Model and Control for Cooperative Energy Management

by

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Submitted to the Department of Electrical Engineering and Computer Science
in partial fulfillment of the requirements for the degree of

Master of Engineering Electrical Engineering and Computer Science

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2010

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Abstract

Proto/Amorphous Cooperative Energy Management (PACEM) aims to build and deploy a highly scalable system for smart power grids that will enable efficient demand shaping for small-user networks. Two key problems are to provide distributed control algorithm for efficient demand shaping and to provide an incentive structure to encourage both users and the electric power sector to opt-in to PACEM. In this thesis, I address the first problem by designing `ColoredPower`, a probabilistic control algorithm. I implemented and tested `ColoredPower` in MIT Proto, building on previous work in spatial computing. Simulations in Proto show that `ColoredPower` operates within 3% error and provides a stable dynamic response time on the order of minutes. To address the second problem, I provide a model for user and power company incentives in PACEM, in the form of the *Colored Procurement Mechanism*, which enables further work in optimal algorithmic mechanism design.

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Acknowledgments

I would like to thank:

My advisors—Jacob Beal for introducing me to this field, his guidance, encouragement and inexhaustible patience, and Hal Abelson, for driving me away from implementation and toward design. Anne Hunter, for making everything possible.

Professor Ignacio J. Perez-Arriaga for his insights about the electric power sector, Associate Professor Constantinos Daskalakis and Yang Cai for showing me the beauty of algorithmic mechanism design, and Professor Dennis Freeman for helping me recognize my first non-linear control problem.

Omari Stephens, for helping me learn Proto two steps at a time. Steven Herbst, Jonathan Spaulding, and TungShen Chew for useful and interesting discussions about feedback and control.

My family, for supporting me no matter what. And my friends, for keeping me sane and reminding me of the light at the end of the tunnel.

This work was partially funded by a grant from the MIT Energy Initiative Seed Fund.

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Chapter 1

Introduction

Until recently, growth in electricity demand in urban areas has been met with growth in power generation. This is not always a feasible solution—building new power plants is expensive and sometimes harmful to the environment. Power generation varies over time, depending on factors like the cost of fuel and the prediction of demand. For newer technologies like solar and wind plants, the power generated changes with the time of day and the weather. The variable demand for electricity means that the power available must always meet the highest possible demand. Instead of simply increasing power generation to meet increasing demand, we could ask people to use less electricity. This is called *demand side* energy management. Simply put, when the demand or "load" on a power grid goes too high, people could turn off unnecessary devices. If a large number of people reduce their electricity consumption by a small amount, there would be no need to generate more costly power.

This type of demand side management, done manually, exists for large-scale energy users e.g. large businesses, manufacturing plants, etc. Small-scale demand management is challenging; individual user consumption is small, yet the total consumption of small-scale consumers is a significant part of the total energy used. My project delivers results toward solving the problem of managing small-scale demand.

1.1 Proto/Amorphous Cooperative Energy Management (PACEM)

Suppose a city power grid is experiencing a heavy load in the middle of the day, and the city needs to reduce power consumption in the city by about 10% in order to function properly. One way to do this is for the power company to cut off power for an arbitrary neighborhood in the city.

What if the power company could instead send out a request saying that the total power consumption needs to be cut by 10%, so it would be great if a few of the non-critical electrical appliances around the city were shut off? By shutting off a few air conditioners, washing machines or other household appliances around the city, the power consumption could easily be brought down, no one would experience a blackout, and for all practical purposes, no real functionality of the city would be lost.

In 2009, residential electricity use accounted for about 35% of the total electricity used in the United States[3]. This is an area of energy use which is usually flexible. Most people may be willing to turn off their front porch light for a couple of hours if it helps the environment. They might also be willing to do their laundry at 9pm instead of 8pm, especially if it means that they get a discount on their electricity bill in exchange. The problem is that no number of call centers can handle these sort of negotiations and control to communicate constantly with every residence, and no one wants to be bothered by a stream of phone calls and run around the house turning devices on and off.

Proto/Amorphous Cooperative Energy Management (PACEM)[7] aims to provide a completely automated solution to this problem. Imagine electrical devices on the power grid being able to communicate among themselves. The power company sends out a request to cut the energy consumption by some amount, and the devices negotiate and decide which of them will shut off, for how long, and at what cost. This is done taking into account how critical each device is (the computer might be more important than the laundry machine), and doing so in a way that is “fair” to everyone

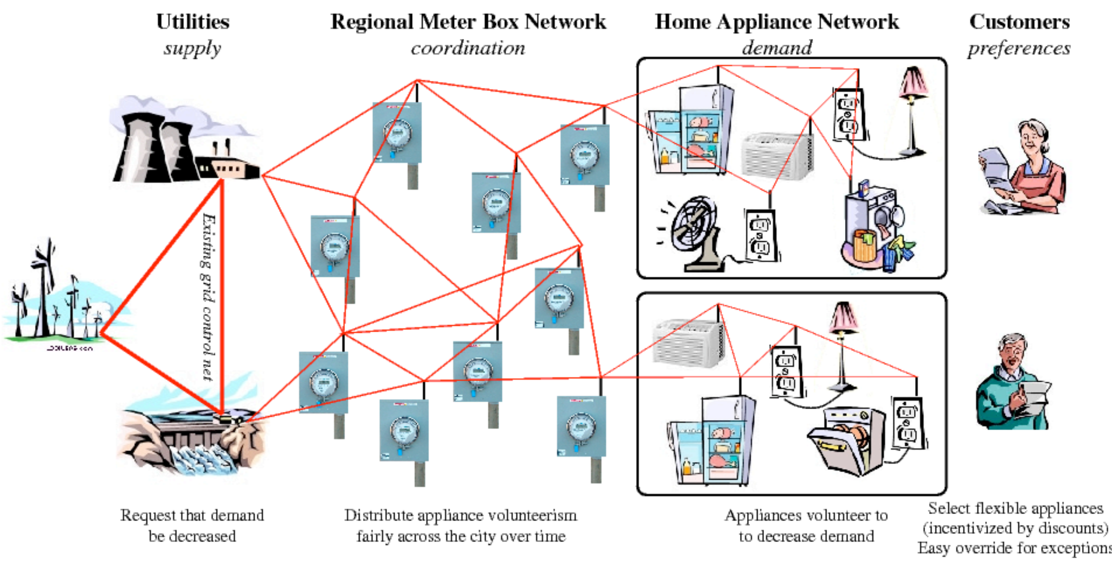


Figure 1-1: From the PACEM whitepaper[7]: utilities supply power and request decreases in demand. Customers specify their flexibility in exchange for lower energy prices. In each home, smart appliances and outlets communicate to decide which devices will provide this demand reduction. A network of smart meters manages the overall demand while an internal wireless mesh network in every home manages the internal demand in a way that is distributed fairly.

(devices which are equally critical are given equal treatment), all in a fraction of the time that it would take for the utility to manually call and negotiate with users. A fully developed PACEM would be able to do all of these things.

1.2 Obstacles to PACEM

I address two key obstacles to realizing PACEM. The first is to design a distributed control algorithm to run on these devices that satisfies a set of well-defined requirements, which translate into real world practicality. This is a problem in the realm of *spatial computing*[1, 21]. I will demonstrate the feasibility of this algorithm, `ColoredPower`, with an implementation in MIT Proto and a comprehensive set of simulations. The second obstacle is to ensure that both end-users and companies in the electric power sector will want to adopt PACEM. This is a problem in the realm of *algorithmic mechanism design*, where we are trying to build an incentive structure to motivate participation in PACEM. I will give a brief explanation of how PACEM can fit into the electric power sector, and some economic models of PACEM that we can use to design optimal incentives.

1.3 Previous Work

1.3.1 Spatial Computing and Proto

A spatial computer is a network of devices distributed through space such that the ability of devices to communicate depends strongly on their proximity[6]. Spatial computing can work using an *amorphous medium abstraction* - i.e. the network of devices is an approximation of an amorphous computational space with a computer at every point in this space. MIT Proto is a high level programming language where programs rely on referencing continuous regions of space and time rather than individual devices. The main advantage in context of PACEM is that the amorphous medium abstraction makes algorithms in spatial computing highly scalable[2]. Devices can be added or dropped from the network, and each device only needs to be able to communicate with a few devices around it in order for the system to work. Further, the proximity-based nature of communication means that no device has access to specific information about a large number of other devices. This is important for privacy concerns, as well as the ability to enforce economic fairness (i.e. no device should be able to "cheat the system" and profit by lying about their preferences or collaborating with a small number of other devices).

A fundamental area of study in distributed computing is distributed consensus - `ColoredPower` depends on the existence of a consensus algorithm that can report estimates about different aggregates in the network of electrical devices, even on a very large network with frequent communication and device errors. Because demand from residence to residence may be quite different, we cannot develop estimates based on sampling, but have to incorporate every single device in the aggregation. While designing `ColoredPower`, I will stick to a simple consensus algorithm, however, this can be substituted with more sophisticated existing algorithms e.g.[17, 18, 14].

1.3.2 Utility and User Incentives

In economics, the field of *Algorithmic Mechanism Design*[8] tackles problems mainly involving "resource allocation" - when the demand for a certain resource does not meet the supply, and every participant in the market is strategically selfish and has different preferences, we need to design a mechanism to ensure that the resource allocator achieves certain goals (e.g. maximum social welfare, maximum profit, etc) There are many different ways to model PACEM in order to design an optimal economic mechanism depending on the economic goals we set for the system. We will try to design applications of existing theoretical approaches in these areas.

1.3.3 Large Scale Demand Response

Manual demand response systems already exist for large energy users. For example, the Xcel Energy-EnerNOC Peak Savings Program[12] in Colorado works with users (usually businesses) that can offer more than 100kW in flexibility (which is large compared to residential power consumption of 1-5kW). This program keeps the flexible demand at these businesses "on call" during the day, and calls the business with an hour notice to request that they cut their power use for 2-4 hours. Businesses are allowed to override cut-requests from EnerNOC if they wish at no penalty. A company called Consumer PowerLine has made progress in providing demand response in urban multiple-family buildings; it builds electricity pools from clients to create a virtual power plant that can be activated with a half-hour notice[19].

In the long term, PACEM would also aim to automate this type of demand response. Currently, PACEM focuses on small-scale residential users. A neighborhood of about 100 residences consuming 5kW of power with about 20% demand flexibility, can provide the same total flexibility(100kW) as a large energy user. This flexibility will usually be more fine-grained than that of a large energy user as well, since a manufacturing plant may only have a single high-consumption device, while there are many small-consumption devices in a residential area.

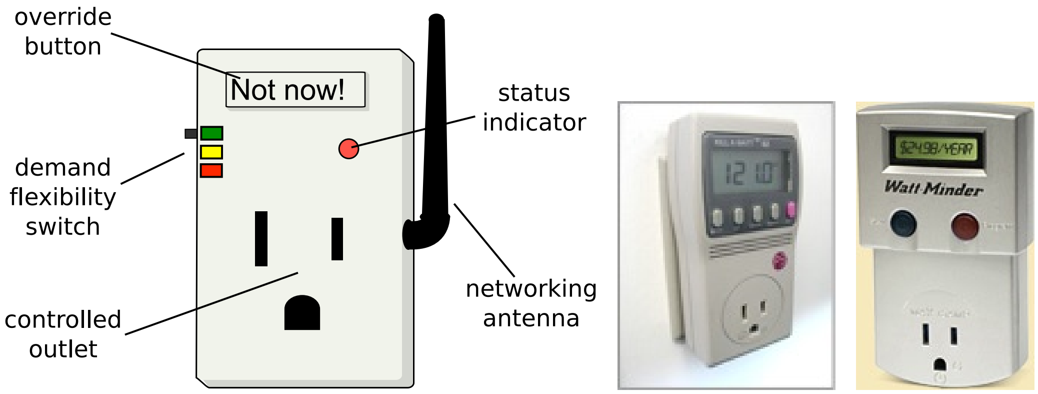
Another concept in controlling demand is dynamic energy pricing[9]. This means that instead of paying a flat rate for electricity (which may change every month or so) users can pay the going market price for electricity whenever they use it. The normalized flat rate means that sometimes, low energy users effectively subsidize high energy users. By charging the going market rate, the rise in peak energy prices can by propagated directly to the user. If a homeowner can see that she is paying a higher price for doing laundry at 8pm than doing it at 9pm, she may choose to do it at 9pm. PACEM is open to the use of any pricing model; both `ColoredPower` as well as the user incentives described in this thesis can operate with either static or dynamic pricing.

1.3.4 Smart Grids and Metering

PACEM relies on smart power metering and smart grid technology, where the core electric power grid is overlaid with intelligent devices that can communicate and do some processing. An example of technology that would enable PACEM is a smart outlet that has the ability to record user preferences and communicate wirelessly within a small home network, such as those shown in Figure 1-2. It would be easy to adapt the design of existing smart outlets such as the Kill-a-Watt or Watt-Minder in order to create outlets that are compatible with PACEM. Another example of smart outlets is in the Long Island Power Authority (LIPA) Edge project. Using Carrier Comfort Choice thermostats coupled with two-way pager communication, it allows customers to control their thermostats via the Internet[5].

1.4 Outline

Chapter 2 characterizes the computational requirements for the `ColoredPower` algorithm and provides a description of the actual algorithm. Chapter 3 describes the experimental verification methods and the simulations run in MIT Proto, making conclusions about the advantages and limitations of the performance of `ColoredPower` under different conditions. The first part of Chapter 4 gives a survey of the electric power sector and economic motivations for the power sector to adopt PACEM. The



(a) PACEM Smart Outlet (b) Kill-a-Watt (c) Watt-Minder

Figure 1-2: From the PACEM whitepaper[7]: A “smart outlet” adapter to plug over an existing outlet (a). The “Not now!” button allows an override, otherwise a three-way switch allows the user to set the importance of the particular device operating on the outlet. The outlet displays its mode with a multi-color LED, and communicates wirelessly with other outlets, appliances, and its meter box. This would be a small upgrade on existing technologies like the Kill-a-Watt (b) and Watt-Minder (c).

second part of Chapter 4 dives into algorithmic mechanism design for user incentives in PACEM. Chapter 5 summarizes the contributions of this project and outlines areas for further study.

Chapter 2

The `ColoredPower` Algorithm

Designing an algorithm to effectively control all the devices on the PACEM network is challenging. It must be quick, fair, and any single device should only turn on or off occasionally. We have developed the `ColoredPower` algorithm as a controller for the PACEM system, addressing these challenges using randomized local actions. When the action distribution is adjusted to compensate for currently uncontrollable appliances, standard feedback controllers can be used to produce local actions that combine to create the desired global effect. In this chapter, I first give an overview of the requirements that `ColoredPower` aims to meet. Then I describe the `ColoredPower` algorithm in detail along with an analysis. I will construct the algorithm in steps, starting with the algorithm for a simple system and building up to `ColoredPower`.

2.1 Algorithm Requirements

The algorithm that we need to control the distributed network of electrical devices must satisfy the following requirements:

1. Demand Flexibility: At any given point in time, the demand for power should have as much flexibility as possible—either to shut down devices that are currently on, or to relax and turn on devices that were shut down for demand response.

2. Dynamic Response: The algorithm must be able to control the *global power consumption*, Q_m such that it tracks a changing *global target* Q_t quickly and reliably. For the current electrical grid, this means a significant response on the order of minutes. Figure 2-2 gives an idea of how fast the algorithm needs to be with regard to the different functions of the electric power sector.

3. Fairness: Because PACEM depends on weakly incentivized participation (see chapter 4), we do not want users of the system to percieve it as unfair, or else they may stop participating. For example, a user may get upset if his air conditioner gets shut off more than his neighbor's. To satisfy this, we require that over a sufficiently long period of time, the expected total power consumption by two identical devices should be the same. At any time, if two devices have the same state, they should have an equal chance of deviating from that state.

4. Privacy: Fine-grained power consumption data is a significant privacy concern, so the data about different users and their devices should remain private. We thus require that global computations operate on many-consumer aggregates (which are by nature anonymized), and that no single device should ever have information about a large number of other individual devices.

5. Scalability: The algorithm must be scalable to very large numbers of devices. For instance, a large city grid might have tens of millions of devices.

6. Non-intrusiveness: The devices running the algorithm should only switch on or off occasionally. A user should always be able to "override" the system on a particular device at any time.

