in additional capacity for profit-seeking firms that they would have independently purchased, the firms could incur lower costs and the governing body would incur higher costs without changing the final market outcome [16]. Lastly, overcapacity does not help with the issues of renewable generation, and would actively discourage investment in the case of days where high generation induces negative prices, as discussed above [13].

So, it appears DR systems can be valuable short-run, and may be worth the investment. Borenstein [5] found that even with minimal elasticity, RTP as a DR system can provide significant efficiency gains for the electricity market [5]. The study found that RTP would reduce peak electricity production significantly, which therefore minimizes the use of inefficient generation capital. Even more interesting to the scope of this paper, in the model used by Borenstein [5], the benefits of RTP decrease with an increase in the number of customers and a decrease in the size of the average customer. This suggests the benefits of RTP are significantly larger for large customers [5]. A caveat is addressed [5] that smaller customers are often more price responsive; a home can deal with reduced AC usage more easily than a large building system, in theory. But, that further implies that particularly price-responsive large customers can reap substantial benefits from a DR system based on RTP.

2.4 Real-Time Pricing in Georgia: Georgia Power

Georgia Power, the utility serving the majority of the State of Georgia's electricity needs, has been employing RTP policies since the early 1990s [4]. As of 2002, it was the "world's largest real-time pricing program" [21], and the program showed continued success throughout the 2000s [15]. Industrial and commercial customers have benefitted from the program, including large multi-state retailers such as Walmart, Lowe's, Kohl's, and BJ's [15], many of whom have changed their building designs and/or energy plans specifically in Georgia stores to take advantage of the program.

The program offers two methods of pricing — either day-ahead (DA) or hour-ahead (HA) — where the prices are updated daily and hourly, respectively. For the DA model, customers are sent a vector of projected prices for each hour of the following day [9]. For the DA pricing, customers need a minimum of 250kW of available load, and for HA the minimum if 5MW.

Part of the reason Georgia Power's RTP programs have been successful is due to the marginal pricing structure [15]. Each customer interested in RTP first develops a Customer Baseline Load (CBL) for their energy use each day of a year, either from historical data or from a reasonable projection. Each customer is charged for their CBL at standard rates to cover base operating costs. Then, the customer's real load each day is compared to their CBL, and the difference is charged at the RTP marginal hourly price, resulting in credits if load is below CBL and costs if load is above CBL [9].

Thus, rather than hold all the risk on the fluctuating energy prices, Georgia Power retains a substantial portion of their revenue since everything is pegged to the CBL for their RTP customers. This maintained revenue is applied to all of their costs equally, so customers not participating in RTP do not receive worse service or infrastructure. And, by reducing demand during peak periods, Georgia Power can avoid building some new generation, a cost savings that applies equally to all customers [15].

Customers are incentivized to shift their electricity usage away from peak pricing, receiving credits in the process. The equation for the pricing is below, and Figure 2 is a graph from a 2015 Georgia Power presentation demonstrating the value of load-shifting as an RTP customer [9].

$$RTPBill = StandardBill + \sum_{allhours} [\{TotalLoad - CBLLoad\}_{perhr} * MarginalPrice_{perhr}]$$

Some RTP programs focus on targeting peak days of extreme pricing, as opposed to offering the service regularly. The Georgia Power RTP programs are available on all days, and have shown success for commercial and industrial customers throughout the year and especially during the summer [15]. As of 2005, the programs had realized *"five times as much percentage peak load reduction as any other utility program"* [15]. Their largest successes have come from large, price-responsive customers who are able to reschedule energy-intensive events to off-peak hours, and who are willing to maintain this price-responsive behavior for longer time blocks, such as the entire summer or the whole year [4].

2.5 University Campuses as Large Real-Time Pricing System Beneficiaries

American universities whose associated utility employs a RTP system serve as an excellent example of these large, price-responsive customers. Their electricity loads are substantial; they often have the resources, technical expertise, limited budget, and first-adopter interest to employ price-response strategies; and they sometimes have central facilities which manage large processes for an entire campus, such as chilled water cooling systems for the campus air conditioning. Heating, ventilation, and air conditioning (HVAC) systems are an ideal focus for adapting to RTP because they are large scale, scheduled processes whose efficient operation affects a large group of consumers.

The University of California, San Diego, built an on-campus combined heat and power (CHP) plant. The 30MW plant accounts for roughly 92% of the electricity the campus needs [3]. In addition to employing this on-site generation, they use a load-shifting strategy to minimize stress on their campus microgrid. They cool roughly 4 million gallons of water overnight during low electricity demand when they do not have to purchase additional power from the utilities. They then store this water in cooling towers, using it to run the AC system the next day. In doing so, they minimize HVAC-related electricity use during the day, avoiding paying peak prices for external electricity purchased from utilities, and providing a reliable onsite generation facility for the rest of the campus's power needs.

Overall, the CHP plant has saved roughly $8 million yearly, paying back their initial $27 million capital expense in just 5 years [22].

Princeton University has employed a similar system. They installed a 14.6MW CHP plant in 2003, which both responds to RTP from the PJM wholesale power market and employs load-shifting and stored cooling to save on AC costs. During peak pricing periods they can generate electricity onsite to reduce their reliance on the grid, and they further reduce their peak demand by storing water cooled at night to use for the next day's AC operation. In doing so, they avoid paying peak prices and reduce stress on the grid during peak operation [24]. Princeton estimates they save 10-15% on their annual electricity costs, roughly $2.5-3.5 million each year [19].

3 Model Development

3.1 Overview

This paper's focus is on the University of Georgia's chilled water AC system. It operates like the above models, where an industrial-sized chiller cools a large amount of water in a central location, and then distributes the water throughout a piping network that reaches UGA's central campus buildings. This cold water is then used with a heat exchanger to pump cool air into the buildings. Zahedi et al. [27] developed an engineering analysis for this system in 2014, both modelling the daily temperature fluctuations in such a system and examining the benefits of load-shifting in response to Georgia Power's day-ahead RTP program [27]. Their model explored the strategy of cooling the water at night to benefit from off-peak prices, then allowing the cool energy stored in the large amount of water to serve the needs of the AC system, reducing the need for purchasing energy during peak pricing hours [27].

This paper will expand that model in a few ways:

1. Using real Georgia Power RTP data for the 2010-2014 summers to estimate the savings more accurately for the original model

2. Employing an optimization technique to minimize energy costs throughout a day's operation

3. Considering the positive externalities of a reduction in demand during peak hours of a large on-campus load for the rest of the campus's electricity pricing

Each of these methods and their results will be demonstrated in the following sections. Regarding point 3, this paper models a basic energy supply curve for UGA, analyzing how the reduction in quantity of energy demanded by the cooling system (whose operation serves as roughly 25% of the campus's total energy costs) affects the RTP tariff during peak hours, and how that reduction affects the greater campus. A few necessary assumptions are explained for this extension below, just prior to presenting its analysis.

3.2 Original Model

This section will discuss the original model from Zahedi et al. [27]. It will give a cursory summary of the engineering, including relevant formulas which will be used later in the economic analysis.

