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Estimating the Maximum Potential Revenue for Grid Connected Electricity Storage: Arbitrage and Regulation

A Study for the DOE Energy Storage Systems Program

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Abstract

The valuation of an electricity storage device is based on the expected future cash flow generated by the device. Two potential sources of income for an electricity storage system are energy arbitrage and participation in the frequency regulation market. Energy arbitrage refers to purchasing (storing) energy when electricity prices are low, and selling (discharging) energy when electricity prices are high. Frequency regulation is an ancillary service geared towards maintaining system frequency, and is typically procured by the independent system operator in some type of market. This paper outlines the calculations required to estimate the maximum potential revenue from participating in these two activities. First, a mathematical model is presented for the state of charge as a function of the storage device parameters and the quantities of electricity purchased/sold as well as the quantities offered into the regulation market. Using this mathematical model, we present a linear programming optimization approach to calculating the maximum potential revenue from an electricity storage device. The calculation of the maximum potential revenue is critical in developing an upper bound on the value of storage, as a benchmark for evaluating potential trading strategies, and a tool for capital finance risk assessment. Then, we use historical California Independent System Operator (CAISO) data from 2010-2011 to evaluate the maximum potential revenue from the Tehachapi wind energy storage project, an American Recovery and Reinvestment Act of 2009 (ARRA) energy storage demonstration project. We investigate the maximum potential revenue from two different scenarios: arbitrage only and arbitrage combined with the regulation market. Our analysis shows that participation in the regulation market produces four times the revenue compared to arbitrage in the CAISO market using 2010 and 2011 data. Then we evaluate several trading strategies to illustrate how they compare to the maximum potential revenue benchmark. We conclude with a sensitivity analysis with respect to key parameters.

keywords: electricity storage, energy arbitrage, frequency regulation market, storage valuation, linear programming optimization.

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1 Introduction

Electricity storage devices date back to the invention of the zinc-silver primary battery in 1800 by Alessandro Volta [1]. The first large grid-connected energy storage devices were pumped hydroelectric systems constructed in Italy and Switzerland in the 1890's. The first grid-connected energy storage device in the United States was the pumped hydroelectric Rocky River Plant, New Milford, Connecticut which came on line in 1929 [2]. With the advent of modern power electronics and an increased demand for variable generation like wind and solar, there has been a renewed interest in grid-scale electricity storage devices. The different mechanisms for storing electricity can be divided into one of four categories: electrical, mechanical, thermal, and chemical. Examples in the electric category include superconducting magnetic energy storage and capacitors. Pumped hydroelectric power, compressed air, and flywheels represent mechanical storage mechanisms. Batteries are the most common type of chemical storage and ice is the most common form of thermal storage.

Potential benefits of electricity storage include firming of variable renewable generation (e.g. wind and solar), shifting renewable energy from low demand periods to high demand periods, and increased grid reliability (e.g. voltage support and frequency regulation). Potential societal benefits include reduced fossil fuel use and reduced emissions. A complete discussion of potential benefits appears in [3, 4].

Regardless of the application or benefit, electricity storage is ultimately only as valuable as the revenue stream generated by the storage device. In deregulated markets, this revenue stream comes from participating in the markets for energy and ancillary services (e.g. frequency regulation, operating reserves, and voltage support) [5]. In regulated regions, vertically integrated utilities must invest in technologies that provide reliable electricity to the consumer at the lowest cost. In this scenario, electricity storage must be compared to the cost of competitive technologies that provide the capabilities required by the utility. An additional source of revenue is government incentives designed to guide future investment decisions based on the public good.

The two potential revenue streams considered in this paper are energy arbitrage and participation in the regulation market. Arbitrage involves purchasing (charging) energy when prices are low, e.g. during times of low demand, and selling (discharging) energy when prices are high, e.g. during times of peak demand. There are conversion losses when energy is stored, so depending on the conversion efficiency, more energy must be purchased than can be sold. There are also constraints based on the specification of the storage device. Typical constraints include limits on the state of charge and the rate at which energy may be stored or discharged. For example, a storage device that has a full state of charge cannot accept any additional energy. The arbitrage scenario in this paper assumes that all energy transactions occur in the day ahead market for energy. Another possibility is to arbitrage the day ahead market with the spot market.