2.2 The `ColoredPower` Algorithm

Classical control theory provides many ways to track a target value using feedback systems of various types. The problem we are trying to tackle is of the same nature; we need to track the total supplied power i.e. the *global target*, Q_t. We want our

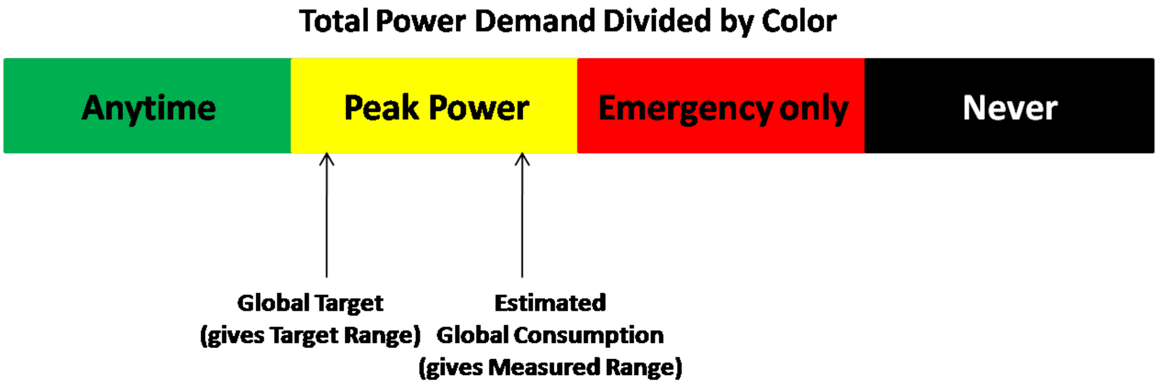


Figure 2-1: Under PACEM, consumers "color" their power demand indicating when it may be controlled. The algorithm tries to reduce the global measured power consumption Q_m from the global total demand Q_d to the global target Q_t.

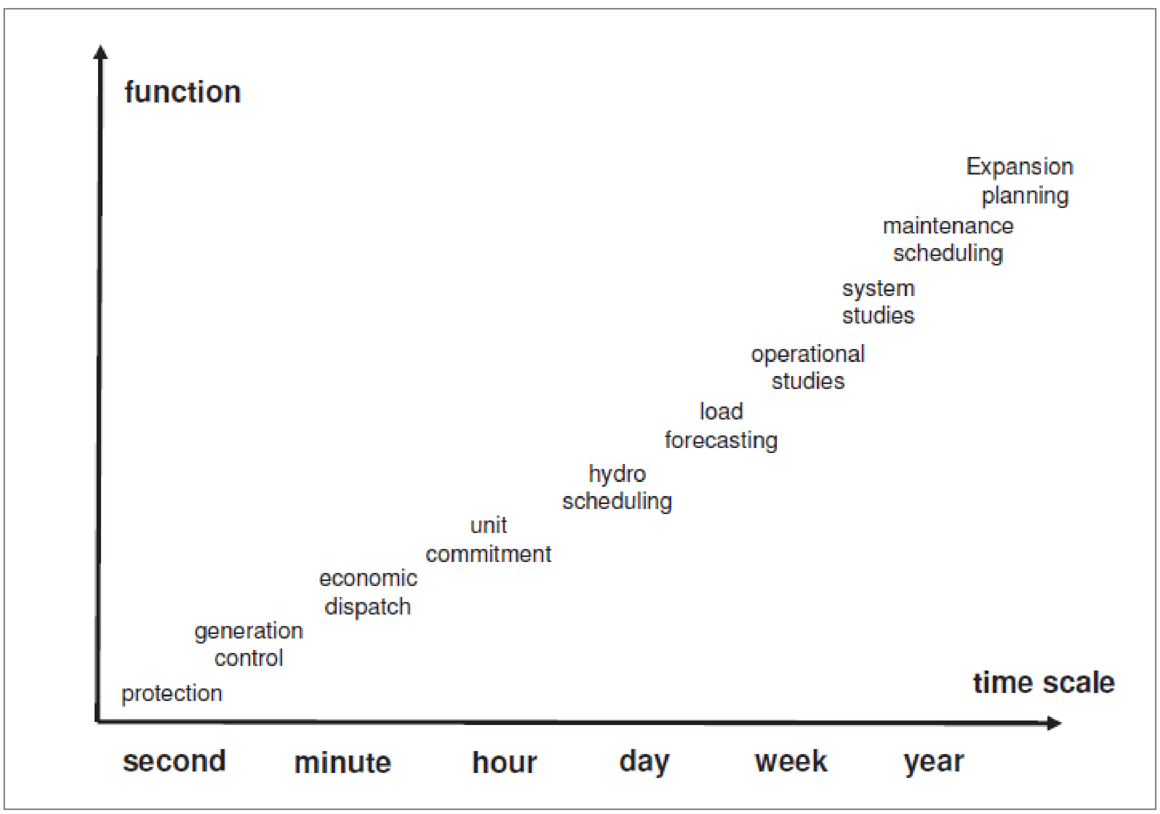


Figure 2-2: Time scale of different control decisions in the power system. PACEM operates on the economic dispatch of generated power.

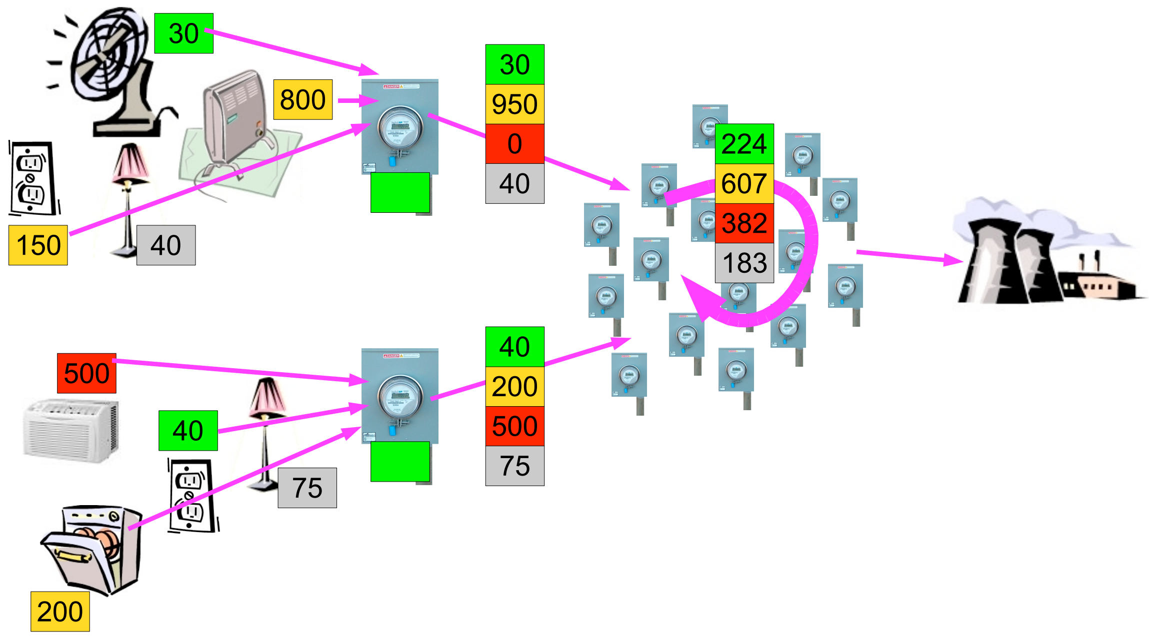
global power consumption, Q_m to follow the global target as closely as possible. The total supplied power has many different factors that go into how it changes over time, including economics of the power companies supplying the power, the capacities and overhead of the generators producing the power, government regulations, and of course the *global demand* for power (called Q_d).

The `ColoredPower` algorithm is designed to fulfill the requirements described in the previous section via distributed probabilistic control. The three main advantages of using a distributed probabilistic approach are speed, robustness, and privacy. The basic idea behind this approach is that instead of trying to aggregate fine-grained data to a central point, all devices share a model of the aggregate system state. When the target consumption Q_t changes, each device independently calculates what percentage of devices should change state overall, and then flips a weighted coin to determine whether it is one of those devices. Although random variance and consumer heterogeneity make it unlikely that this will immediately succeed, it will quickly take consumption much closer to the target. When coupled with a feedback controller, the consumption can be fine tuned to arrive at the target. The law of large numbers plays to our advantage since the more consumers that participate in the system, the better that probabilistic control is expected to perform. The decentralization of control provides robustness, since there need not be any critical points in the network where a small number of failing devices can cripple the system. Since the control is local, data can be aggressively aggregated to preserve privacy. The following sections describe the incremental construction of `ColoredPower`.

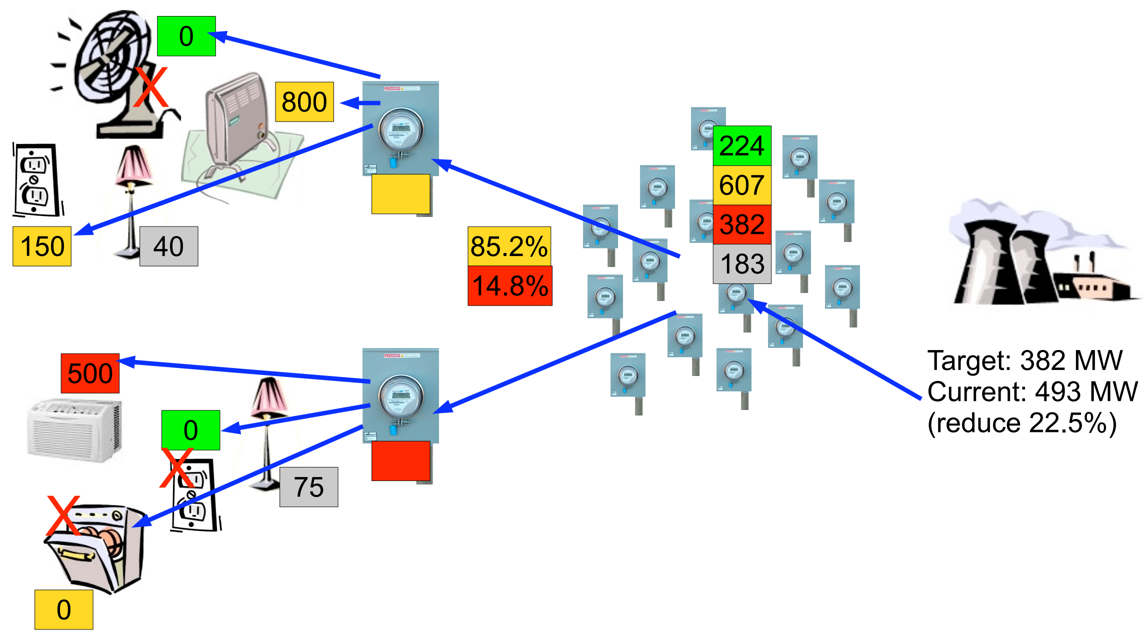
2.3 Building up to `ColoredPower`

Let us begin by defining the base information that we assume is available for the network of devices. For now, we will ignore power coloring and consider all consumption to be in a single category. Each device i holds the following state information:

- n, the total number of devices on the network



(a) Estimation



(b) Control

Figure 2-3: From the PACEM whitepaper[7]: The "`ColoredPower`" algorithm estimates flexibility information from the network via an aggregator tree. The utility then sets a target color range. Each consumer's household randomly chooses a color, shutting off any appliances more flexible than its chosen color. Under the `ColoredPower` algorithm, The gateway device for each household selects a priority level for all appliances in the household, and any appliances beyond that priority shut themselves down (subject to customer override).

- Q_t, the current global target (i.e. total supplied power)

- Q_m, the total measured power consumption on the network (which we wish to control to equal Q_t)

- Q_d, the total power demand from all the devices on the network

- d_i, the device's own measured power demand

- m_i, the device's own measured power consumption (we assume it to be 0 when off and d_i when on)

- t_{flip} The time remaining until the device is next allowed to flip a coin to decide whether to change state

Each device is also assumed to have a clock that measures elapsed time with no more than a small error, and to evaluate its algorithm frequently. Whenever t_{flip} reaches zero, a device will execute its probabilistic control step, then reset t_{flip} to an expected value of T_{flip} (section 2.3.2 describes how T_{flip} is chosen).

We assume that the global state (n, Q_t, Q_m, and Q_d) is provided by a distributed aggregation algorithm with some lag. This lag cannot be less than $\Omega(diameter/c)$, where *diameter* is the number of hops across the network and c is the maximum speed of information flow per hop. In the `ColoredPower` implementation for this thesis, we aggregate using a distance-based spanning tree (as shown in Figure 2-3). We chose this aggregator for simplicity and its $\Theta(diameter/c)$ lag. We expect that a much more robust aggregator is both possible and necessary for a real deployment.

2.3.1 Simple Local Probabilistic Control

The simplest probabilistic control for Q_m to track Q_t is to have device i flip a coin with probability $p_{simple} = \frac{Q_t}{Q_d}$ of turning heads. If the coin falls heads, the device chooses to turn on and consume d_i power, if not, it chooses to turn off and consume

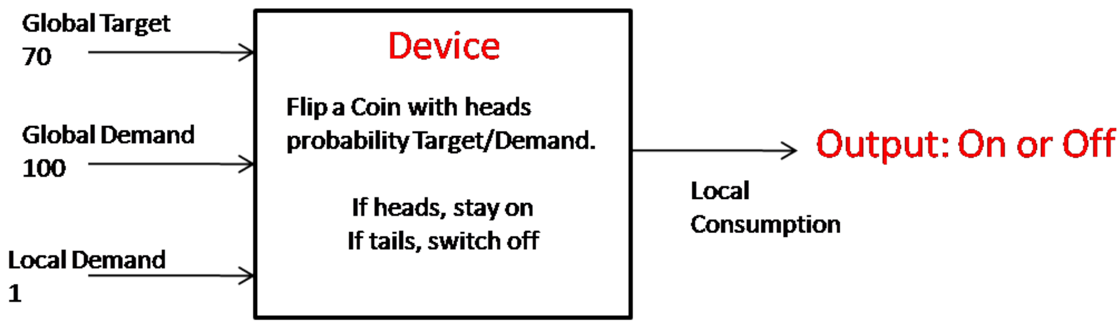


Figure 2-4: The simplest block of local probabilistic control in order to achieve the desired global result in the expected case.

0 power. If each device does this the total consumption will be

$$\begin{aligned}
E[m_i] &= p_{simple} \times d_i && (2.1)\\
&= \frac{Q_t}{Q_d} \times d_i && (2.2)\\
E[Q_m] &= E[\sum_i m_i] && (2.3)\\
&= \sum_i E[m_i] && (2.4)\\
E[Q_m] &= \sum_i \frac{Q_t}{Q_d} \times d_i && (2.5)\\
&= \frac{Q_t}{Q_d} \sum_i d_i && (2.6)\\
&= \frac{Q_t}{Q_d} \times Q_d && (2.7)\\
&= Q_t && (2.8)
\end{aligned}$$

For example, consider 100 devices, each consuming 1 unit of energy (thus the global demand is 100), and the global target is 70. If each device turns on with 70% probability then our expected global power consumption is equal to the global target.

There are two major problems with this design:

1. From iteration to iteration of the local control, there is nothing that prevents an individual electrical device from switching on and off very rapidly; this is not an acceptable solution because the rapid oscillation of a single device is undesirable.

2. The simple probabilistic control does not account for the variance that comes with randomization. It is unlikely that the global consumption actually hits exactly Q_t. Since we are summing n independent identically distributed random variables (because the probability is the same for all the devices), the mean of the sum will be the sum of the means, but and the standard deviation of the sum will be the norm of the individual standard deviations. Thus the global consumption will likely be somewhere in $[Q_t - \sqrt{n * p(1-p)}, Q_t + \sqrt{n * p(1-p)}]$.

2.3.2 Timed Local Probabilistic Control

To address the first problem we add timers to every device which ensure that once a device turns on or off, it stays that way for a period of time. So we introduce the following new parameters for each device.

- t_{fall}: the time remaining until the device is allowed to decrease its power consumption m

- t_{rise}: the time remaining until the device is allowed to increase its power consumption m

Every time a device increases power consumption, t_{fall} gets reset to an expected value of T_{fall}. Similarly, if a device decreases consumption t_{rise} gets reset to an expected value of T_{rise}. Devices that have recently changed state are thus "timed out" and cannot change state again in the opposite direction soon.