As previously mentioned, the model relies on chilled water distribution network. A central chiller is the sole buyer of electricity, and provides enough "cooling" (negative heat) to offset the heat/energy demands of the system. During each hour of the day, total heat energy input and output were calculated, and these values contribute to a change in temperature of the water in the system. The temperature change is scaled by "heat capacity" of the system, which is the resistance to a change in temperature given a change in energy. That relationship is summarized in Equation 1 below:

$$\Delta Q_{net_t} = m * c_p * (T_{t+1} - T_t) \tag{1}$$

where $Q_{net,t}$ is the net heat input into the system at time t (in kilowatt-hours, kWh), $m * c_p$ is the thermal mass of the system times the system's specific heat, which in total is the system's heat capacity (in kWh per degree Fahrenheit), and T_t is temperature at time t in degrees Fahrenheit. Since the model deals with hourly data, t refers to the hour of the day. One complete day is modelled, so t ranges from one to twenty-four.

The energy inputs into the system are the buildings (as they transfer heat to the system through using up the "cooling" of the water) and the soil in which the pipes travel, which conveys heat from the ambient temperature. The thermal mass consists of both the water and the piping in the system, and the heat capacity is calculated from scaling their relative proportions of the total system mass:

$$C_{system} = m_{water} * c_{p_{water}} + m_{piping} * c_{p_{piping}} \tag{2}$$

For the sake of modelling water temperature fluctuations throughout the day, the temperature and net energy input at time t and the total heat capacity (constant over time) are used to determine the next period's temperature. The system is only constrained by water temperature limits – if the temperature goes too low, the water could freeze; if the temperature is too high, the chiller will not function well. The following temperature limits (in degrees Fahrenheit) were used for all iterations of the model:

$$T_t \geq 36 \ \forall \ t \tag{3}$$

$$T_t \leq 45 \ \forall \ t \tag{4}$$

$$T_1 = 40 = T_{24} \tag{5}$$

where Equation 5 is required to ensure the model of a complete day in a "cycle". By ensuring the temperature starts and ends at a given temperature, the findings of modelling a single day can be extended to longer periods of time.

After modelling the temperature, the goal was to calculate total cost. This was a result of hourly energy demand from the chiller and the hourly RTP:

$$Cost_{chiller,day} = \sum_{t=1}^{24} Q_{chiller_t} * Price_t \tag{6}$$

Table 1 includes the input data for the basic model. Included are the hour of the day, the total energy demand from the building AC systems, a 5 year average of summer (June 1 - August 31) ambient temperature from 2010-2014, and the average and "peak day" average electricity prices over that same time period. "Peak day" average is calculated by first finding the single day in each year with the highest single hourly price. Then, the full price curves for these days (23 July 2010, 3 August 2011, 29 July 2012, 12 June 2013, and 23 August 2014) were averaged. A graph of average day and "peak day" pricing is shown in Figure 3.

Note that although the peak days have the highest single price, they did not necessarily have the highest price at all given hours; the approach taken here, rather than maximizing prices at each hour based on the data, approximates the actual price curve that may be experienced on a "peak day". Also note that a distinction should be drawn between "peak day" and peak pricing. "Peak day" RTP rates refer to the described phenomenon above, while any energy curve will exhibit peak pricing during the hottest hours of the day. Anytime the word peak is used without specifically being designated as "peak day" (with quotations), it should be assumed to mean the high pricing during midday, and not the "peak day" prices described above.

Zahedi et al. [27] employed the above equations to compare two different manners of using the system. Both models were developed using Matlab. They modelled the "control" case, where the chiller is run so as to meet demand, maintaining water temperature at 40 degrees Fahrenheit. The control case is how UGA currently operates their chiller system, which is why 40 degrees Fahrenheit was chosen for Equation 5.

They also modelled a load-shifting case, which could be separated into three "steps". First, the chiller is run at high levels during the night and early morning to drop temperature to the lower limit. Then, at an arbitrary time in the late morning (taken as 11:00 am), the chiller is changed to operate at a given fraction of maximum capacity (modelled as 90% here). The idea was that the colder system could serve as a thermal battery of sorts, preventing the increased energy input during the peak hours of the day (12-4 pm) from immediately increasing to the higher temperature limit. Once the higher temperature limit was reached, the chiller was once again set to meet system demand, maintaining the temperature, until another arbitrary time in the early evening (taken as 10:00 pm) after which the chiller was run at high output to reduce the temperature back to the starting temperature of 40 degrees Fahrenheit. By shifting energy away from peak pricing hours, they hoped to demonstrate cost savings. They achieved some savings with this approach of arbitrarily choosing the time of changing behavior and choosing a single, arbitrary capacity reduction.

The water temperature cycle as compared to the control case is shown in Figure 4. The energy path is shown in Figure 5, and the hourly cost results are shown in Figure 6 and Figure 7 for average day and "peak day" pricing, respectively. The resulting energy use results are found in columns 1 and 2 of Table 2, and the cost results are found in columns 1 and 2 of Table 3 for both average day and "peak day" pricing. The differences in energy use and cost (as compared to the control case) are reported in column 1 of Table 4 and Table 5, respectively. Note that "Control" refers to the standard chiller operation employed by UGA, and "Cycle" refers to this arbitrary load-shifting model described in the above paragraph.

It is worth addressing that although the cycle saved money, it actually used more energy throughout a single day. The difference in RTP rates between the off-peak and peak hours are significant enough that an increase in off-peak energy use which is not offset by a reduction in peak energy use can still result in daily energy cost savings.

3.3 Optimization

A natural extension to this model is optimization. By choosing the "best" times to load-shift, and the "best" capacity reduction, and allowing capacity reductions to occur anywhere they are relevant as opposed to solely during midday, this model seeks to minimize total daily costs. The optimization approach described below and the reported results are a novel contribution to the work done by Zahedi et al. [27].

Choosing the correct times to load-shift manifested itself in a choice about the proper temperature path over time. So, the resulting objective function is:

$$\min_{T,capacity} Cost_{chiller,day} = \sum_{t=1}^{24} capacity_t * Q_{chiller_t} * Price_t \tag{7}$$

subject to the following constraints (in addition to Equation 3, Equation 4, and Equation 5 above):

$$\overline{T} = \frac{1}{24}\sum_{t=1}^{24} T_t \leq 40 \tag{8}$$

$$\overline{capacity} = \frac{1}{24}\sum_{t=1}^{24} capacity_t \geq 97.5\% \tag{9}$$

$$T_{t+1} - T_t \leq \left| \frac{Q_{chiller_{MAX_t}} - Q_{input_t}}{C_{system}} \right| \tag{10}$$

where Equation 8 restricts the average temperature (so as to be comparable to the control case), Equation 9 restricts the average capacity value to be the average value in the "cycle" case, so as to give fair comparison. Finally, Equation 10 restricts the temperature change between any two periods to be no larger than the maximum energy difference between the starting period's energy input and the maximum chiller output (both in kWh), scaled by heat capacity (kWh per degree Fahrenheit). This is done to avoid the likely computational scenario of large, oscillating temperature swings, which would be infeasible with the actual chiller machinery. The optimization was done using the "fmincon" routine from the Optimization Toolbox in Matlab.