Regulation up and regulation down (sometimes they are combined into a single regulation quantity) are ancillary services designed to maintain frequency stability. The frequency of the grid is maintained at 60 Hz in the United States and Canada. If the load increases while generation is held constant, the frequency will drop. Similarly, if the load decreases while generation is held constant, the frequency will rise. In order to maintain tight tolerances on the frequency, generation must be constantly dithered so that load and generation are equal. An alternative approach, referred to as demand response, is to modulate the load to meet generation. Price responsive demand response is starting to be used in conjunction with controlling generation in some regions. Depending on the market, a balancing authority or vertically integrated utility will control generation on a second by second basis to track the load. In deregulated regions, the balancing authority must reserve enough regulation capacity to meet expected variations in load. Regulation up is the ability to provide additional generation on command. Regulation down is the ability to reduce generation, or

store power, on demand. Current practice is to reimburse regulation based on capacity along with compensation for any electricity that is purchased or sold. Based on FERC order 755, the industry is evolving towards “pay for performance” where the compensation will be based on the amount of regulation provided (e.g. faster responding devices can provide more benefit and therefore should be compensated appropriately). The analysis in this paper is based on the current remuneration methodology, but can be easily modified to accommodate compensation schemes arising from FERC order 755.

This paper outlines a framework for calculating the maximum revenue from an electricity storage system that participates in energy arbitrage and the regulation market. This implies that the storage device is operating in a deregulated region. The approach is designed to calculate the “best-case” scenario assuming perfect knowledge of past, current, and future prices. This calculation is critical because it provides an upper bound on the revenue that can be collected by a storage facility. This quantity can be used to score other trading strategies and also is useful in estimating an upper bound for the value of the storage facility. The problem is formulated as a linear programming optimization based on the operational constraints of the energy storage system. This paper builds on previous work modeling electricity storage facilities. The energy storage model and linear programming optimization presented in this paper build on the results in [6]. Mokrian and Stephen present a stochastic framework for the valuation of electricity storage and present the linear programming optimization approach as a method for calculating the absolute highest achievable profit from an arbitrage strategy. A related area is the valuation of natural gas storage facilities. Recent work in this area includes [7, 8]. Revenue from energy arbitrage and the regulation ancillary services market are only two of the potential benefits of electricity storage devices. A complete review of potential revenue streams is outlined in [3, 4].

This report is organized as follows: Section 2 presents a model for the energy storage device that is used throughout this paper. Section 3 provides a Linear Programming (LP) optimization approach for estimating the maximum revenue from arbitrage and the regulation market. Section 4 presents a case study for the Tehachapi Wind Energy Storage storage project. Concluding remarks are found in Section 5.

2 Electricity Storage Model

A block diagram representing a typical energy storage system is shown in Figure 1. The power input is electricity that is converted to some type of stored energy. Common energy storage mechanisms include mechanical, electrical, chemical, and thermal [3]. Examples of mechanical storage mechanisms are pumped hydro, compressed air, and flywheels. Superconducting magnetic energy storage and capacitors are examples of electrical storage mechanisms. Batteries are the most common type of chemical energy storage. The most prevalent form of thermal storage is ice. The power output block represents the conversion from stored energy to electricity out. For some types of energy storage, e.g. electrochemical cells, the power input and power output systems are closely coupled. In this case, a bi-directional AC-DC inverter is common. For other types of energy storage, e.g. compressed air, the input power and output power systems are fairly distinct. In this case, the power input system injects compressed air into the reservoir. The power output system combines compressed air with natural gas to run turbines that generate the output electric power.

The key parameters that characterize a storage device are:

- **Power Rating** [MW]: the maximum power of the storage device (charge and discharge). It is possible to have a different power rating for charging and discharging.
- **Energy Capacity** [Joules or MWh]: the amount of energy that can be stored.

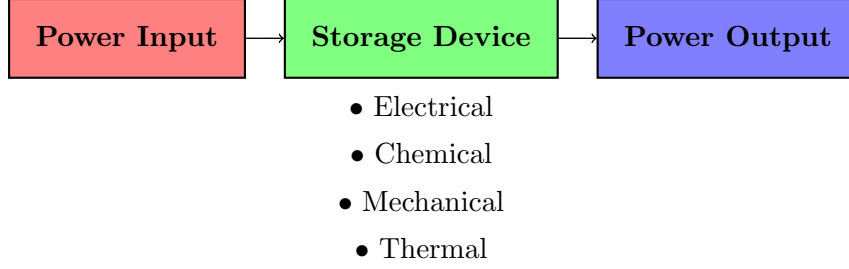


Figure 1: Storage block diagram

- **Efficiency** [percent]: the ratio of the energy discharged by the storage system divided by the energy input into the storage system. Efficiency can be broken down into two components: conversion efficiency and storage efficiency. Conversion efficiency describes the losses encountered when input power is stored in the system. Storage efficiency describes the time-based losses in a storage system.
- **Ramp Rate** [MW/min or percent nameplate power/min]: the ramp rate describes how quickly the storage device can change its input/output power level.