When a timer t_x is reset to an expected value of T_X, it is important that there be a large amount of variance in the value it is reset to. This effectively desynchronizes devices from one another, ensuring that in the expected case, there are always some devices that are allowed to change their state, and therefore some demand flexibility. Therefore, at each reset of a timer t_x, its new value is selected from a uniform random distribution on the interval $[\frac{T_x}{2}, \frac{3 \times T_x}{2}]$.

With the addition of these timers, our prior simple probabalistic control will no longer operate correctly, since timed-out devices are capable of changing state. In

Figure 2-5: Division of devices into three categories based on their fall, rise, and flip timers. If a device is unable to move down, it is 1-fixed, and if it is unable to move up, it is 0-fixed. If it is neither, then it is flippable.

our example, the demand is 100, the target has recently switched from 100 to 70. We would like our local probabilistic control to give us an expected global power consumption of 70. Consider this situation, except 50 devices are timed out and 50 are available for a decrease in power consumption. The probability with which each non-timed-out device decides whether to stay on or turn off is still $p_{simple} = \frac{70}{100} = 0.7$. Then the expected global power consumption at the next step becomes $\sum_{i \in timed\, out} d_i + p_{simple} \times \sum_{i \in not\, timed\, out} d_i = 50 + 35 = 85$, rather than 70 as desired.

We thus need to adjust p_{simple} in some way that will depend on the number of devices that are not-timed-out, in order to maintain the accuracy of our expected global power consumption. To do this we aggregate new global state information about the state of the network. Each device is classified into exactly one of three states (Figure 2-5):

- 1-fixed devices: The number of devices unable to fall at that instant (i.e. recently turned on). The total demand for these devices is denoted by Q_1
- 0-fixed devices: The number of devices unable to rise at that instant (i.e. recently turned off). The total demand for these is denoted by Q_0
- flippable devices: The rest, i.e. the number of devices that are available for local probabilistic control. The total demand for these is denoted by Q_f, and is a measure of the *demand flexibility* of the system.

The 1-fixed and 0-fixed terminology comes from the status of the devices as on (1) or off (0). These values will be collected by global aggregation along with the other aggregate values.Note that by definition,

$$1\,fixed + 0\,fixed + flippable = n$$

and similarly,

$$Q_1 + Q_0 + Q_f = Q_d$$

As opposed to the *Simple Local Probabilistic Control*, where the demand flexibility is Q_d, the demand flexibility is now Q_f, reflecting the fact that the control itself impinges on flexibility. Further, Q_1 demand is already fixed as on, which means that Q_1 power is already being consumed regardless of the control at that moment. In order for the expected consumption to be $p_{simple} * Q_d$, the devices can modify the local probabilistic control as follows:

$$p_{census} = \frac{p_{simple} * Q_d - Q_1}{Q_f}$$

Each device that is not timed out flips a coin with probability p_{census}. If the coin falls heads, the device turns on and consumes d_i power; if not, it turns off and consume 0 power. It is easy to see that if $Q_f = Q_d$, i.e. all devices are flippable, then $p_{census} = p_{simple}$. Note also that if there is not enough demand flexibility to achieve the target, p_{census} will be outside of $[0, 1]$. In this case, we clip it to $[0, 1]$ to get as close as possible to the target.

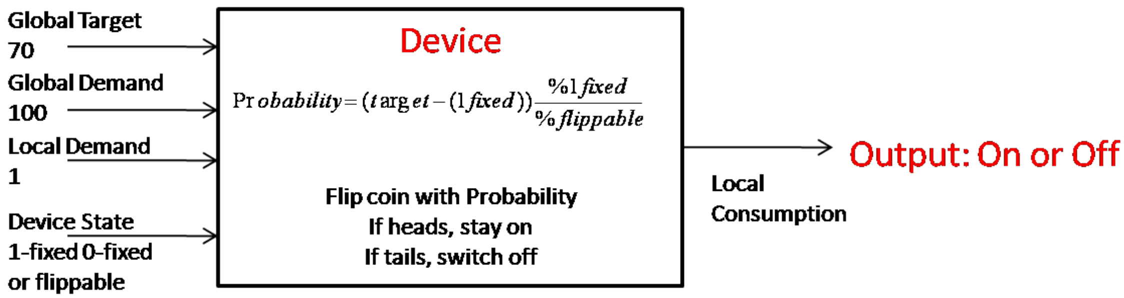


Figure 2-6: Census adjusted probabilistic control

In general, we have

$$\begin{aligned}
E[m_{i\in flippable}] &= p_{census} \times d_i && (2.9)\\
E[m_{i\in(0,1)fixed}] &= d_i, 0 && (2.10)\\
E[Q_m] &= E[\sum_i m_i] && (2.11)\\
&= Q_1 + \sum_{i\in flippable} E[m_i] && (2.12)\\
&= Q_1 + \sum_{i\in flippable} p_{census} \times d_i && (2.13)\\
&= Q_1 + p_{census} \times Q_f && (2.14)\\
&= Q_t && (2.15)
\end{aligned}$$

This timer dependent and census-adjusted local probabilistic control gives us the desired expected global power consumption, while neatly allowing each device to be switched between on and off at a non-intrusively low frequency.

2.3.3 Timed Local Probabilistic Feedback Control

We still need to address the problem of variance. We will do this with feedback control based on the global consumption Q_m. We have chosen to use a simple PID controller. This long-established generic controller, which incorporates a (P)roportional term to address instantaneous error, an (I)ntegral term to address accumulating "past" error, and a (D)erivative term to to predict likely "future" error, is a simple and well-understood starting point for adding feedback control to a system (though we shall see in Section 3.4 that a more sophisticated controller will eventually be needed). I will take a moment here to give more detailed justification for the use of a full PID controller. The distributed consensus algorithm only delivers estimates that get more accurate over time. This means that the values of Q_m, Q_d, Q_f etc. may not always be accurate; in fact, if the target has recently changed, the correct reporting of these values to the different devices will lag behind the actual network state. We take the maximum possible lag in the network and call this the feedback delay. Integral error feedback is a good way to control for delays in measurement. We can use standard tricks such as resetting the integral term periodically, or putting an exponential back-off filter on the integral error in order to deal with situations which have a "badly behaving" target. It is hard for the algorithm to predict how many devices are going to change their status from being fixed to flippable at time t_j, even if the distribution is known at t_{j-1}. If a large number of devices suddenly becomes flippable, then the control probability may not adjust in time and cause overshoot, leading to unstable behavior. Thus, if the error is already decreasing we do not want Q_m to suddenly jump down if a group of devices becomes flippable at that instant. Derivative feedback control addresses this concern. At any point in time, the error in tracking is given by

$$\Delta(Q) = Q_t - Q_m$$

. Using a PID controller, the desired error correction is:

$$\Delta_{PID}(Q) = G_P * \Delta(Q) + G_I \int_0^t \Delta(Q) + G_D * \frac{d}{dt}\Delta(Q)$$

This can be converted into a local probability of change in much the same way as before: $p_{feedback} = \frac{\Delta_{PID}(Q)}{Q_f}$. The expected new value after an expected set of flips (from time t_0 to time $t_1 = t_0 + T_f$) is thus:

$$\begin{aligned}
E[Q_m(t_1)] &= Q_m(t_0) + & (2.16)\\
& \quad E[\sum_{i \in flippable} p_{feedback} \cdot d_i] & (2.17)\\
&= Q_m(t_0) + p_{feedback} \cdot Q_f(t_0) & (2.18)\\
&= Q_m(t_0) + \Delta_{PID}(Q) & (2.19)
\end{aligned}$$

If the gains for the PID controller are stable with respect to the delay in obtaining the aggregate state variables, then Q_m may be expected to converge to Q_t. Unusual in the design of a controller, however, it is important that the control be significantly overdamped. This is because "timed out" devices generally make the system very slow to recover from overshoots. Thus the controller must be overdamped enough that it approaches the target in a series of steps, adjusting the flipping probability using the census as well as the error at every step, and where the probability of random variance causing a significant overshoot on any step is small.

2.3.4 Adapting to a four color system

With *Timed Local Probabilistic Feedback Control*, we now have an algorithm that an control power for a single PACEM "color." All that remains is to extend it to a multiple-color system. Note that while we discuss this algorithm in terms of the four colors in the PACEM proposal, it generalizes trivially to a k-color algorithm.

To generalize from one to multiple colors, we introduce the concept of *Range*. The *Range* is always a real number between 0 (black) and 3 (green), and serves as a numerical relation between an amount of power and the total power demand, which is pre-divided into the four colors. Let $Q_d = Q_d^3 + Q_d^2 + Q_d^1 + Q_d^0$ denoting the division of the total demand into the four colors, green, yellow, red, and black respectively. Each device similarly controls four different demands $d_i = d_i^3 + d_i^2 + d_i^1 + d_i^0$, and has four different kinds of local power consumption $m_i = m_i^3 + m_i^2 + m_i^1 + m_i^0$. Note that each m_i^j is a discrete block of power, i.e. $m_i^j \in \{d_i^j, 0\}$. The maximum i for which

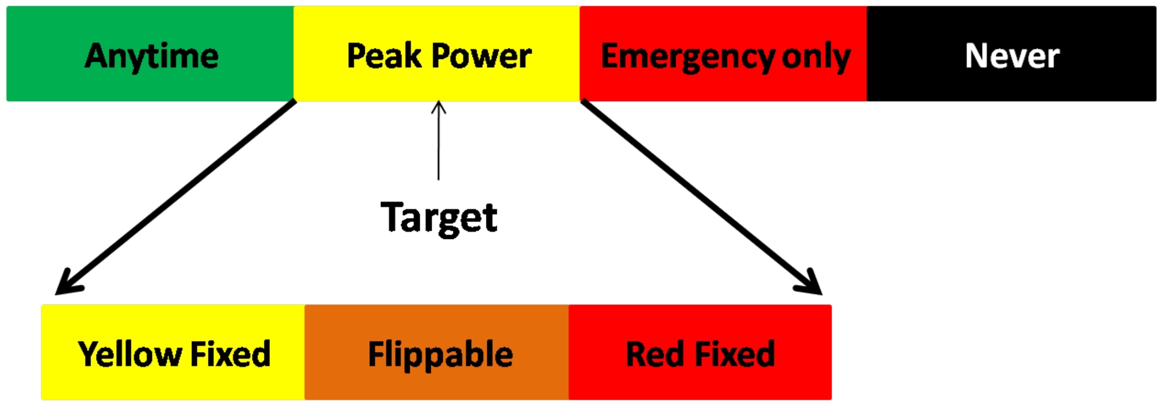


Figure 2-7: The distributed control algorithm, given the global desired and current consumption, produces a global command for the new level. This command must then be translated into a weighted coin-flip, to occur independently at each device, scaled to take into account the fact that the switching-frequency limitation means that some devices not currently controllable.

$m_i^j = d_i^j$ is the color c of the device, e.g. $c = 2$ would indicate the color "yellow."

When a power quantity Q_x has a Range of r_x this means that it includes all of the power "below" it.

$$Q_x = (r_x - \lfloor r_x \rfloor) \times Q_d^{\lceil r_x \rceil} + \sum_{i \leq \lfloor r_x \rfloor} Q_d^i \tag{2.20}$$

$$\lfloor r_x \rfloor = max_i(Q_d^i : Q_x \geq Q_d^i) \tag{2.21}$$

$$\{r_x\} \text{ (the fractional part)} = \frac{Q_d - Q_d^{\lfloor r_x \rfloor}}{Q_d \lceil r_x \rceil} \tag{2.22}$$

For example, a range of 1.3 would mean that Q_x contains all the power in the "red" and "black" blocks and 30% power from the "yellow" block.

The algorithm uses two ranges: the *target range* r_t corresponding to Q_t and the *measured range* r_m corresponding to Q_m (see Figure 2-1). With regards to control, the fractional and integer portions are handled separately. The integer portion is simple: when $\lfloor r_t \rfloor$ changes, every device in the entire block of power changes to be on or off (as appropriate) as soon as t_{fall} or t_{rise} allow the device to. This portion of control is naturally quite fast in achieving its goal.

Let us look at tracking the fractional part. There is a $Q_t^{\lceil r_t \rceil}$ which we need to track using only the $m_i^{\lceil r_m \rceil}$; our integer tracking has already made sure that $\lfloor r_t \rfloor = \lfloor r_m \rfloor$.

The demand is $Q_d^{\lceil r_t \rceil}$ and there is already some $Q_m^{\lceil r_t \rceil}$ which is the power consumption within that block. We just need to use some local probabilistic control which will push $Q_m^{\lceil r_t \rceil}$ toward $Q_t^{\lceil r_t \rceil}$. Wait, this is exactly the problem that we solved using the Timed Local Probabilistic Feedback Control! Instead of $\Delta(Q)$ we will introduce the corresponding error in range,

$$\Delta(r) = (r_t - \lfloor r_t \rfloor) - (r_m - \lfloor r_m \rfloor)$$

. This can be plugged into the PID controller as before to produce a $p_{feedback}$ which, when combined with integer control to produce $r_{adjusted}$, the local *control signal* for each device.

$$r_{adjusted} = \lfloor r_t \rfloor + \frac{\Delta(r) - \frac{Q_1^{\lceil r_t \rceil}}{Q_d^{\lceil r_t \rceil}}}{\frac{Q_f^{\lceil r_t \rceil}}{Q_d^{\lceil r_t \rceil}}}$$

. This completes the feedback controller. Figure 2-8 summarizes the `ColoredPower` algorithm. Each device receives aggregated data in the form of the global target, the global demand, and the global consumption, along with a census of demand flexibility. The device now infers the target range, measured range, and range-error using this input. The device goes through decision-tree based on a state table (Figure 2-9) that takes into account its local parameters: the timers, the local demand, the local measured consumption, etc. The integer part of the range tells the device what its minimum color should be, and the fractional part is converted into a probability with which it should turn on the color above the minimum. Finally, each device supplies the new local energy consumption and device state (which of the three census categories it falls into) into the aggregator, leading to an eventual update of the global state variables.

2.3.5 Handling User Overrides

The way that `ColoredPower` deals with user overrides is to simply transfer the demand which is "overriden" to black for a period of time. For example, if a demand tuple is

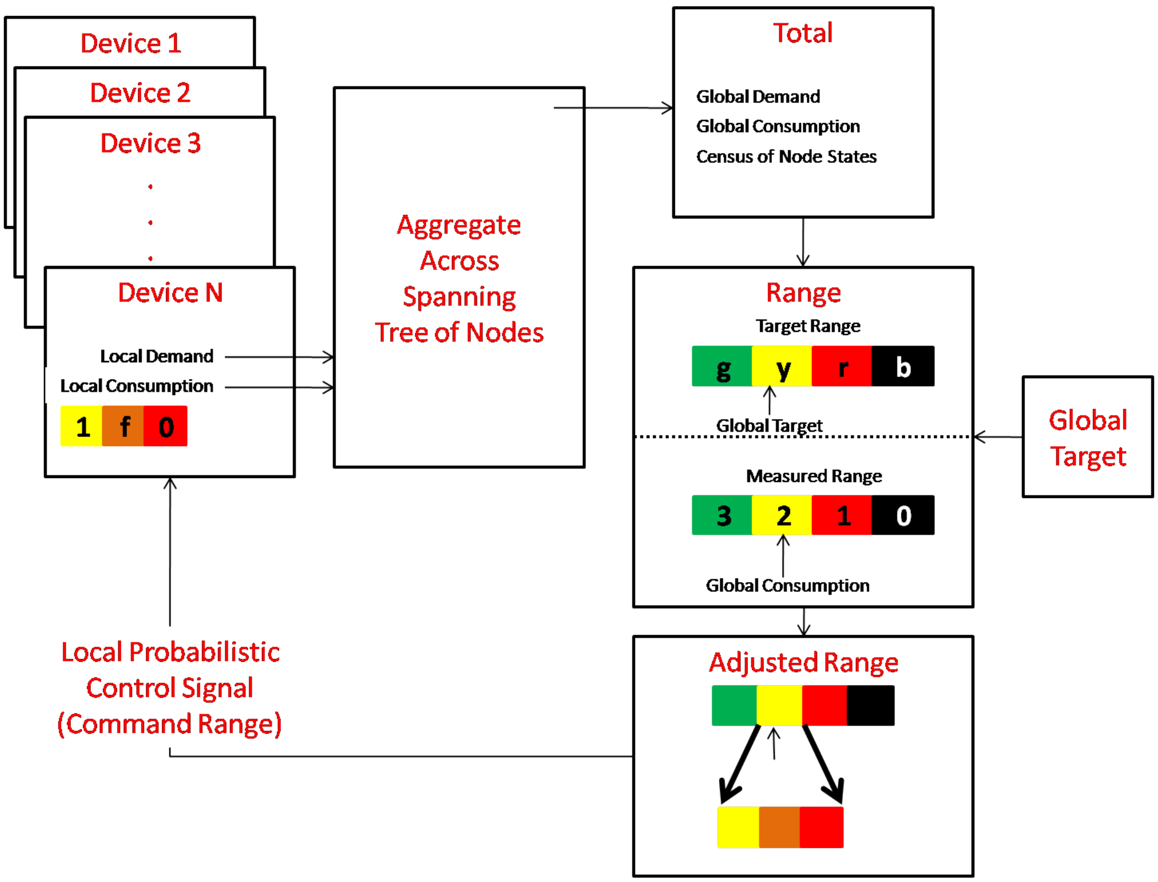
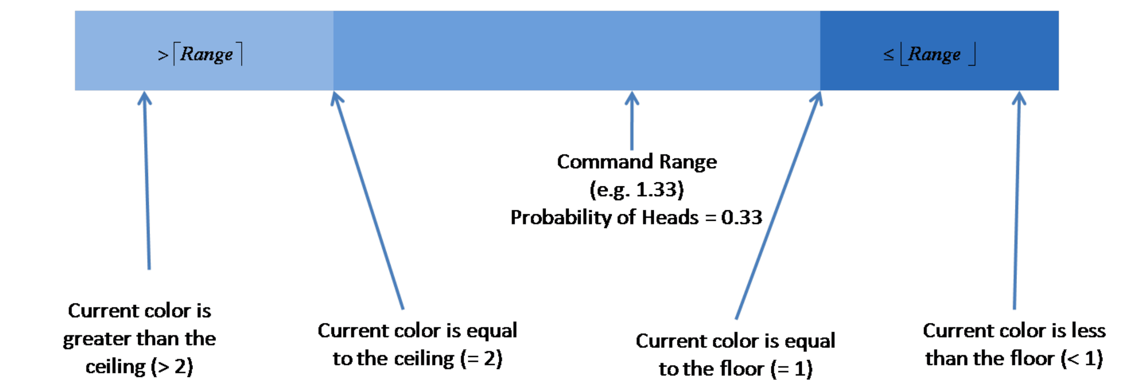


Figure 2-8: The distributed control algorithm, given the global desired and current consumption, produces a global command for the new level.