The model was run for both average and "peak day" pricing, resulting in two separate energy paths and temperature paths. The water temperature cycle as compared to the control case is shown in Figure 4. The energy path is shown in Figure 5, and the hourly cost results are shown in Figure 6 and Figure 7 for average day and "peak day" pricing, respectively. The resulting energy use results are found in columns 1 and 2 of Table 2, and the cost results are found in columns 1 and 2 of Table 3 for both average day and "peak day" pricing. The differences in energy use and cost (as compared to the control case) are reported in column 1 of Table 4 and Table 5, respectively. Note that "Control" refers to the standard chiller operation employed by UGA, and "Cycle" refers to this arbitrary load-shifting model described in the above paragraph.

Note that the optimal operation experienced greater cost savings than the basic cycle model did, compared to the control. Energy savings were also realized by the optimal model, unlike the cycle model. These results were expected, as the cost-minimizing use of the chiller system should result in lower costs than an arbitrary cycle.

3.4 Extension – System Demand Analysis

The above two models have two limitations:

1. They assume the chiller is too small to affect overall system prices (a potential shifting of the supply curve)
2. They ignore the effects the chiller's shift in energy demand could have on the rest of campus's energy prices (a potential slide down the energy supply curve)

This paper will drop each of these assumptions and study their results. Namely, the focus will be on positive externalities that accrue to other buyers of electricity on campus as a result of the DR employed by the chiller system. The analysis of dropping Assumption 2 follows from similar analysis by Walawalkar et al. [25], though their work focused on DR incentive payments from a governing body and did not focus on the implications of RTP information. Dropping Assumption 1 can be thought of as modelling the UGA campus as the entire power grid, wherein a certain percentage of the whole grid's electricity use is subject to DR. The following analysis contributes another novel extension to the work done by Zahedi et al. [27].

The paper will first fit a supply curve for electricity for this "campus grid" based on the energy use in the control case and the provided RTP data (finding a separate supply curve for average day and "peak day" pricing). The change in quantity of electricity demanded at each hour will result in a slide down the estimated supply curve, resulting in a change in electricity price at each hour. It is assumed that the other buyers of electricity on campus will not engage in DR, and thus their total electricity demand remains constant. This approach will then be repeated, instead deriving the supply curves from the optimized energy use found previously. This second approach can be loosely interpreted as the utility deciding to price electricity based on the expectation that the grid continues its optimal DR behavior that it developed in reaction to prior static pricing. This first approach is referred to as "Static Pricing" and the second approach as "Dynamic Pricing" in the ensuing discussion, tables, and figures.

The first step comes from estimating the campus's total electricity demand at each hour. It is assumed that assume the chiller system constitutes a fixed percentage of the campus's total electricity use at each hour. This is a gross simplification for the sake of modelling — although the chiller system may account for a relatively stable percentage of total daily energy use, there is no reason to assume this is true at every hour. In an attempt to stay close to real-world results, 25% has been chosen for the chiller system's percentage of campus energy use, which is thought to be close to the accurate number by Dr. Thomas Lawrence (of Zahedi, Lawrence, Watson and Perry [27]), UGA Engineering Faculty and lead researcher of the campus HVAC systems.

$$Q_{d_{others}} = Q_{d_{control}} * \frac{1 - 0.25}{0.25} \tag{11}$$

$$Q_{d_{campus,control}} = Q_{d_{control}} + Q_{d_{others}} \tag{12}$$

$$Q_{d_{campus,AVG}} = Q_{d_{opt_{AVG}}} + Q_{d_{others}} \tag{13}$$

$$Q_{d_{campus,PEAK}} = Q_{d_{opt_{PEAK}}} + Q_{d_{others}} \tag{14}$$

The first term in Equations 12, 13, and 14 are the demands from the chiller system, where AVG and PEAK in Equation 13 and Equation 14 refer to the optimized energy demand from the chillers under average day and "peak day" pricing, respectively. Note that the "cycle" demand schedule for the chillers was neglected in this extension, as it is irrelevant when the optimized demand schedules are available.

Next, energy supply curves needed to be estimated from the current data. The data constitute price-consumption equilibrium points where demand meets supply. Under the assumption of a static supply curve with a non-static demand curve, these points can be interpreted as the result of the demand curve's shifting due to environmental variables.

Hence, these various equilibrium points "sweep out" the static supply curve. The assumption of a static supply curve appears valid in this case for the following reasons:

1. The supply curve for electricity generation is mostly affected by direct input costs of labor and capital (fuel). Exogenous environmental variations which do affect demand, such as ambient temperature and seasonal changes, should have no measurable effect on the energy supply curve for the scope of this paper, in which quantities such as machine efficiency due to ambient temperature are not considered.

2. Even if seasonal variation does have an effect on supply curves, the data all come from summer electricity use, so no seasonal variation is present to cause a shift in the supply curve.

3. Furthermore, any within-season environmental variation can be explained by the difference in the supply curves for average day and "peak day" pricing. The average day supply curve is assumed to be static throughout the set of summer days experiencing environmental conditions that lead to demand corresponding to average day pricing; similarly, the "peak day" supply curve is assumed to be static throughout the set of summer days experiencing environmental conditions that lead to demand corresponding to "peak day" pricing, including days with very similar price schedules to the actual "peak day" of each year.

Considering the assumption of static supply curves to be valid, the supply curves were estimated via the "sweeping out" approach. The curve fitting was done using Matlab's "lsqcurvefit" routine. For this routine, a functional form must be provided. A basic exponential function (Equation 15) was assumed.

$$P(Q_d) = a_1 * e^{a_2 * Q_d} \tag{15}$$

The parameters are included in Table 6. Keep in mind the price values were in cents, so small parameters are in line with the actual data.

For the “Static Pricing” case, supply curves were fit using the RTP data and $Q_{d_{campus,control}}$ for both the average day and “peak day” cases. These are the blue curves on Figure 8 and Figure 12 respectively, and the data are the red circles. For the “Dynamic Pricing” case, the curves were fit using the RTP data and their corresponding total campus demands for both average day and “peak day” cases, i.e., $Q_{d_{campus,AVG}}$ was used with the average day RTP case. These curves are the green curves on Figure 8 and Figure 12 respectively, and the data are the black crosses.

These supply curves represent a relationship between price and energy. But, our initial RTP data was presented hourly. The resulting hourly price curve from these supply curve derivations have also been graphed for comparison, in Figure 9 and Figure 13 for average day and “peak day” pricing, respectively. Note that overall price smoothing is evident. Prices are higher during off-peak hours and lower during peak hours in both cases. Note also that the dynamic pricing model induces more price smoothing than the static pricing model does, as demonstrated by the off-peak prices that are closer to the day’s average pricing.