For the analysis in this report, we are concerned with the quantity of energy charged or discharged during each time period for each potential activity (e.g. arbitrage or regulation). For arbitrage, the device will maintain a constant output power over each time period. For regulation, it is assumed that the device is capable of tracking the regulation signal. Since the ramping time is negligible compared to the time period (e.g. one hour), it is safe to ignore the effects of ramp rate. If the ramp rate is slow compared to the time period this approximation does not hold and a model that incorporates ramp rate must be employed.

The following parameters capture the storage system constraints:

Storage Parameters

- t time period (e.g. one hour)
- \bar{q}^D maximum quantity that can be sold/discharged in a single period (MWh)
- \bar{q}^R maximum quantity that can be bought/recharged in a single period (MWh)
- \bar{S} maximum storage capacity (MWh)
- γ_S storage efficiency (fraction of stored energy maintained over one period)
- γ_C conversion efficiency (fraction of input energy that gets stored)

Since we have assumed that the ramping time is negligible, the maximum quantity that can be sold/discharged in a single period is equivalent to

$$\bar{q}^D = (\text{Maximum discharge power level}) \times (\text{time period}) \quad (1)$$

Likewise, the maximum quantity that can be bought/recharged in a single period is equivalent to

$$\bar{q}^R = (\text{Maximum recharge power level}) \times (\text{time period}) \quad (2)$$

For a storage device that provides only one service, e.g. arbitrage, there are two decision variables:

Decision Variables

- q_t^D quantity of energy sold (Discharged) at time t (MWh)
- q_t^R quantity of energy purchased (Recharged) at time t (MWh)

The decision variables are assumed to be non-negative quantities. The state of charge S_t at any time t is given by

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D \quad (3)$$

The state of charge at time t is the state of charge at time $t - 1$ adjusted for storage losses plus any net charging (adjusted for conversion losses) minus the quantity discharged in the time period. Additional constraints include:

$$\begin{aligned} 0 &\leq S_t \leq \bar{S}, \text{ for all } t \\ 0 &\leq q_t^R \leq \bar{q}^R, \text{ for all } t \\ 0 &\leq q_t^D \leq \bar{q}^D, \text{ for all } t \end{aligned} \quad (4)$$

For a device that is participating in arbitrage and the regulation market, a few additional quantities must be incorporated into the storage device model. Assuming a separate market for regulation up and regulation down, the decision variables are:

Decision Variables

q_t^D	quantity of energy sold (Discharged) at time t (MWh)
q_t^R	quantity of energy purchased (Recharged) at time t (MWh)
q_t^{RU}	quantity of energy offered into the regulation up market at time t (MWh)
q_t^{RD}	quantity of energy offered into the regulation down market at time t (MWh)

Once again, the decision variables are assumed to be non-negative quantities. For energy arbitrage, the scheduled and actual quantities are equal. For the regulation market, a resource usually offers a capacity and there is no guarantee that all of the offer will be accepted. Fortunately, since frequency regulation is concerned with the short-term balance of load and generation to maintain system frequency, regulation signals are usually zero mean over longer time periods. This time period varies depending on the market characteristics. For CAISO, the regulation need can have a non-zero mean for up to several hours. On the other hand, the PJM regulation need is zero mean over most 1-hour intervals. A representative regulation command signal is shown in Figure 2.

In order to quantify the change in state of charge from participation in the regulation market, it is useful to define the regulation up efficiency γ_{ru} as the fraction of the regulation up reserve capacity that is actually employed in real-time (on average). Similarly, the regulation down efficiency γ_{rd} is the fraction of the regulation down reserve capacity that is actually employed in real-time (on average). For Figure 2 the regulation up/down efficiency is approximately 13%. Another assumption is that the regulation signal is allocated equally among participating regulation resources, e.g. over any given time period the regulation signal for each resource is proportional to the total regulation need. The scale factor is the quantity offer by that resource divided by the total quantity procured.