Current color is greater than the ceiling (> 2)

Fall Timer	Flip Timer	New Color
> 0	x	Same as before
0	> 0	Ceiling of Range
0	0, flip heads	Ceiling of Range
0	0, flip tails	Floor of Range

Current color is equal to the ceiling (= 2)

Fall Timer	Flip Timer	New Color
> 0	x	Same as before
0	> 0	Same as before
0	0, flip heads	Ceiling of Range
0	0, flip tails	Floor of Range

Current color is equal to the floor (= 1)

Rise Timer	Flip Timer	New Color
> 0	x (don't care)	Same as before
0	> 0	Same as before
0	0, flip heads	Ceiling of Range
0	0, flip tails	Floor of Range

Current color is less than the floor (< 1)

Rise Timer	Flip Timer	New Color
> 0	x	Same as before
0	> 0	Floor of Range
0	0, flip heads	Ceiling of Range
0	0, flip tails	Floor of Range

Figure 2-9: The state table based on the target range, measured range, and timers

(d^3, d^2, d^1, d^0), and the user overrides a request from `ColoredPower` to shut off all green power, then the new demand tuple for the user is $(0, d^2, d^1, d^3 + d^0)$. `ColoredPower` assumes that only a small fraction of users on the network will override a particular color of power at any given time. In Chapter 4 we will look at some of the reasoning behind this assumption.

The presented design of `ColoredPower` gives a promising distributed probabilistic control solution for PACEM. It addresses in theory, most of the requirements that were outlined at the beginning of the chapter including speed, robustness, and privacy. The next chapter attempts to verify these claims.

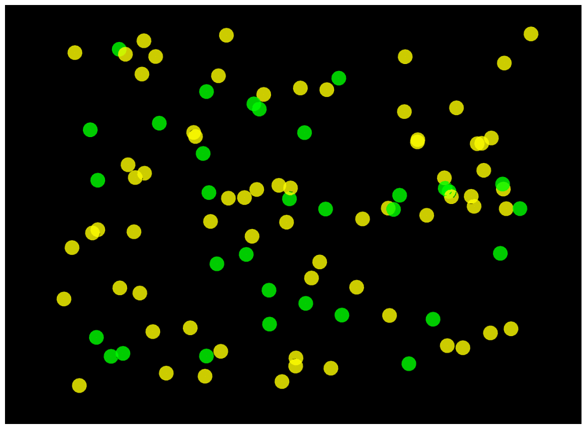
Chapter 3

Implementation and Testing of `ColoredPower`

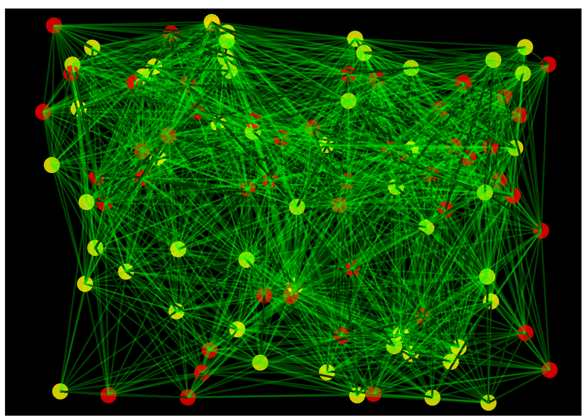
This chapter describes a series of experiments and presents the results of simulating `ColoredPower` in the Proto simulator, demonstrating that `ColoredPower` behaves as desired.

I implemented `ColoredPower` in Proto[6], a high level language where programs are described in continous regions of space and time, rather than individual devices. As described in earlier sections, Proto depends on the *amorphous medium abstraction*, which views a network of devices as an approximation of a computational material with a processor at every point. This continuous abstraction makes programs in Proto highly scalable: if a program works for a neighborhood, it is almost certain to work for an entire metropolitan area. Figure 3-1 shows an example of how the the Proto simulator looks while running `ColoredPower`.

Given a working implementation of the `ColoredPower` algorithm, we are in a position to verify the predicted behavior of the algorithm by analyzing results from the Proto simulator. The simulator takes snapshots of the state of every device which can be post-processed.



(a) Stepping between Green and Yellow



(b) Stepping between Yellow and Red with network links shown

Figure 3-1: A visualization of devices on the PACEM network using the Proto simulator. Each device is a disc. The color of the disc indicates the power consumption level of the device.

3.1 Experiment Setup

For verifying the predicted behavior of `ColoredPower`, we start with the simple case of homogeneous demand across residences, with the following parameters:

- A network of $n = 100$ devices. These devices are distributed randomly in a 100×100 unit square. Each device has a communication radius of 50 units. Thus, the expected diameter for the network is 3.

- We create a demand profile for each device, starting with a fixed tuple of $(d^3, d^2, d^1, d^0) = (3, 6, 7, 4)$ units of power demand in the green, yellow, red and black blocks respectively. The total possible consumption in the system is therefore $Q_d = 100 \times (3 + 6 + 7 + 4) = 2000$ units. This means that $(Q_d^3, Q_d^2, Q_d^1, Q_d^0) = (300, 600, 700, 400)$

- We choose T_{flip} randomly in the interval of $[2, 8]$ seconds with $E[T_{flip}] = 5$ seconds

- We choose T_{rise} and T_{fall} randomly in the interval $[500, 1500]$ seconds with the $E[T_{rise}] = E[T_{fall}] = 1000$ seconds

- The PID controller uses two sets of gains: $\{0.5, 0.08, 0.3\}$ and $\{0.4, 0.1, 0.4\}$, the two best performing values found via a heuristic parameter search.

- To prevent over-impact from accumulated error, integral error is given a window of 50 seconds and an exponential backoff filter of coefficient 0.5.

- System state is sampled every 10 seconds.

3.2 Homogeneous Demand

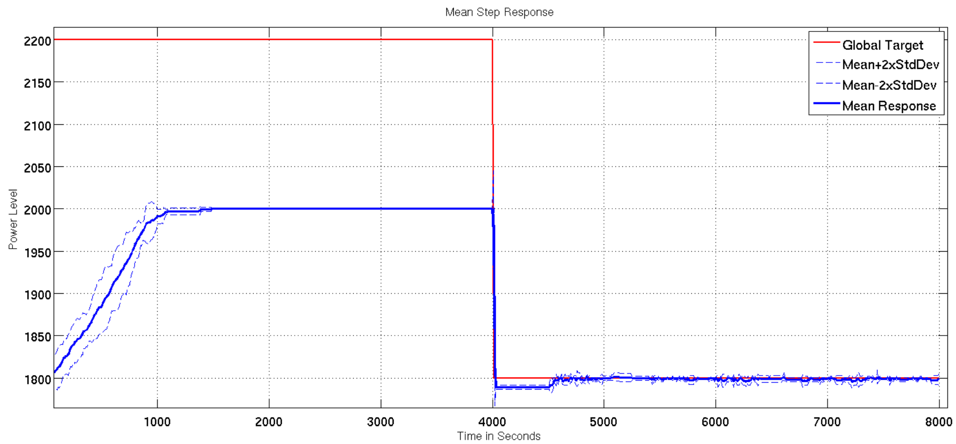
We begin by verifying that the algorithm works correctly under homogeneous demand conditions. We examine behavior using two target profiles: square wave and sinusoidal. The square wave shows us the step response of the system and gives an estimate of behavior in worst case conditions, e.g. if a power plant suddenly fails, or a major transmission network failure causes effective demand to suddenly drop. The sinusoidal case shows the system response to smoother, incremental changes. Each simulation is run for 10 cycles to find expected and worst case behavior.

The step response is tested using a square wave with a period of 8000 seconds, with one experiment for steps between every possible pair of colors except black (since consumption cannot fall below red), using the following values for Q_t: 2200, 1800, 1400, and 500. Step response graphs are shown in Figure 3-2 and Figure 3-2.

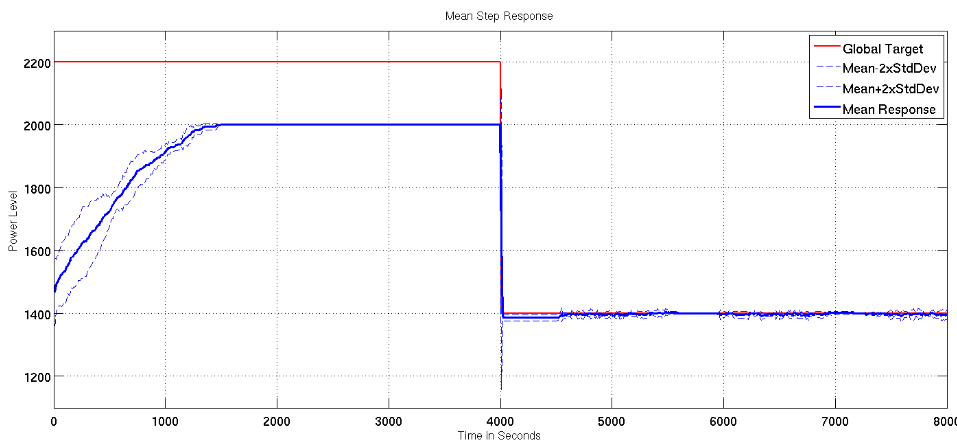
To evaluate the performance of the square wave family we use the measure of convergence time. This is defined as the first time after which the measured consumption stays within 3% of the target for more than 300 seconds (a tolerance below 3% would only allow a single device to be wrong in some situations. The overall convergence times are shown in Table 3.2. As can be seen, fall times are generally significantly better than rise times (due to an intentional bias in the construction of the feedback control), but in all cases the system begins responding rapidly and is nearly complete within 20 minutes.

We tested the incremental tracking using sine waves with periods 100 to 4000, scaled and offset such that the peak is at 2000 (Q_d) and the trough is at 400 (Q_d^0). Each sine wave was run for 40,000 seconds to get at least 10 periods worth of response data. Figure 3-3 shows a typical long period response: good tracking on the falling curve and a long delay on the rising curve.

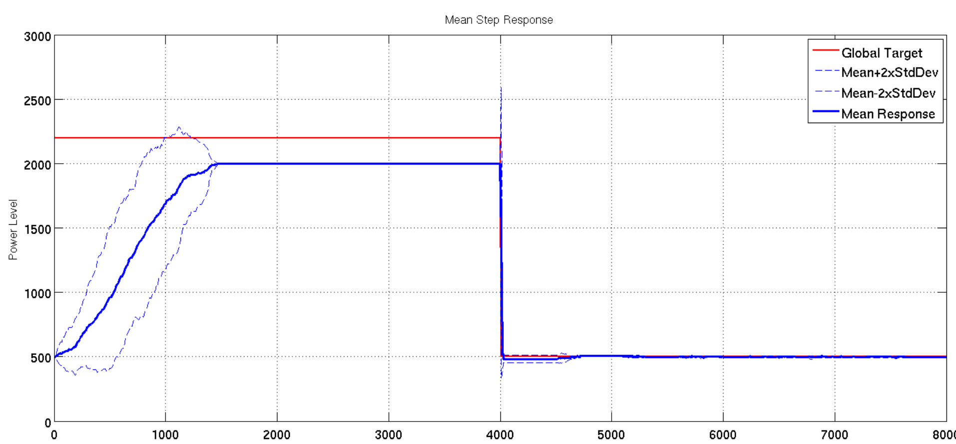
We further measure performance by the phase lag between the measured consumption and the target. This phase lag is computed by minimizing the root mean squared error (RMSE) between the measured consumption and a sine wave with the target's frequency and amplitude (Figure 3-4). The system tracks well with longer periods above 2000. Below 2000, when the half-wave period is shorter than the convergence time, tracking begins to break down, failing completely at high frequencies.



(a) Between > Green and Green

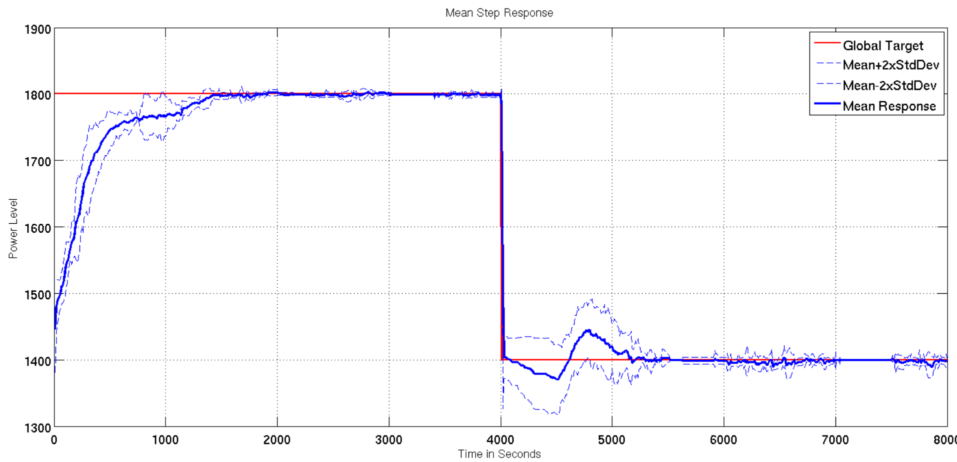


(b) Between > Green and Yellow

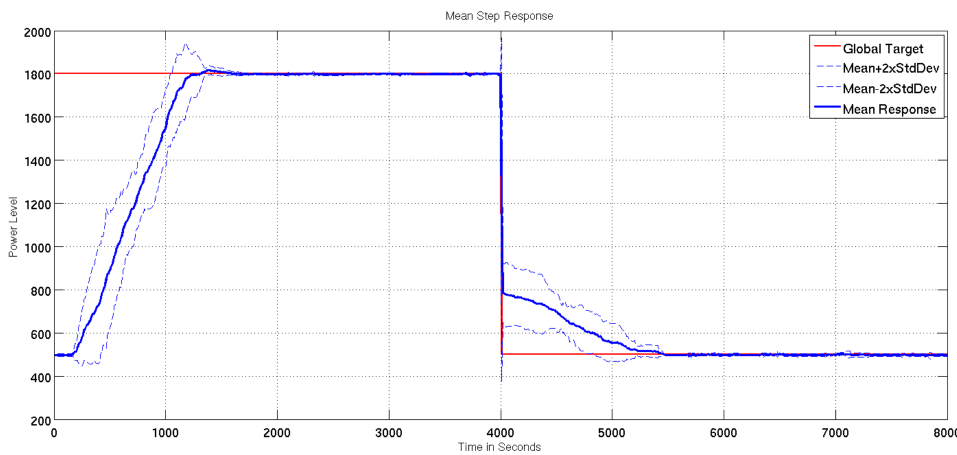


(c) Between > Green and Red

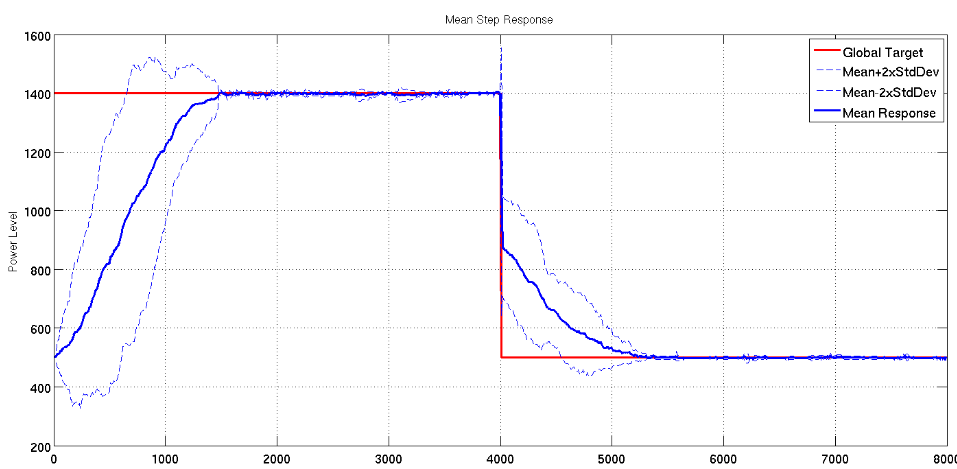
Figure 3-2: Graphs showing the average case response to a target square wave which switches between > Green and the colors in the demand spectrum