In both the static and dynamic pricing cases, the approach of Walawalkar et al. [25] was followed. The effects of sliding along the energy supply curve due to the reduced quantity demanded were analyzed, and the resulting cost change at each hour was measured. The two relevant quantities are what Walawalkar et al. [25] call A and B. B is the cost savings for the chiller system. A is the cost savings for the rest of campus resulting from the decreased price induced by the chiller system’s demand response. Since the chiller system accounts for a significant portion (25%) of total system demand, the resulting demand decrease from the chiller system constitutes a substantial enough demand reduction to cause a price reduction. Since the non-chiller portion of campus has constant demand, the price reduction results in cost savings. In the static pricing case, this price reduction is 34.41% for average day pricing and 54.28% for "peak day" pricing during the hour in which price peaks each day. In the dynamic pricing case, the price reduction is 34.82% for average day pricing and 53.36% for "peak day" pricing during the hour in which price peaks each day

This phenomenon is graphed for the hour in which price peaks each day in Figure 10, Figure 11, Figure 14, and Figure 15 for the static pricing (average day and "peak day") and dynamic pricing (average day and "peak day") situations, respectively. The area shaded yellow corresponds to quantity A, and the area shaded pink corresponds to quantity B. Note that although A is larger than B during this representative hour, this is not necessarily true over an entire day. There are hours where A is smaller than B, or hours where A is more negative than B due to a price increase.

The demand curves on those representative graphs are shown as a solid blue line for the original campus demand and a dashed blue line for the campus demand while the chiller system employs a DR strategy. These demand curves are shown as perfectly price-inelastic. At first this seems counterintuitive, since one of the major premises of this model is the price-responsiveness of the campus's chiller system. However, the price-responsiveness of the chiller system is captured by the horizontal shift of the price-inelastic demand curves. In practice, this demand shift at each hour would be known a day in advance, by predicting an optimal demand path for the following 24 hours when the day-ahead RTP rates were reported. Since the remainder of the campus's electricity demand is assumed to be constant, as discussed above, demand is constant at each hour for a given 24 hour RTP vector. Thus, representing the demand curves as perfectly price-inelastic is valid. In order to model the price-elasticity of demand, this model would have to be applied to a series of daily RTP data, where the price elasticity at each hour would be estimated from analyzing price-quantity equilibria for each hour each day. This analysis was outside the scope of this paper, but is a valid future research endeavor.

It is evident that at peak price each day, quantity A is significantly larger than quantity B. This represents a large positive externality for the rest of campus due to the chiller system's demand response. So, extending our analysis to an entire grid, the DR actions of a fairly small set of actors can provide large positive effects for the grid consumers as a whole. Over an entire day, this effect is reduced, as explained above. Hours where prices increase due to higher off-peak demand can result in cost increases for consumers not employing DR. The total daily savings are shown in Table 8 and Table 9 for static pricing and dynamic pricing, respectively. These are "best case" numbers, as an income effect could occur due to the consumers' recognized savings, and they could begin consuming more electricity and reduce their daily savings.

Also note from Table 8 and Table 9 that the dynamic pricing externalities are smaller than the static pricing externalities. This is to be expected, as the utility is adapting their supply curve to the actual optimal behavior by the campus, and recapturing some of quantities A and B, which are wealth transfers from the utility company to the chillers (B) and the rest of campus (A) in the first place. Price smoothing can be considered as an "intangible" positive externality - smoother prices means more predictable demand for utilities, which means their generation can be scheduled more optimally. Furthermore, they can resist employing inefficient "peaker" generation to meet demand during peak hours, providing further savings.

Note that this model differs from that of [25], who were looking at overall energy demand and prices and studying DR incentive payments. Instead of a single graph, there will be a graph of each of these cases for all 24 hours of a day, corresponding to the shift in quantity demanded and resulting price shift at each hour.

As in the original model, total costs are reported in Table 7. Note these numbers are for all of campus, so they are scaled significantly. The scaling is not exactly 4x, because the fitted pricing curves result in slightly different costs at each hour.

4 Conclusion

Assuming this model is an accurate representation of the real-world system, clear energy and cost savings can be realized by employing demand response with available real-time price information. If the chiller system is considered too small to affect system prices, operating the chiller more optimally can result in fairly significant daily cost savings for the chiller systems. This is expected, and may motivate operation policy for similar large industrial systems if they are rescheduled. This lends credence to findings discussed previously, that RTP-based DR policies are beneficial for large-scale industrial processes.

The case where the chiller system's electricity demand is large enough that its actions can affect prices was also considered. This is equivalent to modelling an entire isolated grid with a single generator, wherein a certain percentage of the consumers (25%, here) engage in demand response due to price signals from reported RTP rates. In this case, smaller savings are seen for the chiller system, but significant savings are seen for the rest of the grid (quantity (A) in Table 8). These savings are a positive externality induced from the DR-users' behavior that constitutes a wealth transfer from utility companies to non-DR-using consumers. If the utility begins catering its prices to the system's optimal operation, savings are reduced for grid members because the utility is recuperating some of this wealth transfer (see Table 9), but positive savings are still experienced by both users and non-users of DR.

These savings result from price smoothing induced from the DR behavior, shown in Figure 9 and Figure 13. This price smoothing is an "intangible" externality for utilities, as they can better forecast generation needs and avoid use of inefficient “peaker” generation technologies. These results directly bolster grid reliability. So, DR use from a somewhat small percentage of grid consumers can benefit themselves, other grid users, and utilities, through lower overall energy costs and overall grid reliability.

Future research could attempt to measure the intangible price smoothing externality, by collaborating with Georgia Power and understanding their costs resulting from “peaker” generation and unstable price projections as well as the value they (or their overseeing RTO) place on reliability. If utilities or RTOs value this reliability enough, incentive payments for load-shifting could be considered (possibly paid from a “tax” collected by non-DR members of the grid), and studies like that of [25] could be conducted to discern the optimal incentive payment. Other questions of concern could be environmental effects from CO_2 emissions, analyzing both the type of generation fuel employed and the results from the “cycle” case where daily cost is reduced but energy use is increased. The effects of onsite generation could also be explored, and this analysis could be combined with an emissions analysis, as onsite renewables generation could be considered - the DR activity could help hedge the variability of supply inherent to renewable energy sources.

5 Figures and Tables

5.1 Figures (All Items Without Citations are Original)

Demand Response Programs

1. Incentive-Based Programs (IBP)
   - Classical
     - Direct Control
     - Interruptible/Curtailable Programs
   - Market Based
     - Demand Bidding
     - Emergency DR
     - Capacity Market
     - Ancillary Services Market

2. Price-Based Programs (PBP)
   - Time of Use (TOU)
   - Critical Peak Pricing (CPP)
   - Extreme Day CPP (ED-CPP)
   - Extreme Day Pricing (EDP)
   - Real Time Pricing (RTP)

Figure 1: Classification of Demand Response Programs [2]