The state of charge at time t for a device participating in arbitrage and regulation is given by

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D + \gamma_c \gamma_{rd} q_t^{RD} - \gamma_{ru} q_t^{RU} \quad (5)$$

subject to the following constraints

$$\begin{aligned} 0 &\leq S_t \leq \bar{S}, \text{ for all } t \\ 0 &\leq q_t^R + q_t^{RD} \leq \bar{q}^R, \text{ for all } t \\ 0 &\leq q_t^D + q_t^{RU} \leq \bar{q}^D, \text{ for all } t \end{aligned} \quad (6)$$

Participating in regulation down provides the opportunity to increase the state of charge subject to the regulation down efficiency and the conversion efficiency. Participation in regulation up provides the opportunity to decrease the state of charge subject to the regulation up efficiency. The quantities allocated to regulation up and regulation down reduce the maximum potential quantities allocated to arbitrage subject to the charge/discharge constraints of the device. This next section presents an approach to maximize revenue using these storage models.

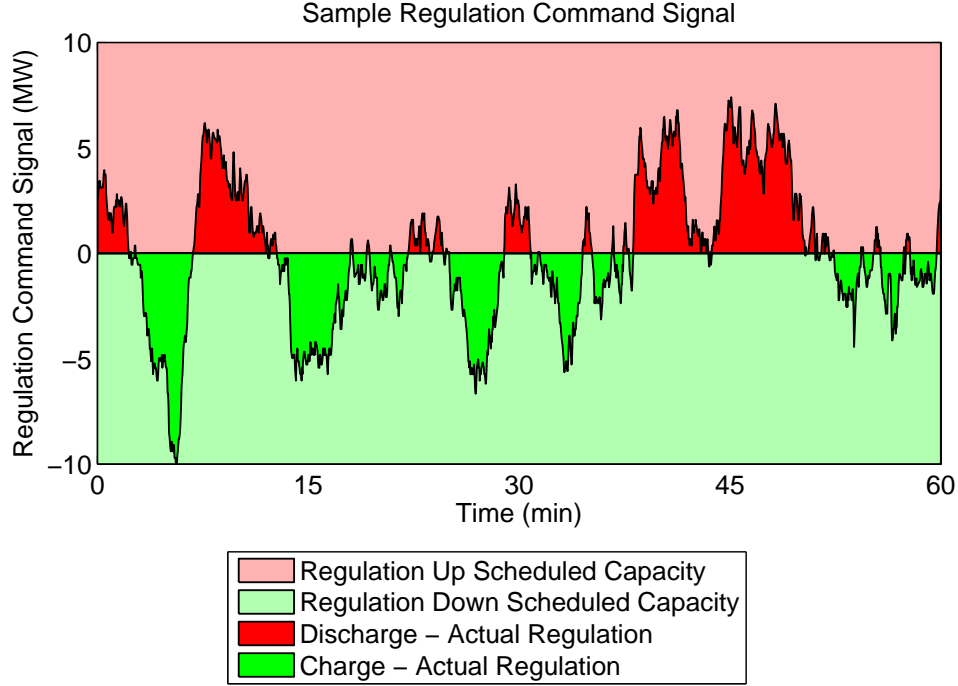


Figure 2: Representative regulation command signal.

3 Maximizing Revenue: A Linear Programming Optimization Approach

The standard Linear Programming (LP) optimization formulation, which minimizes a linear function of the state, $f^T x$, subject to constraints, is typically defined as [9]

$$\min_x f^T x \text{ such that } \begin{cases} Ax \leq b \\ A_{eq}x = b_{eq} \\ lb \leq x \leq ub \end{cases} \quad (7)$$

The problem of maximizing revenue from an energy storage device is naturally formulated as an LP optimization problem. The next two sections combine the energy storage model with a cost function to maximize the revenue in two different scenarios: arbitrage and arbitrage combined with participation in the regulation market.