(a) Between Green and Yellow



(b) Between Green and Red



(c) Between Yellow and Red

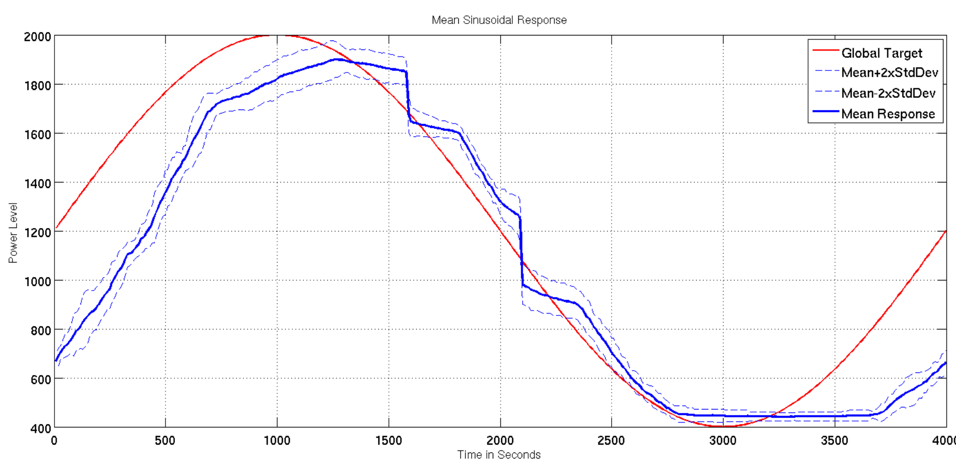
Figure 3-2: Graphs showing the average case response to a target square wave which switches between > Green and the colors in the demand spectrum

Color Combo	High Value	Low Value
>Green-Green	2200	1800
>Green-Yellow	2200	1400
>Green-Red	2200	500
Green-Yellow	1800	1400
Green-Red	1800	500
Yellow-Red	1400	500

Table 3.1: Power values for the square wave family of experiments

P,I,D	Fall Convergence Time		Rise Convergence Time	
	Mean ± Std.Dev.	Worst	Mean ± Std.Dev.	Worst
0.5,0.08,0.3	700 ± 530	1700	1130 ± 400	1760
0.4,0.1,0.4	920 ± 490	1640	1150 ± 390	1630

Table 3.2: Convergence Times for Homogeneous Demand



(a) Response to sine wave target with period 4000 seconds

Figure 3-3: Graph showing the response of `ColoredPower` to a sinusoidal target

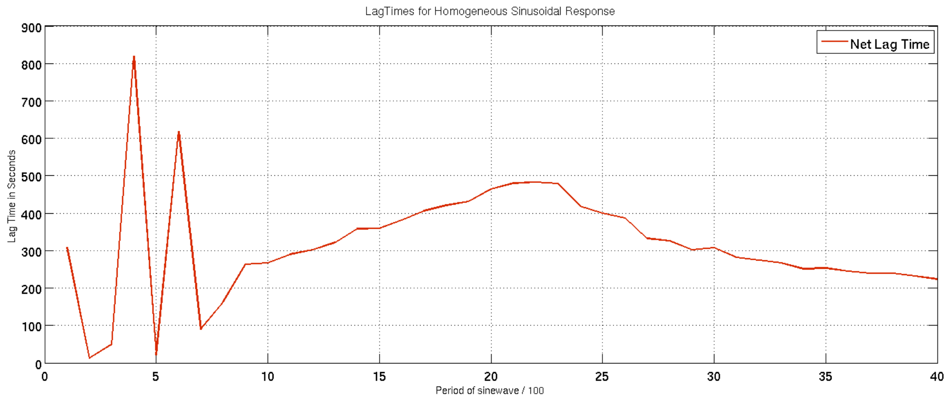


Figure 3-4: Lag Times vs. Period for PID gain values of 0.5, 0.08 and 0.3. The lag times for the other PID triple look very similar.

P,I,D	Fall Convergence Time		Rise Convergence Time	
	Mean ± Std.Dev.	Worst	Mean ± Std.Dev.	Worst
0.5,0.08,0.3	1240 ± 300	1690	1300 ± 520	1830
0.4,0.1,0.4	1220 ± 420	1780	1300 ± 480	1780

Table 3.3: Convergence Times for Heterogeneous Demand

3.3 Heterogeneous Demand and Overriding

In the next set of experiments, we move closer to a real-world situation. Here, users have different demand profiles and a small but variable number of users override the system. The experiments in this situation verify that the simplifying assumptions made while designing `ColoredPower` do not fail in a more general case.

To model heterogeneous demand, we change the demand profile from being fixed at $(3, 6, 7, 4)$, to use (d^3, d^2, d^1, d^0) such that each d^i is an integer chosen at random between 0 and 10 (inclusive). Over 10 different randomly generated demand profiles, we look at the step response using a square wave as before. The results are shown in Figure 3-5 and Table 3.3. We find that convergence times are comparable to those of homogeneous demand with the exception of fall mean time, which is slightly worse. Repeating the sine wave experiment for periods over 2000, we find that the tracking quality is analogous as well.

The way that `ColoredPower` deals with overrides is to simply transfer the demand which is "overriden" to black for a period of time. For example, if a demand tuple

P,I,D	Fall Convergence Time		Rise Convergence Time	
	Mean ± Std.Dev.	Worst	Mean ± Std.Dev.	Worst
0.5,0.08,0.3	1240 ± 570	2370	1310 ± 490	2250
0.4,0.1,0.4	1250 ± 580	2080	1310 ± 530	2150

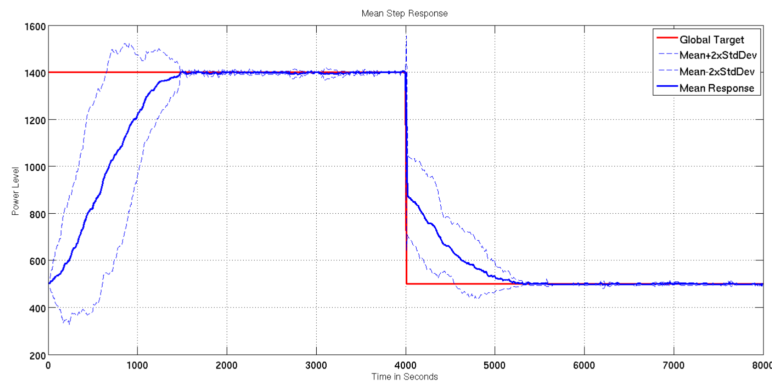
Table 3.4: Convergence times for heterogeneous demand with overrides

is (d^3, d^2, d^1, d^0), and the user overrides a request from `ColoredPower` to shut off all green power, then the new demand tuple for the user is $(0, d^2, d^1, d^3 + d^0)$. We model a small fraction of overriding by having each device make an occasional independent decision about whether to override each color d^i. The likelihood of override is fixed at 5% and the device decides on average every $T_{override}$ seconds, where $T_{override}$ is distributed identially to T_{fall} and T_{rise}. Whenever there are overrides in the system, we can expect that the feedback system in `ColoredPower` will respond as soon as the new local demand profiles are reflected in the global demand estimate. Since only a small number of users override the system, we still expect there to be enough devices such that the system is flexible enough to adapt even with the reduction in demand flexibility. The results are shown in Figure 3-5 and Table 3.4. As can be seen, the mean behavior is the same as without override, but the worst case is higher, likely due to occasionally small perturbations.

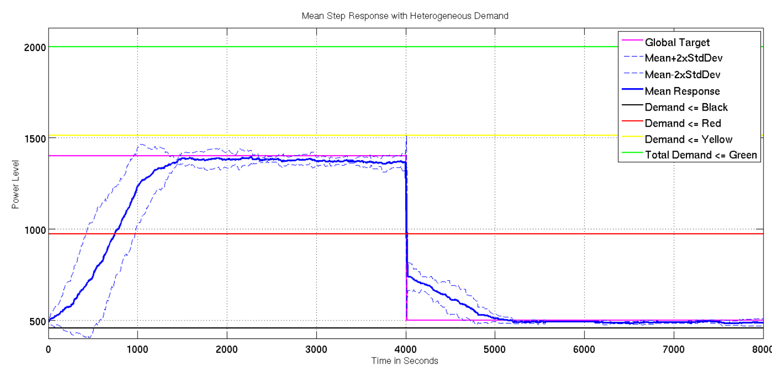
3.4 Diameter Variance and Scalability

Finally, we verify that the algorithm is scalable by increasing both the diameter of the network and the number of devices. For larger networks with increasing diameters, we expect that the performance of `ColoredPower` will be better in terms of convergence time and accuracy for small steps in the global target (due to higher demand flexibility) but the lag time for a fast changing global target (like the sinusoidal family) will be progressively worse.

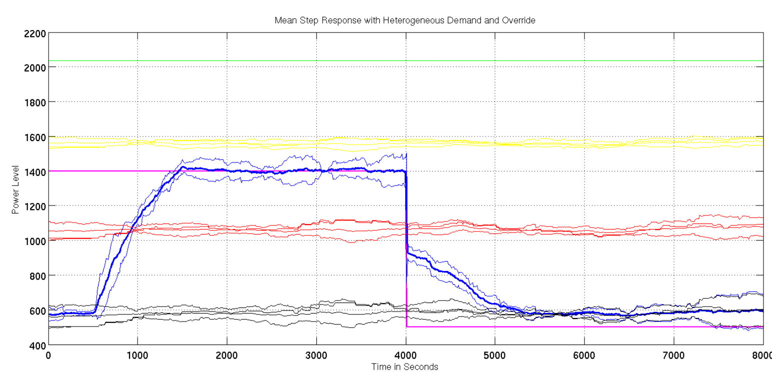
The experimental setup uses rectangular boxes of increasing area, with a fixed communication *radius* of 20. We use a fixed width $x = 20$ for these experiments, and a varying length y starting at 100. The number of devices on the network is equal



(a) Homogeneous



(b) Heterogeneous



(c) Overrides

Figure 3-5: Comparison of homogeneous demand (top) and heterogeneous demand response. The graph showing heterogeneous demand (center) also has the different demand values marked with the appropriate colors. The graph showing heterogeneous demand with overrides allowed (bottom) includes the mean and std. dev. of the global demand values.

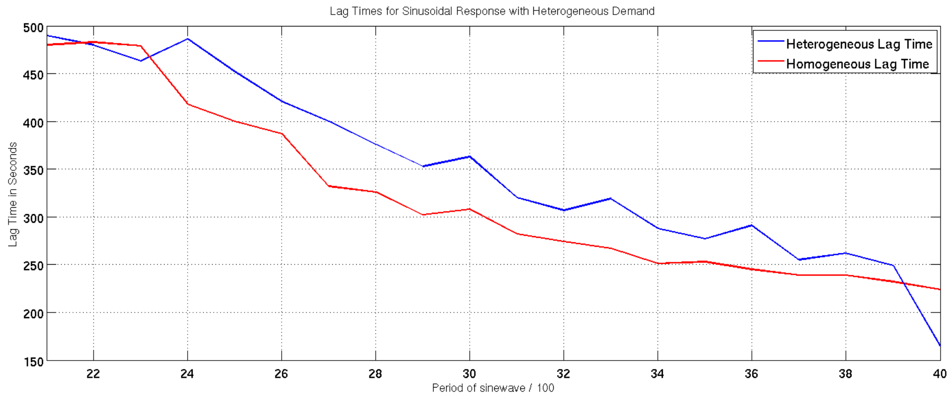


Figure 3-6: Lag Times vs. Period for PID gain values of 0.5, 0.08 and 0.3 for the response to heterogeneous demand compared to the response to homogeneous demand.

Diameter	Fall Convergence Time		Rise Convergence Time	
	Mean ± Std.Dev.	Worst	Mean ± Std.Dev.	Worst
15	450 ± 104	590	915 ± 45	1000
20	400 ± 55	450	932 ± 54	1000
25	388 ± 88	540	928 ± 38	970
50	792 ± 382	1120	910 ± 139	1130
100	1138 ± 25	1170	865 ± 45	900

Table 3.5: Convergence times for varying diameter

to y so as to maintain a dense distribution. Since x is small compared to y, we can use an approximation of the true network diameter as the number of hops required to cover the length y of the box (density is high enough that the stretch from indirect travel is only a few percent[13]). Thus the diameter is

$$diameter = \lceil \frac{y}{r} \rceil$$

As can be seen from Table 3.5, performance improves significantly for larger numbers of devices, but falls again as lag rises. We expect that part of the degrading performance may be due to the PID gain parameters being unable to scale to arbitrary lag. In the long term, a more sophisticated adaptive control will be necessary.

3.5 PID Gains

The following method was used to choose the PID gains used in the experiments described above:

1. Run a parameter sweep across P-gains for the square wave family for a P-controller. Choose the three best performing P-gains.

2. Run a parameter sweep across I-gains for the square wave family for a PI-controller with P-gain from the above results. Choose the three best performing I-gains.

3. Run a parameter sweep across D-gains for the square wave family for a PID-controller with different PI gain combinations from the above results. Choose the three best performing D-gains.

4. Run the resulting PID combinations on the sinusoidal family. Pick the best performing combination.

Some notes of interest regarding these gain values. The integral gain is small compared to the proportional and derivative gain. In a non-distributed system, one would expect the integral gain to be higher in order to get a fast response. In this PID controller, the more we try to lower the convergence time, the more oscillations (although damped) we will get in the beginning of a step response. It is undesirable to require devices to turn on or off unnecessarily, so the gains are chosen to be more "cautious".

This chapter verifies that the simplifying assumption of homogeneous demand in `ColoredPower` is a practical one. The experiments described show that with a more adaptive feedback control, PACEM can meet its real world design requirements.

Chapter 4

Incentive Design

We have identified the users and the "utility" or "power company" as stakeholders in the proposed system of PACEM. However, the "power company" is more than just a single entity trying to make money by selling power. The electricity that powers a household light bulb comes from a complex system of both public and private sector industries, with multiple stakeholders who want different things. We must therefore, identify exactly where in this economic system PACEM would fit in, and how that part of the system can be incentivized to use PACEM. This chapter only deals with the electric power sector in the United States.

This chapter begins with a brief overview of the electric power sector and how it relates to PACEM. The bulk of the chapter deals with the problem of designing practical user incentives in an electricity spot market with the goal of maximizing the surplus of the entity running the market. I will present a *Colored Procurement Mechanism* which models PACEM in the domain of algorithmic mechanism design. I do this starting with a very simple case where there are only 2 users participating in the PACEM network with 2 possible preferences, and then try to generalize this scenario for application in a real world PACEM.