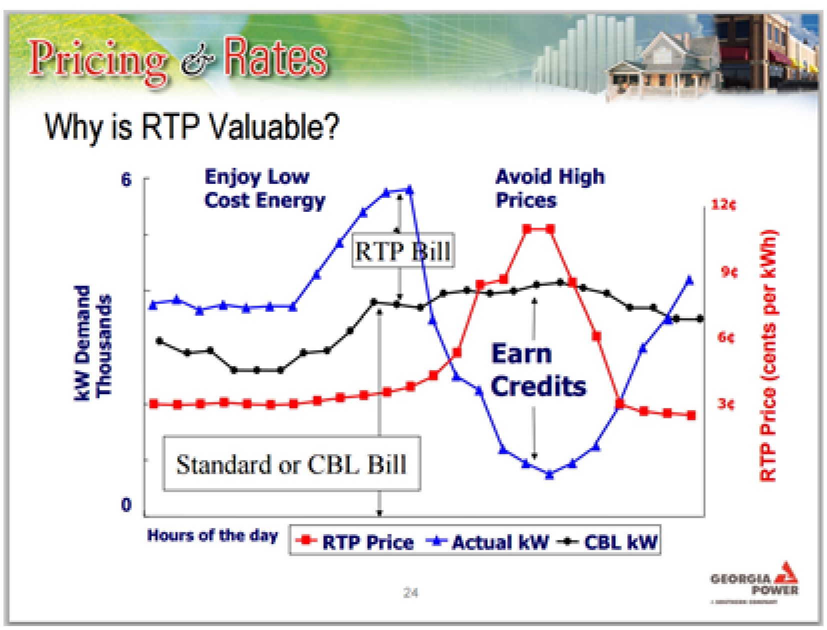

Figure 2: Georgia Power Rates Pricing [9]

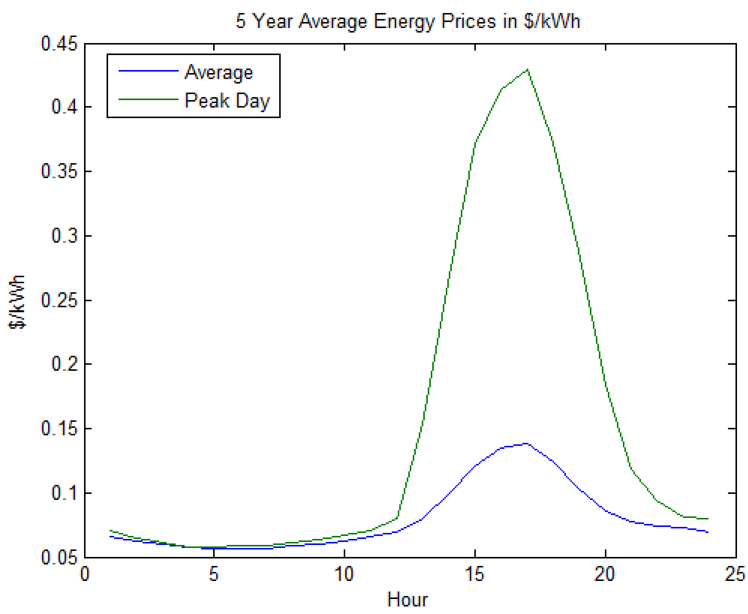

Figure 3: 5 Year Average RTP Data - Average Days and "Peak Days"