3.1 Arbitrage

From the previous section, the model for the storage device participating in arbitrage is given by:

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D \quad (8)$$

The constraints on the state of charge S_t , the quantity purchased q_t^R , and the quantity sold q_t^D at each time step t are given by:

$$\begin{aligned} 0 \leq q_t^D \leq \bar{q}^D & \text{ bounds on the discharge quantity at time period } t \\ 0 \leq q_t^R \leq \bar{q}^R & \text{ bounds on the charge quantity at time period } t \\ 0 \leq S_t \leq \bar{S} & \text{ bounds on the state of charge quantity at time period } t \end{aligned} \quad (9)$$

For a storage device engaging in arbitrage, we are trying to maximize the profit from buying energy at low prices and selling energy at higher prices, subject to the constraints of the storage facility. The quantity we are solving for is the amount of energy bought (charged) and sold (discharged) at each time step. Thus x is defined as

$$x = \begin{bmatrix} q_1^D \\ q_2^D \\ q_3^D \\ \vdots \\ q_T^D \\ q_1^R \\ q_2^R \\ q_3^R \\ \vdots \\ q_T^R \end{bmatrix} \quad (10)$$

where q_t^D is the quantity of energy discharged (sold) at time period t while q_t^R is the quantity of energy used for recharging (bought) at time period t . When the device is recharged, some of the energy is lost from inefficiency. The conversion efficiency γ_c is the fraction of purchased electricity that gets stored. Likewise, the storage device loses small amounts of energy over each time period. The storage efficiency γ_s , defined as the fraction of stored electricity maintained over one period, captures this loss. Using these two parameters, the recursion equation describing the amount of energy S_t stored in the facility at time period t is given by:

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D \quad (11)$$

Assuming an uncharged initial condition, $S_0 = 0$, the terms of the storage model for the first few time steps are listed below:

$$\begin{aligned} t=1 \quad S_1 &= \gamma_c q_1^R - q_1^D \\ t=2 \quad S_2 &= \gamma_s (\gamma_c q_1^R - q_1^D) + \gamma_c q_2^R - q_2^D \\ t=3 \quad S_3 &= \gamma_s [\gamma_s (\gamma_c q_1^R - q_1^D) + \gamma_c q_2^R - q_2^D] + \gamma_c q_3^R - q_3^D \\ t=4 \quad S_4 &= \gamma_s [\gamma_s [\gamma_s (\gamma_c q_1^R - q_1^D) + \gamma_c q_2^R - q_2^D] + \gamma_c q_3^R - q_3^D] + \gamma_c q_4^R - q_4^D \end{aligned}$$

Writing this in matrix form yields the first inequality constraint for the storage device:

$$A_s x = S, \text{ where } A_s = [A_d | A_r] \quad (12)$$

with

$$A_d = \begin{bmatrix} -1 & 0 & 0 & 0 & \dots & 0 \\ -\gamma_s & -1 & 0 & 0 & \dots & 0 \\ -\gamma_s^2 & -\gamma_s & -1 & 0 & \dots & 0 \\ -\gamma_s^3 & -\gamma_s^2 & -\gamma_s & -1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -\gamma_s^{T-1} & -\gamma_s^{T-2} & -\gamma_s^{T-3} & -\gamma_s^{T-4} & \dots & -1 \end{bmatrix} \quad (13)$$

$$A_r = \begin{bmatrix} \gamma_c & 0 & 0 & 0 & \dots & 0 \\ \gamma_s \gamma_c & \gamma_c & 0 & 0 & \dots & 0 \\ \gamma_s^2 \gamma_c & \gamma_s \gamma_c & \gamma_c & 0 & \dots & 0 \\ \gamma_s^3 \gamma_c & \gamma_s^2 \gamma_c & \gamma_s \gamma_c & \gamma_c & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_s^{T-1} \gamma_c & \gamma_s^{T-2} \gamma_c & \gamma_s^{T-3} \gamma_c & \gamma_s^{T-4} \gamma_c & \dots & \gamma_c \end{bmatrix} \quad (14)$$

$$S = [S_1 \quad S_2 \quad S_3 \quad \dots \quad S_T]^T \quad (15)$$

Additional inequality constraints come from the maximum charge/discharge per time period and the maximum storage capacity of the facility:

$$0 \leq q_t^D \leq \bar{q}^D, \quad 0 \leq q_t^R \leq \bar{q}^R, \quad 0 \leq S_t \leq \bar{S} \quad (16)$$

The first two constraints are handled by the upper and lower bounds on the quantity being solved for, $lb \leq x \leq ub$.

$$lb^{2Tx1} = [0 \quad \dots \quad 0]^T, \quad ub^{2Tx1} = [\bar{q}^D \quad \dots \quad \bar{q}^D \quad \bar{q}^R \quad \dots \quad \bar{q}^R]^T \quad (17)$$