4.1 The Electric Power Sector

The electric power sector is very time sensitive due to the technology that is used for power distribution. Electric power grids are dynamic in the sense that electricity must be supplied exactly when it needs to be consumed. At every point in time, the power grid has to ensure a balance between the demand and supply of power on the network. The failure of a single component of the power grid can have devastating consequences; thus there must be many safeguards in the operation, planning, and policy surrounding the electric power sector.

From the time electricity is generated at a power plant to when it powers a light bulb in a household, it must interact with separate entities that perform the following functions[4]. The relationship between these entities is shown in Figure 4-1.

1. Generation

   The electricity that goes into the power grid comes from a multitude of different power generators, whether they are wind, solar, thermal, nuclear or hydro. These generation plants are operated by public or private institutions for profit.

2. Transmission

   The high-voltage transmission grid is a type of wholesale market for electricity, which connects generator facilities to cities or other areas of high energy consumption. Transmission is run by an entity separate from the generator and the distributor, and is either in the public sector or a regulated private sector.

3. Distribution

   This low-voltage grid delivers electricity from the transmission grid to the end users. Distribution involves the equivalent of a retail market for electricity; the distributor is the "utility" that retail consumers interact with.

4. Regulation

   There is a regulatory authority (generally government-controlled and centralized) which enforces high level power grid decisions like the total capacity of the grid, the coupling (and de-coupling) of the different parts of the power sector, etc.

5. Consumption

   For our purposes, the end user is a house owner consuming between 1 and 5 KW of electricity in a residential neighborhood in an urban area. In PACEM, it is important how a user's consumption compares to the overall load on the grid, and how it compares to other user's consumption.

6. Protection and Control

   These are safety nets in the form of control systems at various points in the electricity supply chain. They are analogous to a "fuse" which is blown whenever something goes wrong to protect an electrical device. They are not very relevant to the discussion of PACEM incentives, however, they will raise important integration and compatibility issues if PACEM is to be deployed on a large scale.

4.2 Power Sector Incentives

Most of the real time operating functions in the power system described above are based on safety rather than economic motivations. With newer pricing models and technologies, real time electricity pricing has become a reality in some places using smart grids as evidenced by the Federal Energy Regulatory Commission's Assessment of Demand Response and Advanced Metering[20]. However, this pricing still can only motivate the choices of individual consumers and not necessarily the operations of electricity distribution.

The basic regulatory rules prohibit any single entity from participating in a monopolistic/regulated activity (like constructing the physical distribution lines) and a competitive activity (like generating energy or selling retail energy) at the same time. The distributing activity is regulated so that it is obligated to supply in the area of its

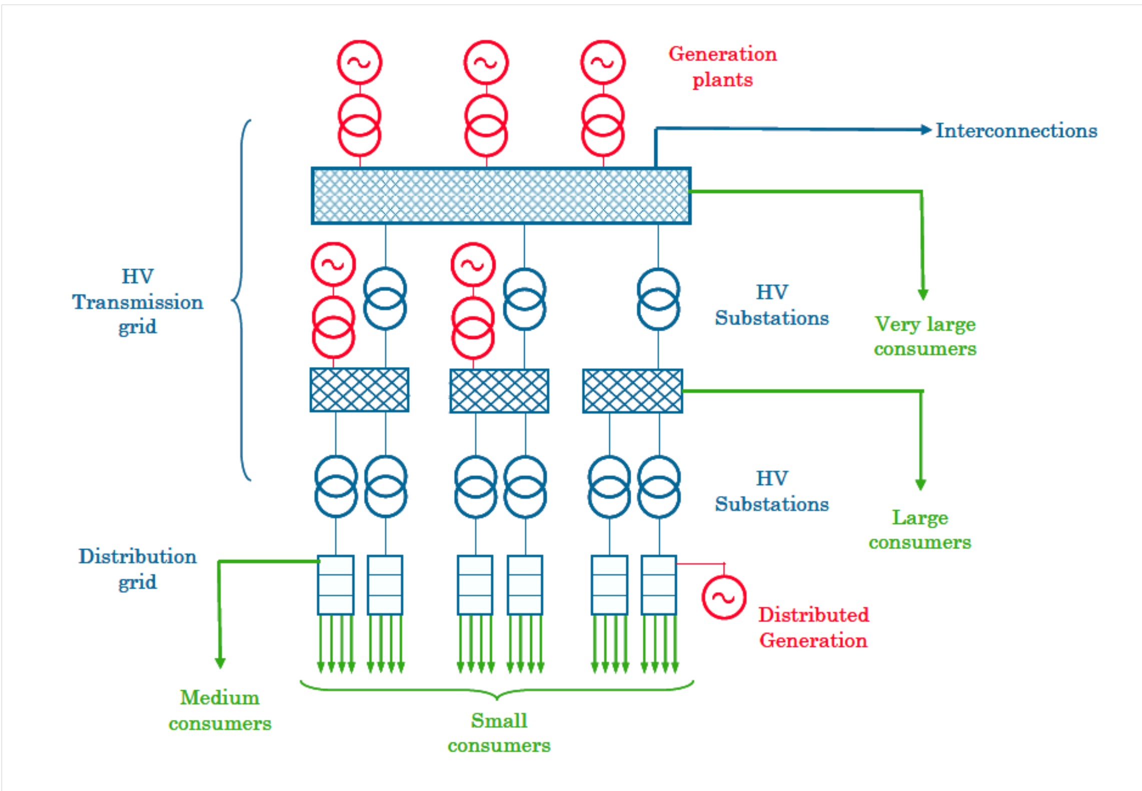


Figure 4-1: Components of a Power System from “Electric Energy Systems: Analysis and Operation”[4]

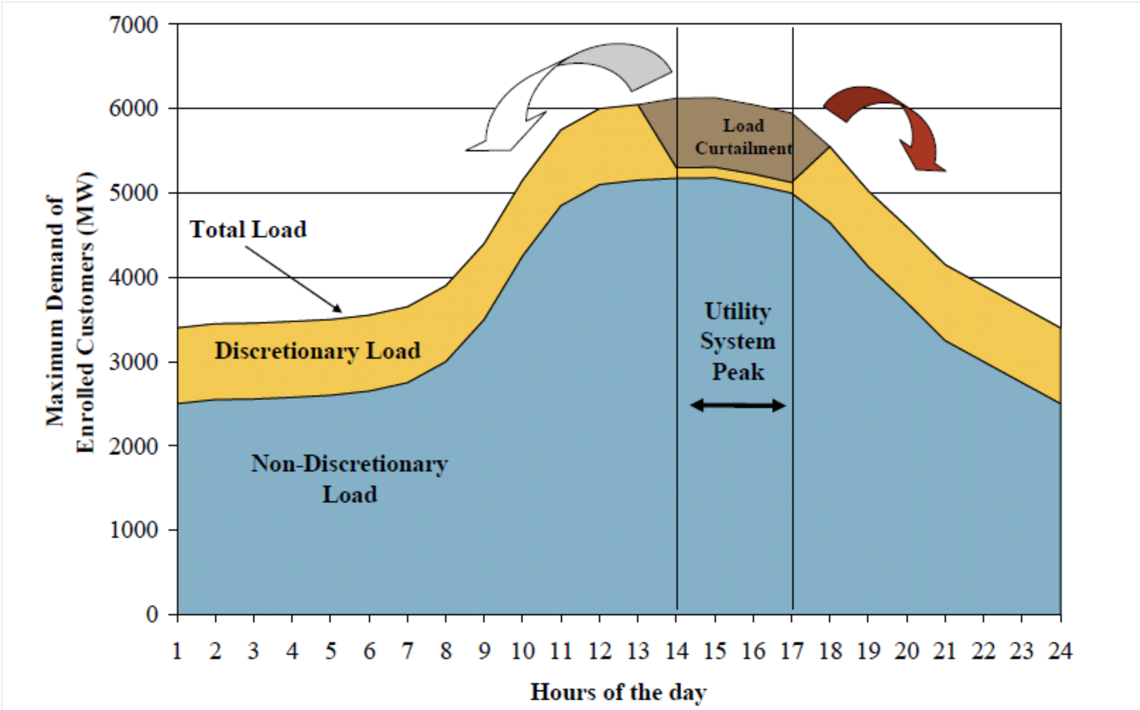


Figure 4-2: Source: Federal Energy Regulatory Commission (FERC). This figure shows how a utility can achieve peak reduction in the power load via demand reduction.

jurisdiction[4]. Figure 4-2 shows in concept the regulated, "non-discretionary" power supply vs. the additional discretionary supply that a utility normally provides.

There are many decisions to be made on a relatively small time scale regarding protection, generation control, economic dispatch, and unit commitment in this system (Figure 2-2 describes this timescale). PACEM aims to operate on a time scale which will enable very fast decision making and dispatch of these functions.

Since the retail electric utility buys electricity at a wholesale price from a spot market, the electric utility may not have any immediate monetary incentive to use PACEM. Figure 4-3 gives us an idea of the incentives that utilities may have to implement a demand response program like PACEM. As can be seen, the non-monetary benefits of PACEM are much lower in priority.

The regulatory body's job is to maximize the social utility by making provision that protect consumers and investors in the electricity market. It is in this body's interest in today's energy hungry world to reduce demand, and so this body has incen-

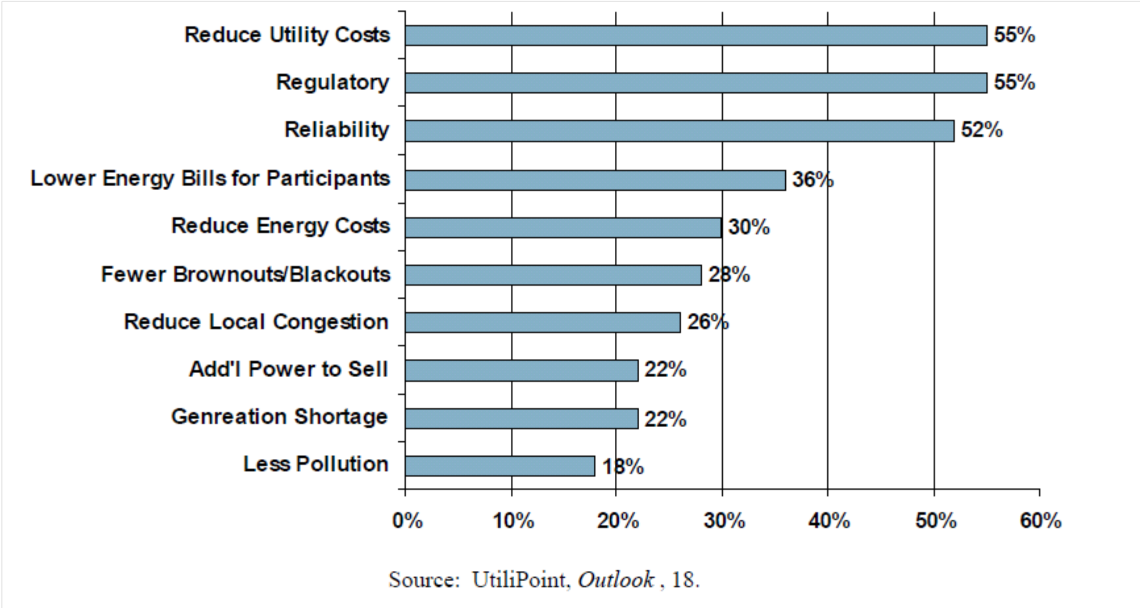


Figure 4-3: This graph describes the results of a survey conducted by a company called UtiliPoint[19]. Each bar represents the primary incentive for implementing a demand reduction program as reported by the utilities included in the survey.

tive to support the implementation of PACEM. Currently, a lot of supply-generation facilities are required to keep generators on reserve to account for sudden rises in electricity demand. The installation and maintenance of these extra generation units is not profitable. PACEM offers a solution to deal with sudden spikes in demand without requiring the additional safety generation unit. The disadvantage of depending on the regulatory body to provide incentives is that it may be very slow and interacts strongly with the external political environment.

PACEM, and `ColoredPower` in particular, can easily integrate with any pricing model which relies on non-specific information about electricity demand. For instance, customers can use either variable-market-priced or linearly-priced electricity even though they may be on the same PACEM. This is possible because `ColoredPower` makes no assumptions about the price of electricity at any given device; each device uses the relation between demand and supply (which does not depend on price) to make decisions. It would be easy to add a layer of decisionmaking in each device that is dependent on the relationship of that device with the electricity distributor(s), but independent of other individual devices' decisions.

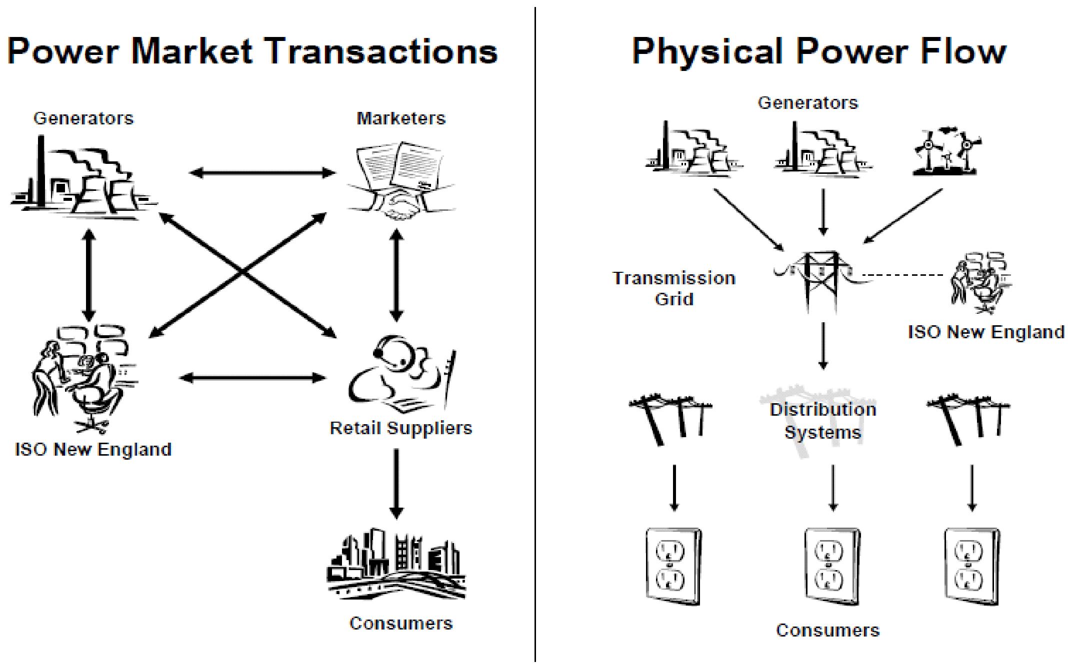


Figure 4-4: Figure from Factsheet 2 of the New England Power Generator's Association[15]. The figure shows an example of the relation between market transactions and power transactions in New England. The ISO is the Independent System Operator.

4.2.1 Electricity Spot Markets

Even with many safeguards and regulations in place, the demand and supply of electricity often do not meet. A *spot market* for electricity pricing exists for these situations[15]. An attempt is made to achieve *market clearing* i.e. total demand meets total supply. An example of the relation between the spot market and the actual power distribution is shown in Figure 4-4. In a spot market, generators submit offers, and the authority (generally the Independent System Operator (ISO)) chooses which and how many generators to schedule depending on the demand from consumers. For the purposes of modeling mechanism design, we assume that it is possible for the generator to be the direct provider and negotiator of energy with the end users in such a spot market. We can assume this since the suppliers of electricity (generators, wholesalers, and retailers) can negotiate using their offers, and the ISO is generally non-profit.

4.3 Introduction to Consumer Incentives and Mechanism Design

The primary incentive for a user opting into PACEM is a monetary kickback from the energy savings in the system. EnerNOC has already proven that some types of consumers are willing to participate in demand-response programs in order to save energy and money. Also, consumers want more hard data about their energy usage and in the long term, and we might design a way to provide them with usage statistics in greater detail through PACEM. Some consumers may be willing to pay higher prices to maintain the convenience of electricity; if this group of consumers is large enough, the utility may not be able to provide a sufficient monetary incentive. In this case, we could try and negotiate with the regulatory authority in the public sector to subsidize the monetary incentives in the interest of social welfare.