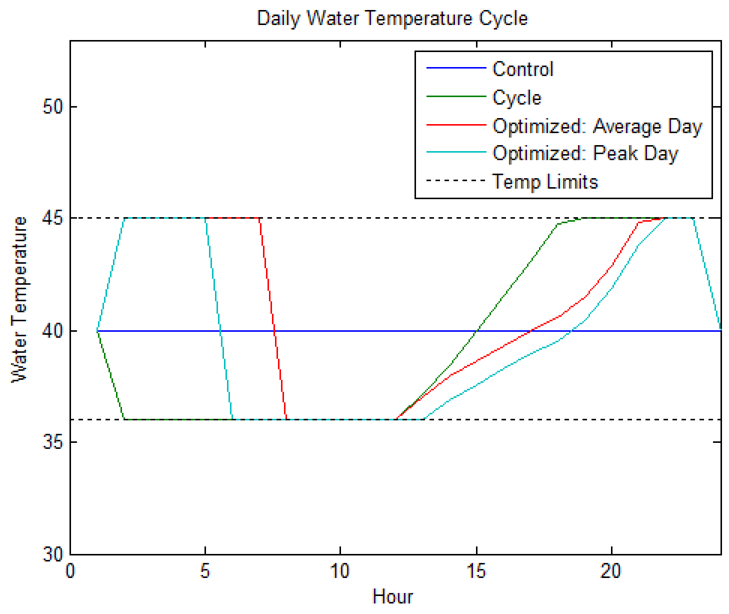

Figure 4: Water Temperature Cycle

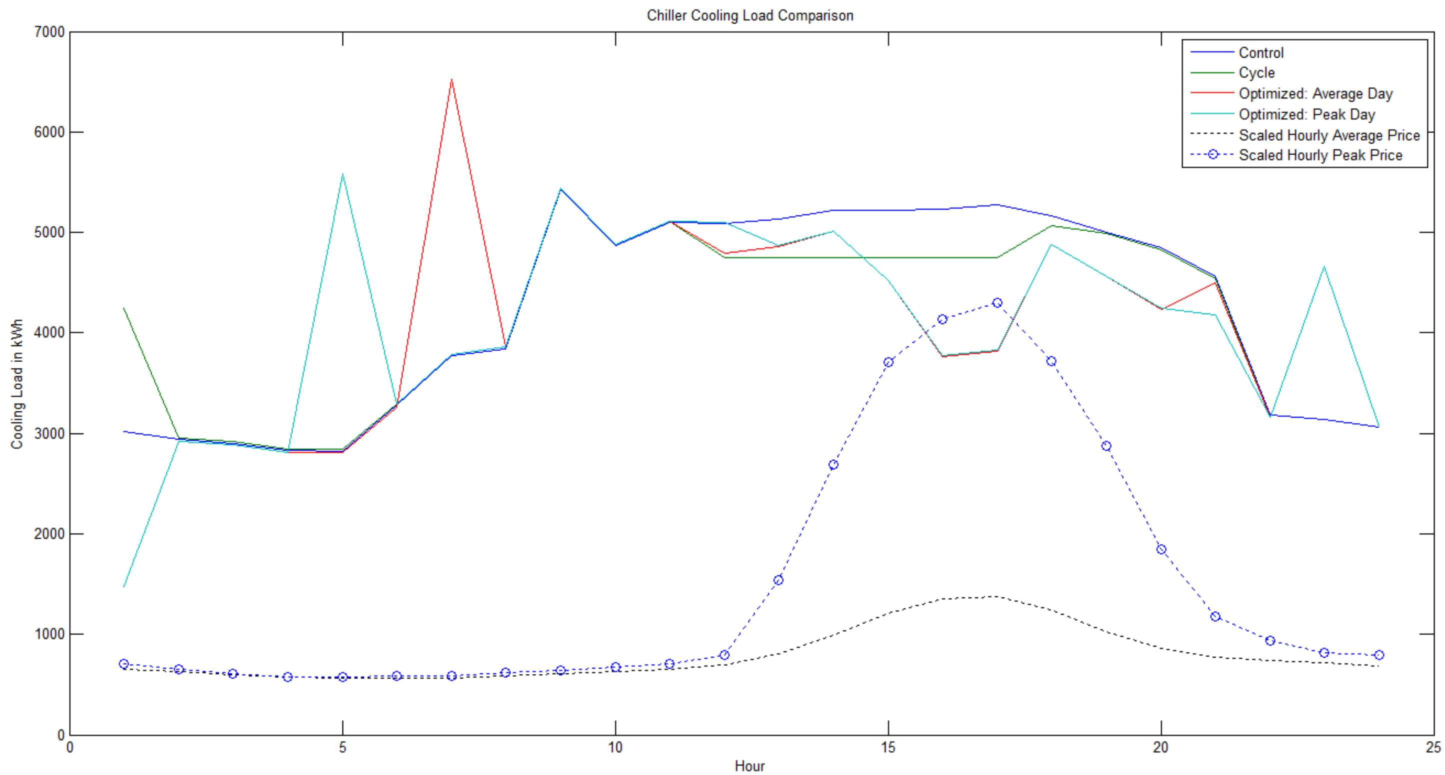

Figure 5: Total Chiller Output

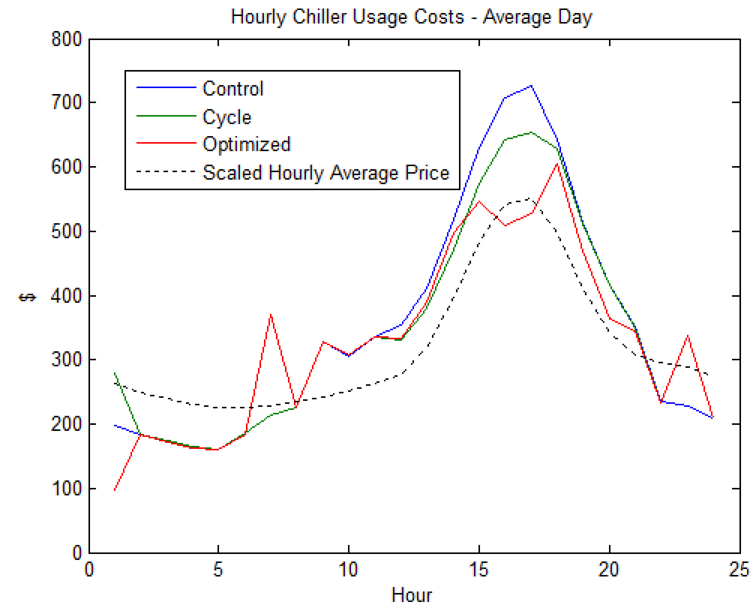

Figure 6: Daily Chiller Costs Comparison - Average Day

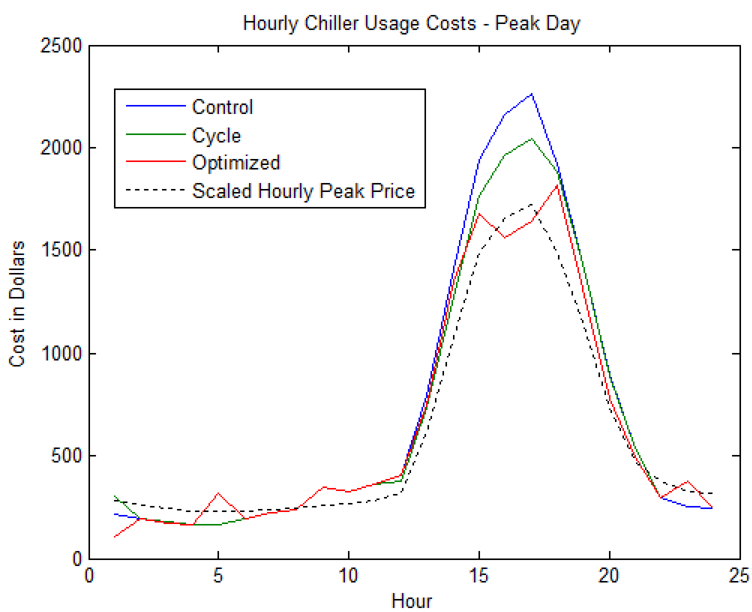

Figure 7: Daily Chiller Costs Comparison - “Peak Day”