The last constraint must be handled as outlined below.

$$\text{combining } 0 \leq S_t \text{ and } S \leq A_s x \text{ yields } -A_s x \leq 0 \quad (18)$$

$$\text{combining } S \leq A_s x \text{ and } S_t \leq \bar{S} \text{ yields } A_s x \leq \bar{S} \quad (19)$$

combining the above two inequalities in matrix form yields the following system of equations:

$$Ax \leq b, \text{ where } A = \begin{bmatrix} -A_s \\ A_s \end{bmatrix}, \quad b = [0 \quad \dots \quad 0 \quad \bar{S} \quad \dots \quad \bar{S}]^T \quad (20)$$

The financial quantities of interest are:

- P_t Price of electricity (LMP) at time t (\$/MWh)
- C_d Cost of discharging at time t (\$/MWh)
- C_r Cost of recharging at time t (\$/MWh)
- r Interest rate over one time period

For this analysis, the cost terms are assumed to be 0 since we are focusing on maximizing revenue. If there are costs associated with charging or discharging, e.g. the system has a limited cycle life so the cost of charging or discharging can be quantified, this term may be considered. If the costs are included, the same approach can be employed to maximize profit. The cost function (or revenue) that we are trying to maximize is given by:

$$J = \sum_{t=1}^T [(P_t - C_d)q_t^D - (P_t + C_r)q_t^R] e^{-rt} \quad (21)$$

$$f = \begin{bmatrix} (P_1 - C_d)e^{-r} \\ (P_2 - C_d)e^{-2r} \\ (P_3 - C_d)e^{-3r} \\ \vdots \\ (P_T - C_d)e^{-Tr} \\ -(P_1 + C_r)e^{-r} \\ -(P_2 + C_r)e^{-2r} \\ -(P_3 + C_r)e^{-3r} \\ \vdots \\ -(P_T + C_r)e^{-Tr} \end{bmatrix} \quad (22)$$

Since we are trying to maximize profits and need to formulate the problem as a minimization problem, we can define a new cost function J^* that is the negative of the original cost function. Therefore, minimizing J^* maximizes the profits from the facility.

$$J^* = -f^T x \quad (23)$$

3.2 Arbitrage and Regulation

The model for the storage device participating in arbitrage and the regulation market is given by:

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D + \gamma_c \gamma_{rd} q_t^{RD} - \gamma_{ru} q_t^{RU} \quad (24)$$

where S_t is the state of charge, q_t^R is the energy purchased, q_t^D is the energy sold, q_t^{RU} is the reserve capacity offered into the regulation up market, and q_t^{RD} is the reserve capacity offered into the regulation down market at each time step t . γ_s is the storage efficiency (fraction of stored energy maintained over one period), γ_c is the conversion efficiency (fraction of input power that gets stored), γ_{ru} is the regulation up efficiency (fraction of reserve capacity that is actually employed in real-time), and γ_{rd} is the regulation down efficiency (fraction of reserve capacity that is actually employed in real-time).

The state of charge S_t , the quantity purchased q_t^R , the quantity sold q_t^D , the quantity offered into the regulation up market q_t^{RU} , and the quantity offered into the regulation down market q_t^{RD} at each time step t are constrained by:

$$\begin{aligned} 0 \leq q_t^D + q_t^{RU} \leq \bar{q}^D & \quad \text{bounds on the energy discharged at time period } t \\ 0 \leq q_t^R + q_t^{RD} \leq \bar{q}^R & \quad \text{bounds on the energy charged at time period } t \\ 0 \leq S_t \leq \bar{S} & \quad \text{bounds on the state of charge quantity at time period } t \end{aligned} \quad (25)$$

It is important to note that under these assumptions energy allocated for the regulation up/down market reduces the amount of energy that may be sold/purchased for arbitrage.