For the rest of this chapter, we will assume that PACEM is able to provide monetary incentives comparable to consumers' value of electricity. Under this condition, we assume that every user is trying to maximize his/her own monetary savings from participating in PACEM. Further, we only look at cases of reducing demand i.e. where the power generated is insufficient to meet consumer demand. We will not look at situations where the power generated is greater than the consumer demand.

4.3.1 Mechanism Design Terminology

- Incentive Compatibility: In PACEM, users report their preferences which are aggregated and sent to the utility. We would like to design a system where users are motivated to report their preferences honestly. This is to say that when we design an incentive system for the users of PACEM, a user should not be able to "game the system" by misreporting her preferences to achieve a higher payoff than what she would get if she was honest. Such mechanisms are called *incentive compatible* or *truthful* mechanisms.

- Individually Rational: Under the assumption that all users are rational, no user should ever get a negative payoff or penalty for participating in PACEM. If a user has nothing to lose by participating in a mechanism, i.e. her *utility* is always ≥ 0, then the mechanism is called *individually rational*.

- NPT: Many scenarios in mechanism design assume *No Positive Transfers*, which means that if a user does not come out ahead in the game, then she gets no benefit. Particularly, if a user does not "win" in an auction or other resource allocation game, her utility is 0. We will assume NPT for our design. However, this may not be true if there is a significant payment to users for just participating in PACEM, which does not depend on their demand reduction.

- Envy-free: An auction is envy-free if after the auction is run, no bidder would be happier with someone else's outcome. We would like PACEM to be envy-free, because this is a key to users perceiving PACEM as a "fair" system. We will not investigate envy-free-ness here, but note that PACEM is promising in this regard since the design of `ColoredPower` is expected to produce the same results for two identical users when averaged over time.

- Collusion-resistant: We would like PACEM to be collusion-resistant, i.e. no user can obtain a higher profit by collaborating with other users.

- Competitive-ratio: We define the competitive-ratio as the factor by which the auctioneer has to pay extra by running a real time mechanism, as opposed to the optimal solution when the auctioneer knows all information about the user/bidder. Here, the "optimal fixed pricing solution" is defined as the incentive distribution that maximizes the utility's profit if the utility knows all the information about every individual device.

- Constant-competitive: In order to encourage the power sector to adopt PACEM, we would like a mechanism that will guarantee a certain profit, which is a constant factor of the optimal fixed pricing solution (and does not depend on other situational variables). In other words, this is a mechanism which has a constant competetive ratio.

- Auctioneer: In this case, this is the electricity supplier/generator. In context of the power sector, this is the authority that runs the spot market for electricity whenever power generation does not meet consumer demand. The auctioneer in this case is always trying to either maximize his profit by selling something to the network of users or trying to be as frugal as possible when buying goods from the network of users.

- Profit/Surplus Maximizing: An auction is said to be a profit maximizing if it achieves the maximum possible profit/surplus for the auctioneer under the initial conditions of the auction.

Normally, when the devices in a residence are on PACEM, the user is implicitly participating in the economic mechanism that goes along with it. We grant the user the ability to choose whether she wants to override the system during every decision cycle in PACEM. In an individually rational mechanism, the user would never override the system unless he/she values the use of a device more than the incentive payment offered for shutting it off. There will be times when this will happen e.g. during the Super Bowl, a lot of users may override their television sets. For this analysis, we assume that mass-overrides are infrequent.

Now let us put some of the quantities from `ColoredPower` in context. Recall that the three important aggregate quantities in the system are Q_t, the availability of power, Q_d, the demand for power, and Q_m, the measured power consumption. The goal is for Q_m to match Q_t as closely as possible. From the user point of view, Q_d is split into green, yellow, red, and black. We generalize that $Q_d = \sum^k Q_d^k$ for a k-colored system. User i has demand d_i^k for k-colored energy. There is some set of valuation functions V which distinguishes between the values that a user has for different kinds of energy. Consistent with the coloring system, the valuation function $v_i \in V$ for user i satisfies $v_i^{k-1} \geq v_i^{k-2} \ldots v_i^1$. The auctioneer's constraint is a monetary budget, B. In any mechanism, the auctioneer would like to retain as much of B as possible while meeting some goals.

4.3.2 Application of the Digital Goods Auction

There are many mechanisms already designed which deal with resource-allocation situations. The most relevant one is the digital goods auction[11]. However, this mechanism is not the best model for PACEM. To see why, let us try to apply this mechanism in the relatively simple case of homogeneous demand under the following assumptions:

- $d_i^k = \{0, 1\} \forall i, k$
- None of the players have prior-information about the other players' values or bids.
- Use a "money is the good, demand reduction is the payment" model.

The digital goods auction decision problem asks whether any solution exists to this allocation problem. This is followed by the application of $\textsc{ProfitExtract}_R$, an algorithm from [11]. $\textsc{ProfitExtract}_R$ as defined for this problem has a target profit R and sells to the largest group of n bidders that can equally share R and charges R/n to each seller in this group. Here the target profit is $R = Q_d - Q_t$, and each user who contributes to this profit must pay $\frac{Q_d - Q_t}{n}$ where n is the total number of contributors to demand reduction. $\textsc{ProfitExtract}_R$ is known to be truthful and provide a profit of R provided that the total value held by the users is at least equal to R. Since the auctioneer is looking for a profit of *exactly* $R = Q_d - Q_t$, we do not have to do any further optimizations to maximize R (unlike the digital goods auction). $\textsc{ProfitExtract}_R$ can be modified to work for non-homogeneous users as well. However, this is only under the condition there exists a solution to the underlying optimization problem which is to construct a bundle of goods which is exactly equal to R. In the case that there is no group of bidders such that the total demand reduction adds up to $R = Q_d - Q_t$, then the auctioneer can simply choose the highest $Q_{t*} < Q_t$ where a group does exist. One problem with this approach is that a group of bidders may have a monopoly if it is the only group which satisfies the optimization problem.

While this method looks appealing, it does not let us account for the idea of the "discretized bidding" by the users which is caused by the system of colors. Further, this method is also based on the idea that none of the players in the game have any information at all about the other players. A better approach may be to look at this system as a Bayesian optimization mechanism problem, i.e. a mechanism design which assumes some information about the probabilistic distributions of the private information held by different players, and which also takes into account the discretized bidding due to the color system. In the following sections we will try to accomplish the following:

- Describe a practical economic model for the cooperative energy management system and identify the requirements.
- Design a mechanism which will address all the stakeholders' goals and the requirements of the model.
- Analyze the mechanism and propose further work to improve upon it.

4.4 Cooperative Energy Management Model

We look at the capacity to produce demand reduction as the capacity to produce a certain quantity of goods. The cost of producing the goods is the same as the cost of not using a particular device. So we have a market where there is a single buyer (the power company) and a number of sellers (the devices). For our model, we will assume that each device consumes the same amount of power; we normalize this to be exactly 1 indivisible unit. This is a reasonable approximation since PACEM will be operating on a very large number of devices where each device consumes a very small amount of electricity compared to the total reduction required. PACEM requires all the devices in the same color preference in a single home to have the same state, which is not the case in this model; however it would be easy to add this constraint once we devise a good incentive system. Thus, every device has the capacity to produce 1 unit of the good at some cost (which is different for each device). We normalize the cost per

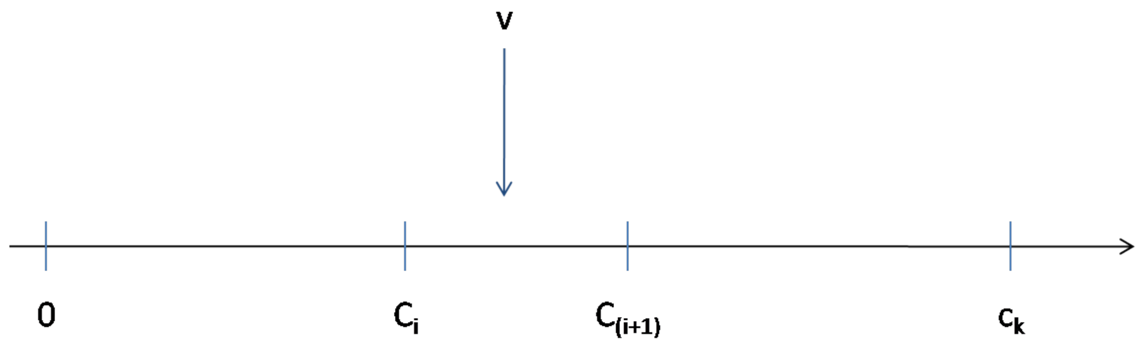


Figure 4-5: Value of a seller's good for color c_{i+1}

good to be in $[0, 1]$. However, each device can only be set to one of a finite number of colors, k. The important thing to note is that for any cost v of a device, there exist unique colors c_i and c_{i+1} such that $c_i < v \leq c_{i+1}$ and in this case, the "truthful" bid for the device is c_{i+1}. We say that c_{i+1} is the truthful bid because it is the lowest bid which is individually rational, i.e. the lowest bid that will earn a non-negative profit. The buyer, ideally, should not have to pay any more than this lowest bid.

The goal of the buyer is to purchase $q = Q_t - Q_d$ goods at a minimum price. Thus, it does not matter to the buyer if a device bids lower than its truthful bid. This is because if a device sells something for less than its value, that is a better deal than the buyer expects to have. So, we will not worry about underbidding in this model. We normalize the color system such that every c_i falls between 0 and $c_k = 1$.

Thus, we can describe our desired mechanism, M, to operate in the following manner:

Definition 1. *A Colored Procurement Mechanism M takes the following inputs*

1. *B, the total budget of the buyer*

2. *n, the total number of sellers/goods*

3. *$q \in 0, \ldots, n$, the total number of goods that the buyer wishes to purchase*

4. *$b(i) \in K : K \subset [0, 1], |K| = k$, the bids of sellers $i \in [n]$. Every bid $b(i)$ must be equal to one of $c_1, \ldots, c_k$*

and outputs $p(c)$, the payments offered by the buyer to sellers who bid $c \in K$

Thus, the buyer's surplus is $B - \sum_i p(i)$. We would like to design a mechanism which maximizes the buyer's surplus while being individually rational. Unfortunately, it has been shown that it is impossible to design a mechanism which is incentive compatible, profit maximizing, and collusion-resistant all at the same time[10]. We will stick to the first two and then try to get as close to collusion resistance as possible.

4.5 2 Color Systems

If $k = 1$ the system reduces to the trivial case where there is only one bid allowed for the sellers. So we start by looking at a system with $k = 2$. This means that there is essentially a partition in the value-space $[0, 1]$ at some value c where the "truthful" bid for all sellers below c is c and all sellers above c is 1. Similar to `ColoredPower`, ties in bids from sellers are broken via coin flip.

4.5.1 2 Color with 2 Sellers

We start with the simple case with just 2 sellers, assuming that the buyer wants to purchase 1 unit. So $n = 2$ and $q = 1$. We also assume that the buyer's budget $B = 1$, i.e. the buyer will always have a non-negative surplus. The buyer collects the bids from the players and offers one of them a payment in exchange for their good. The buyer wants to structure the payment to ensure that the sellers are truthful in their bids. For now we assume that there is no collusion.

It is easy to see that in the cases where both sellers' values fall into the same partition the buyer can trivially enforce truthfulness. In the case where both sellers have values higher than c only the truthful bid gives them non-negative profits, and if they are both lower than c then deviating from the truthful bid gives them 0 profit. Suppose seller 1 has value $v_1 \leq c$ and seller 2 has value $v_2 > c$ and they both report truthfully. The buyer buys from seller 1 since it is the highest surplus. Then seller 2

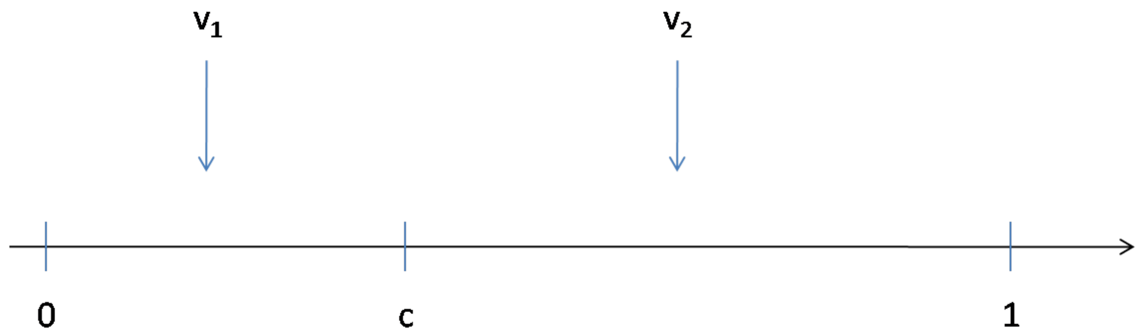


Figure 4-6: Two color, 2 seller game

makes no profit, while the profit for seller 1 is

$$\Pi_1^{truthful} = p(c) - v_1$$

where $p(c) \geq v_1$ is the payment offered by the buyer to seller 1. The only possible deviation for seller 1 is to misreport his value as $> c$, i.e. 1. If seller 1 misreports, he is not guaranteed to sell since he will be tied with seller 2 and the tie will be broken with a coin flip by the buyer. The expected profit for seller 1 is thus

$$E[\Pi_1^{misreport}] = \frac{1}{2}(p(1) - v_1)$$

The incentive compatibility condition says that:

$$\begin{aligned} \Pi_1^{truthful} &\geq E[\Pi_1^{misreport}] && (4.1) \\ p(c) - v_1 &\geq \frac{1}{2}(p(1) - v_1) && (4.2) \\ p(c) &\geq \frac{p(1)}{2} + \frac{v_1}{2} && (4.3) \end{aligned}$$

Since $B = 1$, $p(1) = 1$ in order to preserve individual rationality. Thus, in order to get seller 1 to be truthful, the buyer must pay at least the RHS value in the above inequality. Since the buyer does not know anything about seller 1 except for $v_1 \leq c$,

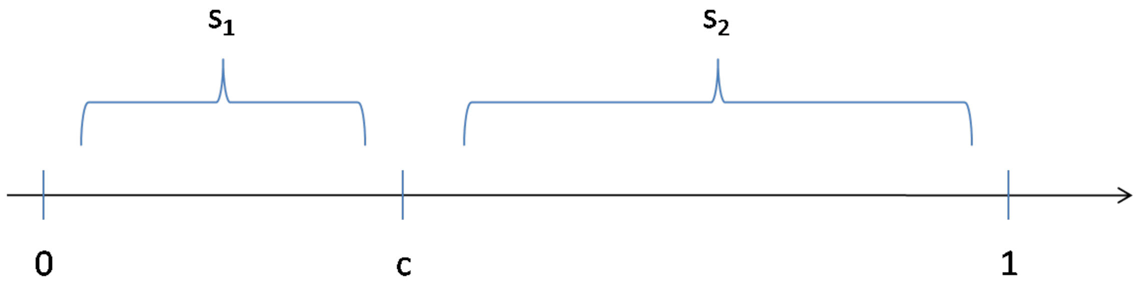


Figure 4-7: Two Color, n seller game

we get a lower bound for the payment which is

$$p_{min}(c) = \frac{1}{2} + \frac{c}{2}$$

Note that $p_{min}(c) > c$ for $0 < c < 1$.

4.5.2 2 Color with n Sellers

The more general 2 color case is one with n sellers where the buyer wishes to purchase q units. Assume that s_1 sellers have values less than c while s_2 sellers have value greater than c such that $s_1 + s_2 = n$. Suppose everyone bids truthfully. The s_2 group does not have any incentive to deviate from their truthful bid, since 1 is the only bid that gives them non-negative returns. If $q < s_1$, none of the sellers from that group will deviate since deviating will give them a profit of 0 (because the buyer will not need to buy any goods from the s_2 group). $q \geq s_1$ gives a situation similar to the one above, where the s_1 sellers in the left partition have a guaranteed sell, while the s_2 sellers in the right partition have a probabilistic one. In this case, for a seller in the left partition with value v_1 and a seller in the right with v_2 we have

$$\begin{aligned}
\Pi_1^{truthful} &= p(c) - v_1 && (4.4)\\
\Pi_2^{truthful} &= (p(1) - v_2)\frac{q - s_1}{s_2} && (4.5)\\
\Pi_1^{misreport} &= (p(1) - v_1)\frac{q - s_1 + 1}{s_2 + 1} && (4.6)\\
\Pi_2^{misreport} &\leq 0 && (4.7)
\end{aligned}$$

Thus our only incentive compatibility condition is

$$
\begin{aligned}
\Pi_1^{truthful} &\geq \Pi_1^{misreport} && (4.8)\\
p(c) - v &\geq (p(1) - v)\frac{q - s_1 + 1}{s_2 + 1} && (4.9)\\
p(c) &\geq v + (p(1) - v)\frac{q - s_1 + 1}{s_2 + 1} && (4.10)\\
p_{min}(c) &= c + (p(1) - c)\frac{1 + q - s_1}{1 + s_2} && (4.11)
\end{aligned}
$$

assuming that $p(1) = 1$ and $max(v) = c$.