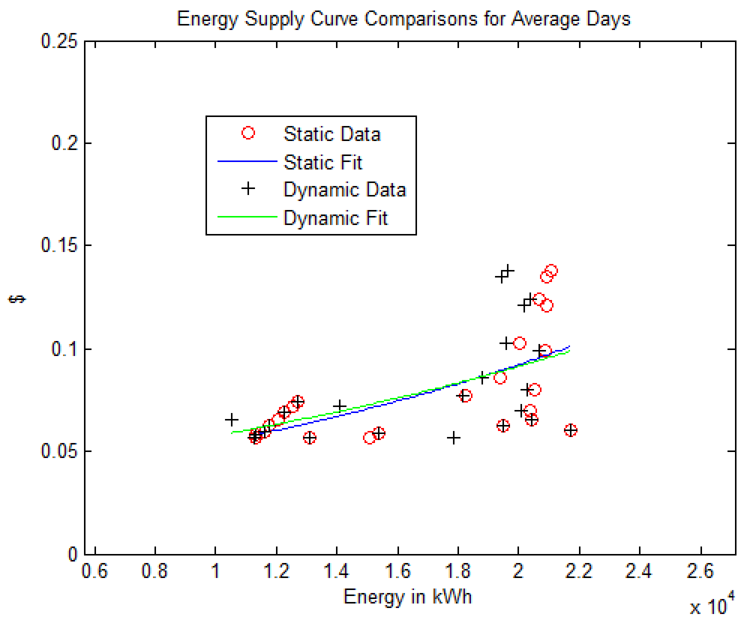

Figure 8: Total Campus Supply Curves - Average Day

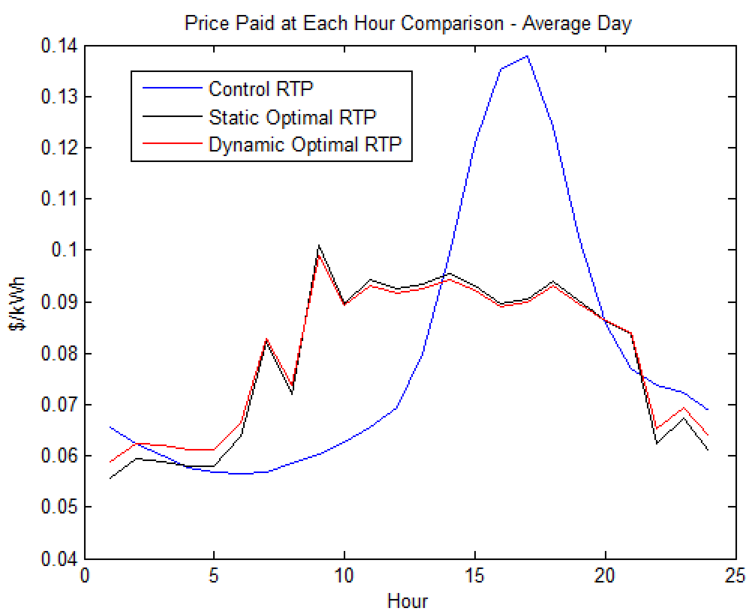

Figure 9: Total Campus Hourly Price Comparison - Average Day

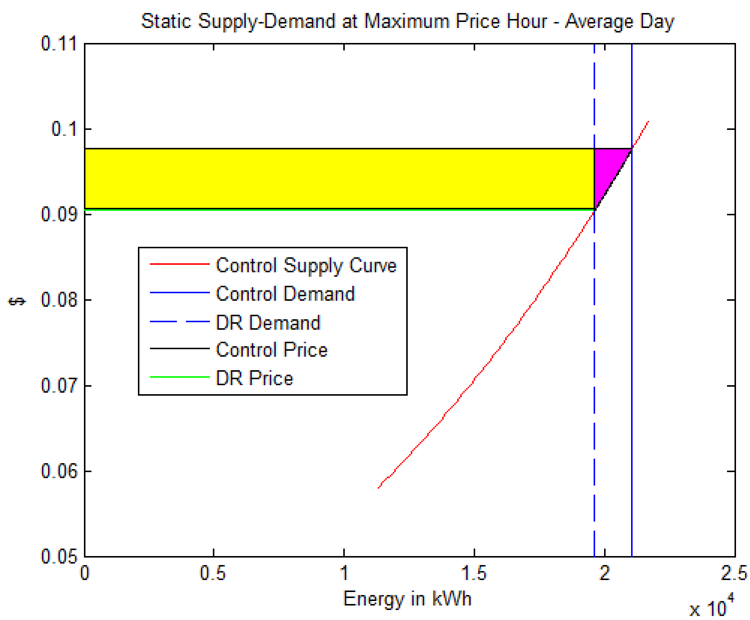

Figure 10: Static Supply-Demand Change at Maximum Price Hour - Average Day

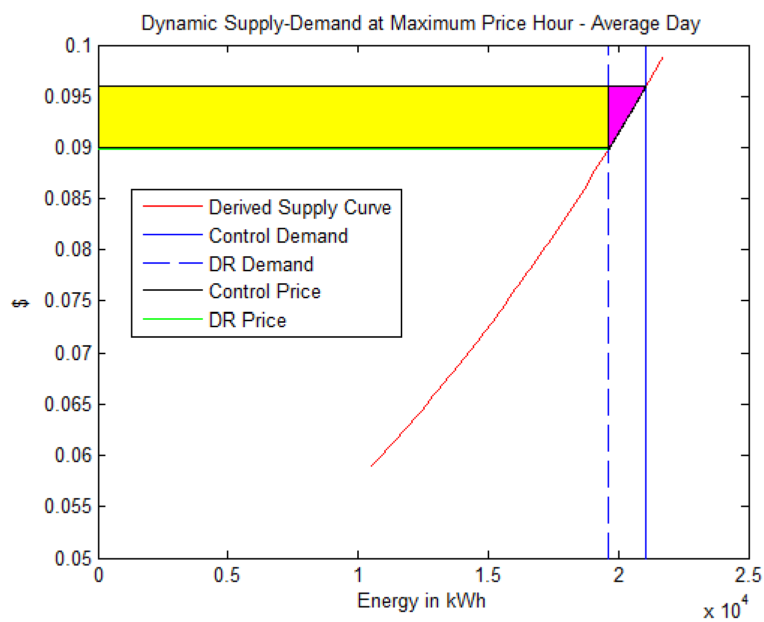

Figure 11: Dynamic Supply-Demand Change at Maximum Price Hour - Average Day

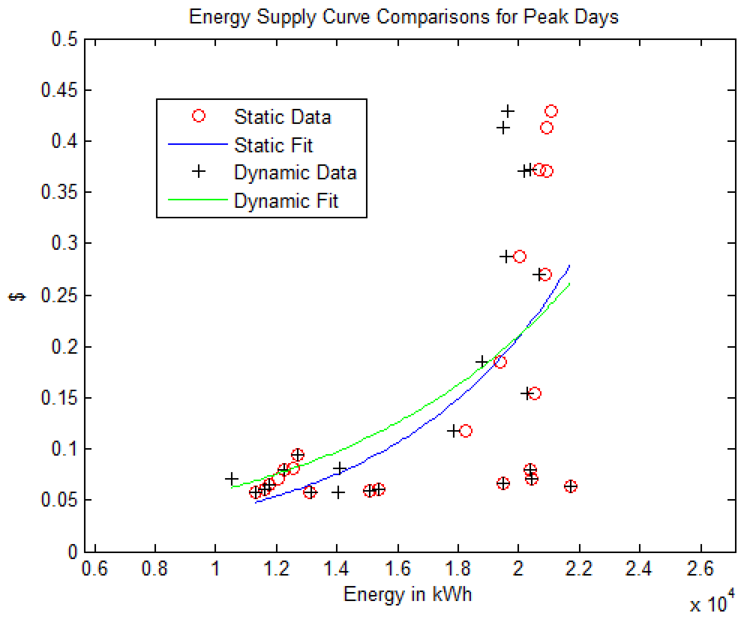

Figure 12: Total Campus Supply Curves - "Peak Day"

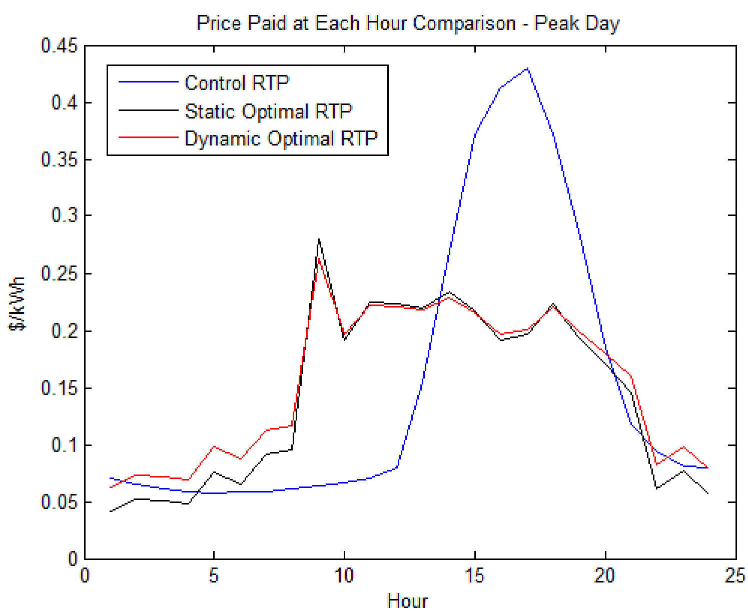

Figure 13: Total Campus Hourly Price Comparison - "Peak Day"