For a storage device engaging in energy arbitrage and the regulation market, we are trying to maximize the revenue from arbitrage opportunities and selling ancillary services, subject to the constraints of the storage facility. The quantity we are solving for is the amount of energy bought (charged) and sold (discharged) at each time step as well as the amount offered into the regulation up and regulation down markets. There are T time steps in the analysis and the length of the time step is the time interval employed by the electricity market (e.g. 1 hour). For this analysis, we consider regulation up and regulation down as two separate markets. If the region of interest combines both types of regulation into one market, the analysis is simplified. Thus x is defined as

$$x = \begin{bmatrix} q_1^D \\ \vdots \\ q_T^D \\ q_1^R \\ \vdots \\ q_T^R \\ q_1^{RU} \\ \vdots \\ q_T^{RU} \\ q_1^{RD} \\ \vdots \\ q_T^{RD} \end{bmatrix} \quad (26)$$

where q_t^D is the quantity of energy discharged (sold) at time period t , q_t^R is the quantity of energy used for recharging (bought) at time period t , q_t^{RU} is the amount of energy offered into the regulation up market at time t , and q_t^{RD} is the amount of energy offered into the regulation down market at time t . When the device is recharged, some of the energy is lost from inefficiency. The conversion efficiency γ_c is the fraction of purchased electricity that gets stored. Likewise, the storage device loses small amounts of energy over each time period. The storage efficiency γ_s , defined as the fraction of stored electricity maintained over one period, captures this loss. Some fraction of the regulation up/down offers are accepted. This is captured by defining the regulation up efficiency γ_{ru} and the regulation down efficiency γ_{rd} . There are some constraints on γ_{ru} and γ_{rd} that must be observed. For example, it is not possible to provide 100% of the offered regulation up and down in a time period. One way to look at the parameters γ_{ru} and γ_{rd} is to define them as

$$\gamma_{ru} = \alpha_{ru}\mu_{ru}, \quad \gamma_{rd} = \alpha_{rd}\mu_{rd}, \quad \alpha_{ru} + \alpha_{rd} = 1, \quad 0 \leq \mu_{ru}, \mu_{rd} \leq 1 \quad (27)$$

where α_{ru} represents the fraction of the time period that the capacity reserved for regulation up is called upon and α_{rd} represents the fraction of the time period that the capacity reserved for regulation down is called upon. Therefore, $\alpha_{ru} + \alpha_{rd} = 1$. μ_{ru} represents the average fraction of the regulation up offer called upon when regulation up is needed. Likewise, μ_{rd} represents the average fraction of the regulation down offer called upon when regulation down is required. These parameters are illustrated in Figure 3. In order to further clarify the definitions of these terms, below are the calculations to determine the proper values from empirical data.

$$\alpha_{ru} = \frac{\text{number of RU AGC samples in the period}}{\text{number of AGC samples in the period}} \quad (28)$$

$$\alpha_{rd} = \frac{\text{number of RD AGC samples in the period}}{\text{number of AGC samples in the period}} \quad (29)$$

$$\mu_{ru} = \frac{\sum \text{RU AGC samples in the period}}{\text{number of RU AGC samples in the period}} \left(\frac{\text{one time period}}{q_t^{RU}} \right) \quad (30)$$

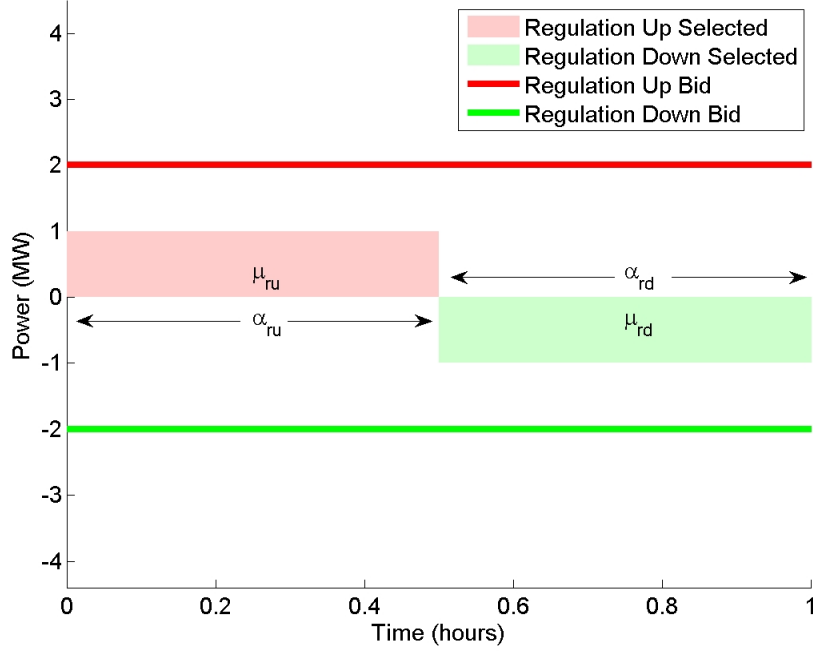


Figure 3: Illustration of regulation up/down parameters, $\alpha_{ru} = 0.5$, $\alpha_{rd} = 0.5$, $\mu_{ru} = 0.5$, $\mu_{rd} = 0.5$, $\gamma_{ru} = 0.25$, $\gamma_{rd} = 0.25$, $q_t^{RU} = 2$ MWh, $q_t^{RD} = 2$ MWh.