The second term in the equation describing $p_{min}(c)$ gives us the cost of truthfulness, i.e. if the buyer knew every individual seller's actual value, then he could get away with paying c to all of the sellers whose values are less than c, regardless of their bids. By agreeing to pay the extra factor, the buyer ensures that every seller's best response is to bid truthfully. Note that this extra factor is always non-negative for $q > s_1$.

The cost of truthfulness as described above is strongly dependent on how s_1 and s_2 relate to q. If s_2 is very large compared to $q - s_1$, then the cost of truthfulness will be very low. On the other hand, if $s_1 + s_2$ is only slightly greater than q, then the cost of truthfulness is very high. In the limit case where $s_1 + s_2 = n = q$, the buyer must buy from every single seller at the highest price. Indeed, substituting $q - s_1 = s_2$ in the expression for $p_{min}(c)$ gives us

$$
\begin{aligned}
p_{min}(c) &= c + (p(1) - c)\frac{1 + q - s_1}{1 + s_2} && (4.12)\\
&= c + (p(1) - c)\frac{1 + s_2}{1 + s_2} && (4.13)\\
&= c + (p(1) - c) && (4.14)\\
&= p(1) && (4.15)
\end{aligned}
$$

The above arguments show that in order for the buyer to compute $p_{min}(c)$ apriori, he must know s_1 and s_2. This may not be practical in a real setting, which poses a problem. A more reasonable approach is for the buyer to have some information

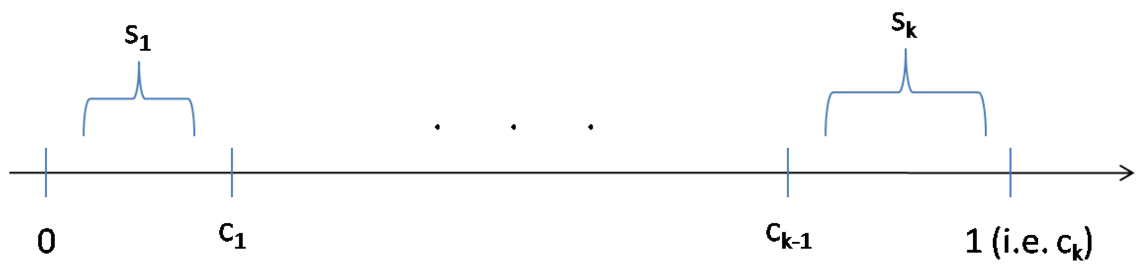


Figure 4-8: k colors, n sellers

about the distribution of the seller's values in [0,1]. The buyer can then estimate $E[s_1] = n \times Pr(v \leq c)$ and $E[s_2] = n \times Pr(c < v \leq 1)$. Then the term $\frac{1+q-s_1}{1+s_2}$ is replaced by $E[\frac{1+q-s_1}{1+s_2}]$ to achieve truthfulness in expectation.

4.6 k Color Systems

In order to extend our 2 color system, we use the following claim

Claim 1. *If* $\sum_{j \leq i} s_j < q < \sum_{j \leq i+1} s_j$, *then*

$$p_{min}(c_i) = c_i + (p(c_{i+1}) - c_i)\frac{1 + q - \sum_{j \leq i} s_j}{1 + s_{i+1}}$$

The condition on q means that deviating more than one color above the true bid will give the seller at most 0 profit. In PACEM terms, if the demand reduction q is satisfied by devices set to green and yellow, then a device changing its bid from green to red will not turn off and get 0 incentive payment. On the other hand, bidding truthfully will give the seller $p(c_i) - v$. Thus the only deviation is one color up, which reduces to the 2 color scenario. Replacing s_1 and s_2 with the appropriate indices and cumulative quantities gives us the claim. This claim gives the buyer a payment system to ensure truthfulness of sellers in color c_i or higher.

The problem at hand now is how to incentivize the sellers from c_1 to c_{i-1} to be truthful. If $\sum_{j \leq i} s_j < q$ then those sellers will receive the highest profit from bidding c_i, although their truthful bid might be much lower. I claim that in this situation, the buyer must pay each seller with value $\leq c_{i-1}$ the same amount as the sellers bidding

c_i, otherwise all of those sellers will have incentive to deviate to bidding c_i.

4.7 Analysis and Implementation

We have seen that the cost for truthfulness is $(p(c_{i+1}) - c_i)\frac{1+q-\sum_{j\leq i} s_j}{1+s_{i+1}}$. In the optimal deterministic situation where the buyer knows every seller's true value, this cost is 0. The overpayment of the buyer can be characterized as $argmax_i(\frac{p_{min}(c_i)}{c_i})$, i.e. this the maximum factor by which the buyer has to overpay compared to a complete-information system in order to maximize his surplus. In the k color system, we have that $p_{min}(c_{j<i}) = p_{min}(c_i)$ so this will depend on the distribution of the c_i's.

For the 2 color system, assuming that $p(1) = 1$ we have a competitive ratio of

$$
\begin{aligned}
R &= \frac{p_{min}(c)}{c} && (4.16)\\
&= 1 + \frac{(1-c)}{c}\frac{1+q-s_1}{1+s_2} && (4.17)\\
&\leq 1 + \frac{1-c}{c} = \frac{1}{c} && (4.18)
\end{aligned}
$$

This is because $\frac{1+q-s_1}{1+s_2}$ is upper bounded by 1. Depending on the value of c, this ratio can be made arbitrarily large. This shows that the value of c is very important to how well the mechanism will perform. In the limit case where $c = 1$, we observe that the ratio is 1, since the only allowed bid and payment is 1. The competitive ratio can never be more than 1, since the cost of truthfulness will always be positive. Since the buyer wants to maximize surplus, he wants to minimize the competitive ratio while preserving the other requirements of the system.

Now let us consider what happens if prior to designing the mechanism the buyer has the power to choose k and the value of every c_i. At this point in time the buyer knows only the distributions of the sellers' values v and the distribution for q. We look at the special case relating to cooperative energy management where $k = 3$ (actually there are 4 settings for the devices, but the "black" setting is equivalent to non-participation in the mechanism). Assuming a Gaussian distribution for q, we want q to be somewhere between two well chosen values of c_1 and c_2 with high

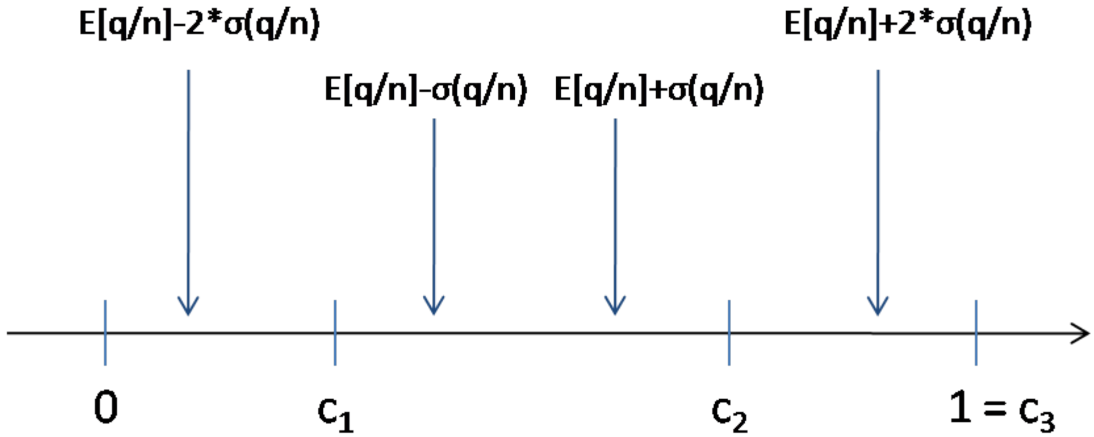


Figure 4-9: Choosing c_i in a 3 color system

probability, such that the incentive payment $p_{min}(c_1)$ occurs with high probability. The smaller the difference between c_1 and c_2, the smaller the cost of truthfulness, but the lower the probability of q actually falling between them. We need a way to minimize the expected cost of truthfulness in this scenario. I will not address this problem here, but suggest a starting point for this line of analysis.

The particular assignment described in Figure 4-9 is given by

$$c_1 = E[\frac{q}{n}] - \sigma(\frac{q}{n}) \tag{4.19}$$

$$c_2 = E[\frac{q}{n}] + \sigma(\frac{q}{n}) \tag{4.20}$$

This assignment means that q will fall between c_1 and c_2 with high probability. Although this may not result in the minimum expected cost of truthfulness, the predictability of the cost of truthfulness will be a benefit to the utility.

Now that we have looked at the economics behind incentivization, we can try to give a tangible way of incentivizing PACEM. We set the following requirements in order for the incentives to be practical from the perspective of real-world user expectations:

1. There should be incentive for a user to participate as long as his/her flexibility is non-zero

2. The incentive should reflect the total demand reduction provided by a user

3. There should never be any penalties to the user

An individually rational mechanism would address 3, while the colored procurement mechanism will address 2. To address 1, we might add some small incentive for user participation, although this violates the NPT condition. This **should not** depend on what color or amount the demand flexibility is, since this would require designing another mechanism which deals with truthfulness of users when they "opt in" to PACEM. Such a mechanism would follow many of the arguments given for the procurement mechanism, but would make the opt-in process unnecessarily complicated, which is undesirable. Further, if the participation incentive is substantial, users may opt in to the system and set it to always override. Thus the initial incentive can come in the form of a free installation of the smart outlets required for participation in PACEM.

Users have the opportunity to optimize their preferences for maximum demand reduction once they participate in PACEM, and the payoff from demand reduction is designed to be much higher than that of "opting in" in order to encourage users to commit flexibility first and preferences later. A user setting their preferences is analogous to placing bids during the procurement scenario. Another factor which can be incorporated in this model is dynamic energy pricing[9, 16], that would encourage users to provide more flexibility during peak hours and less flexibility during low-load hours.

In this chapter, we have made progress in designing a user incentive system for PACEM in the form of *Colored Procurement Mechanisms*. This class of mechanisms is useful since it allows for integration with randomized algorithms such as `ColoredPower` and provides a concrete way to quantify the cost of enforcing truthfulness in user preference reporting. The next step is to solve the optimization of the cost of truthfulness.

Chapter 5

Contributions and Future Work

This thesis takes a significant technological step forward in making demand side cooperative energy management a possibility for small-scale energy users. The ColoredPower algorithm along with the incentive structure forms a system that is highly scalable for large networks in metropolitan areas. This system helps PACEM achieve its design goals of demand flexibility, dynamic response to changing demand and availability of power, and non-intrusiveness and privacy for the end user, all while being easy and cheap to install.

The ColoredPower algorithm is a probabilistic distributed algorithm that runs simultaneously on a large number of devices in order to accurately control the aggregate power consumed by devices that are "on" to a target value in a non-intrusive way by ensuring that any single device does not turn on or off rapidly. This is a contribution to the field of randomized distributed control that allows for changing local and global conditions, unavailability of parts of the network for long periods of time and provides a control system to make randomized local actions turn into accurate global behavior. Although ColoredPower is only described in terms of a 4 color system, it is easy to see that it is applicable to a k-color system as well.

The ColoredPower algorithm is not limited to PACEM in its application. The ideas behind ColoredPower can describe decentralized algorithms that run on every individual component of a distributed system in order to control an aggregate property of the system, while allowing for changing availability of the components in the

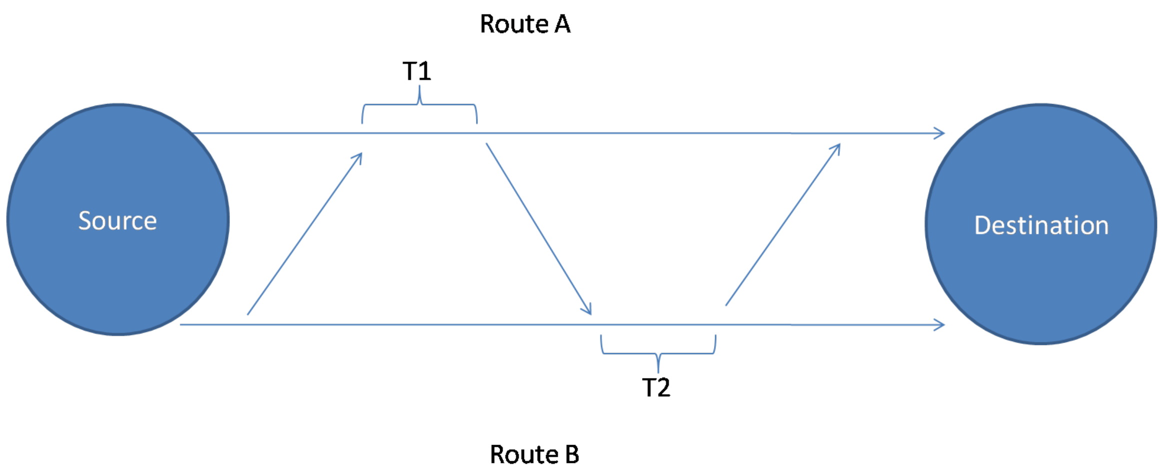


Figure 5-1: A simple traffic routing problem

system. For instance, it may be possible to adapt and expand `ColoredPower` for other distributed resource and task allocation scenarios, such as bandwidth allocation on networks or vehicle traffic routing. Consider the traffic routing problem as shown in Figure 5-1, where there are n vehicles trying to get from a source to a destination. There are two available highways, A and B, with some crossroads connecting them. Vehicles can only decide to switch between highways if they are near a crossroad. Once they switch from one highway to another, they cannot switch back until they get to the next crossroad. The vehicles are equipped with short-range radios that periodically give them estimates about the total number of vehicles on A and B. The problem is to route traffic in real time so that neither highway is too congested, with the constraint that no single vehicle should have to switch highways significantly more times than other vehicles, since the added travel distance is inconvenient. One can imagine a `ColoredPower` type algorithm operating in each vehicle which decides with some probability whether to switch highways.

The incentive structure that I have proposed ensures that users will not try to game the system under certain conditions. Algorithmic mechanism design is a relatively new field at the junction of economics and computer science, and it is important for the theoretical results to be applied in practical scenarios such as the one described by PACEM. Large scale demand response exists because it is more profitable and easy to implement with a very small number of users. A good incentive structure will enable participation by a large number of small scale users. If implemented correctly, small scale demand response can be just as, if not more profitable for the electric power sector and for the users.

Lastly, PACEM is a system conceived with the goals of saving energy, being environmentally conscious, and working toward a more efficient society. This thesis contributes to all of these efforts.

5.1 Future Work

The algorithm we describe has a few limitations that should be addressed in future work. For instance, the PID gains that are used in the experiments are not suitable for every type of network. In fact, I suspect that the optimal values for these gains depend on the network diameter. It would be possible to design an improved version of `ColoredPower` using dynamic PID gains that depend on factors like the network diameter, the census of the system, and the absolute value of the target Q_t. Further, it is unclear that a PID controller is the best feedback controller for the job. Further work should investigate other types of tracking controllers, which may achieve better results.

There is much work in the area of mechanism design in the context of distributed probabilistic control that can be done. For instance, designing a collusion resistant online mechanism would have the potential to benefit PACEM. In the current network topology, no user knows specific information about users other than her neighbors. I predict that this mechanism will likely be resistant to collusion by very small fraction of users on the network. Future work includes quantifying exactly how collusion resistant the Colored Procurement Mechanism can be, and what improvements can be made in this area. In a real world setting, users may use non-PACEM networks (e.g. the Internet) to exchange information and increase their profits. The mechanism could then be manipulated by large groups of users whose total pool of demand flexibility is comparable to the total demand reduction needed; it is doubtful that we can design a system which will be resistant to collusion among arbitrarily large groups of users.

Finally, the next biggest step toward the realization of PACEM is to use prototype devices to verify that the algorithm and incentive structure (perhaps with some of the above mentioned improvements) can work on a real system. This will set the stage for deploying PACEM for actual consumers.

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