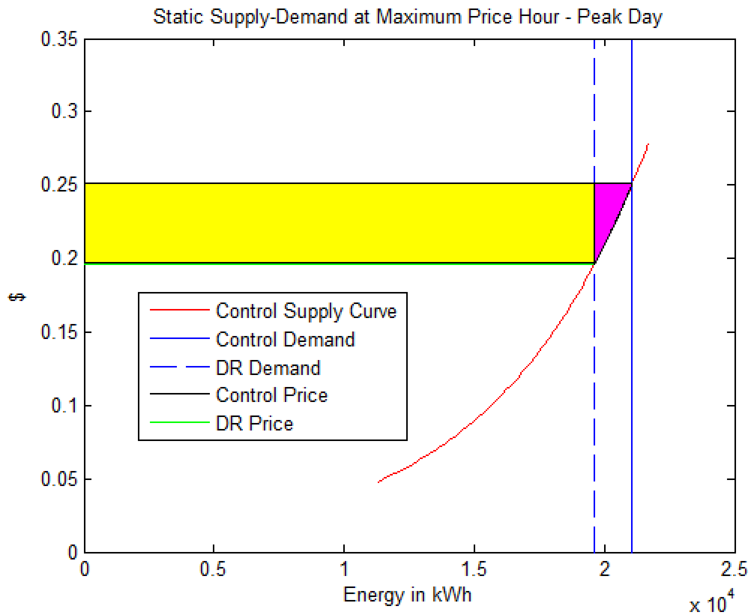

Figure 14: Static Supply-Demand Change at Maximum Price Hour - "Peak Day"

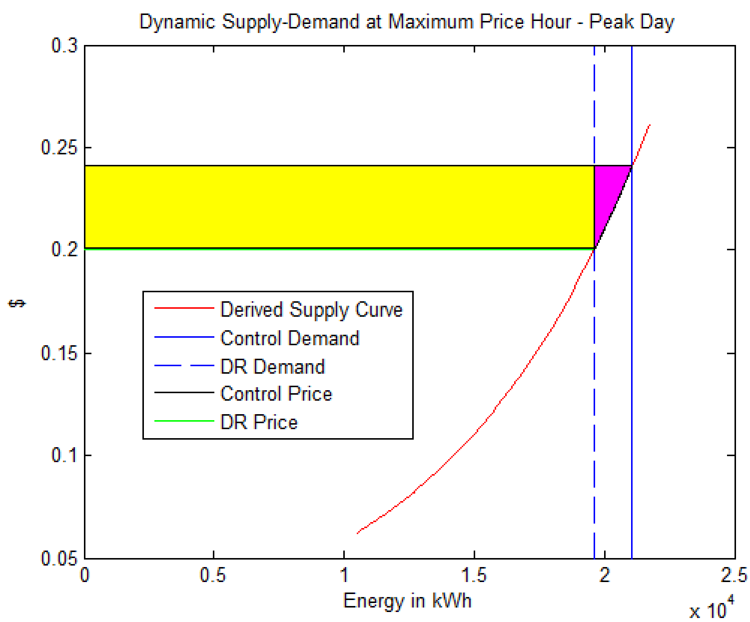

Figure 15: Dynamic Supply-Demand Change at Maximum Price Hour - "Peak Day"

5.2 Tables (All Items Without Citations are Original)

Table 1: Input Data for Chilled Water System

Hour	Total building load (tons cooling)	Ambient Temp. (F) (5 year Average)	Real-Time Electricity Price (\$/kWh) (5 Year Average)	Real-Time Electricity Price (\$/kWh) (5 Year "Peak Day" Average)
1	820	76.62	\$ 0.0656	\$ 0.0706
2	800	75.27	\$ 0.0625	\$ 0.0652
3	790	74.27	\$ 0.0599	\$ 0.0606
4	770	73.32	\$ 0.0578	\$ 0.0580
5	770	72.55	\$ 0.0567	\$ 0.0575
6	900	71.94	\$ 0.0564	\$ 0.0583
7	1040	71.43	\$ 0.0568	\$ 0.0591
8	1060	71.53	\$ 0.0585	\$ 0.0614
9	1510	72.10	\$ 0.0604	\$ 0.0640
10	1350	73.08	\$ 0.0628	\$ 0.0670
11	1415	74.39	\$ 0.0657	\$ 0.0706
12	1410	76.31	\$ 0.0695	\$ 0.0796
13	1420	78.19	\$ 0.0800	\$ 0.1540
14	1440	82.18	\$ 0.0992	\$ 0.2692
15	1440	84.47	\$ 0.1208	\$ 0.3713
16	1440	86.01	\$ 0.1352	\$ 0.4131
17	1450	87.05	\$ 0.1378	\$ 0.4297
18	1420	87.26	\$ 0.1241	\$ 0.3717
19	1375	86.69	\$ 0.1027	\$ 0.2875
20	1330	86.24	\$ 0.0859	\$ 0.1844
21	1250	84.76	\$ 0.0770	\$ 0.1183
22	860	83.03	\$ 0.0739	\$ 0.0939
23	850	81.28	\$ 0.0723	\$ 0.0814
24	830	78.83	\$ 0.0688	\$ 0.0797

Table 2: Daily Energy Use Totals - Chiller Only

Energy Totals (kWh)			
Control	Cycle	Optimum: Average Day	Optimum: “Peak Day”
100921.00	100971.95	97807.81	97904.24

Table 3: Daily Costs Comparison - Chiller Only

Cost Totals			
	Control	Cycle	Optimum
Average Day	$ 8,412.96	$ 8,298.23	$ 7,891.23
“Peak Day”	$ 17,145.57	$ 16,502.84	$ 15,352.00

Table 4: Energy Use Difference from Control Case - Chiller Only

Energy Savings from Control Case (kWh)		
Cycle	Optimum: Average Day	Optimum: “Peak Day”
50.95	-3113.19	-3016.76

Table 5: Cost Savings from Control Case - Chiller Only

Cost Savings from Control Case		
	Cycle	Optimum
Average Day	$ 114.73	$ 521.72
“Peak Day”	$ 642.72	$ 1,793.57

Table 6: Parameters for Supply Curve Fitting ($P(Q) = a_1 * e^{a_2 * Q}$)

Parameters				
Parameter	Static Model: Average Day	Static Model: "Peak Day"	Dynamic Model: Average Day	Dynamic Model: "Peak Day"
a_1	3.174E-02	7.028E-03	3.626E-02	1.620E-02
a_2	5.33E-05	1.70E-04	4.62E-05	1.28E-04

Table 7: Total Energy Costs - Derived Supply Curves

Total Costs				
	Static Pricing: Control	Static Price: Optimal	Dynamic Price: Control	Dynamic Price: Optimal
Average Day	$ 33,675.32	$ 32,976.82	$ 33,755.54	$ 33,122.05
"Peak Day"	$ 68,457.71	$ 63,761.32	$ 70,517.16	$ 66,890.19

Table 8: Static Pricing Cost Difference

Static Pricing Cost Difference		
	Campus Savings (A)	Chiller Savings (B)
Average Day	$ 293.41	$ 381.60
"Peak Day"	$ 2977.44	$ 1843.50

Table 9: Dynamic Pricing Cost Difference

Dynamic Pricing Cost Difference		
	Campus Savings (A)	Chiller Savings (B)
Average Day	$ 186.64	$ 343.14
"Peak Day"	$ 658.49	$ 1,033.58

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