$$\mu_{rd} = \frac{\sum \text{RD AGC samples in the period}}{\text{number of RD AGC samples in the period}} \left(\frac{\text{one time period}}{q_t^{RD}} \right) \quad (31)$$

It is important to note that the characteristics of the AGC signal controlling the storage device must follow this model in order for this analysis approach to be valid. In other words, the statistics of the AGC signal must not vary greatly over time. In statistical terms, weak-sense-stationarity is sufficient where the mean and covariance of the AGC signal do not change over time. This is not difficult, one scenario that meets these requirements is to require that the AGC signal to the storage device have zero mean over the time period. This is an operational requirement for flywheel devices. If the characteristics of the AGC signal do not follow the model, the state of charge cannot be computed reliably because of the path dependency induced by the characteristics (uncertainty) of the control signal. In this case, Monte Carlo simulations must be applied to estimate the maximum revenue from the system. Assuming the AGC signal follows the model presented above, the recursion equation describing the amount of energy S_t stored in the facility at time period t is given by

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D + \gamma_c \gamma_{rd} q_t^{RD} - \gamma_{ru} q_t^{RU} \quad (32)$$

Assuming a completely discharged initial condition, $S_0 = 0$, the terms of the storage model for the first few time steps are listed below:

$$\begin{aligned}
t=1 \quad S_1 &= \gamma_c q_1^R - q_1^D + \gamma_c \gamma_{rd} q_1^{RD} - \gamma_{ru} q_1^{RU} \\
t=2 \quad S_2 &= \gamma_s (\gamma_c q_1^R - q_1^D + \gamma_c \gamma_{rd} q_1^{RD} - \gamma_{ru} q_1^{RU}) + \gamma_c q_2^R - q_2^D + \gamma_c \gamma_{rd} q_2^{RD} - \gamma_{ru} q_2^{RU} \\
t=3 \quad S_3 &= \gamma_s [\gamma_s (\gamma_c q_1^R - q_1^D + \gamma_c \gamma_{rd} q_1^{RD} - \gamma_{ru} q_1^{RU}) + \gamma_c q_2^R - q_2^D + \gamma_c \gamma_{rd} q_2^{RD} - \gamma_{ru} q_2^{RU}] + \\
&\quad \gamma_c q_3^R - q_3^D + \gamma_c \gamma_{rd} q_3^{RD} - \gamma_{ru} q_3^{RU}
\end{aligned}$$

Writing this in matrix form yields the first inequality constraint for the storage device:

$$A_s x = S, \text{ where } A_s = [A_d | A_r | A_{ru} | A_{rd}] \quad (33)$$

with

$$A_d = \begin{bmatrix} -1 & 0 & 0 & 0 & \dots & 0 \\ -\gamma_s & -1 & 0 & 0 & \dots & 0 \\ -\gamma_s^2 & -\gamma_s & -1 & 0 & \dots & 0 \\ -\gamma_s^3 & -\gamma_s^2 & -\gamma_s & -1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -\gamma_s^{T-1} & -\gamma_s^{T-2} & -\gamma_s^{T-3} & -\gamma_s^{T-4} & \dots & -1 \end{bmatrix} \quad (34)$$

$$A_r = \begin{bmatrix} \gamma_c & 0 & 0 & 0 & \dots & 0 \\ \gamma_s \gamma_c & \gamma_c & 0 & 0 & \dots & 0 \\ \gamma_s^2 \gamma_c & \gamma_s \gamma_c & \gamma_c & 0 & \dots & 0 \\ \gamma_s^3 \gamma_c & \gamma_s^2 \gamma_c & \gamma_s \gamma_c & \gamma_c & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_s^{T-1} \gamma_c & \gamma_s^{T-2} \gamma_c & \gamma_s^{T-3} \gamma_c & \gamma_s^{T-4} \gamma_c & \dots & \gamma_c \end{bmatrix} \quad (35)$$

$$A_{ru} = \begin{bmatrix} -\gamma_{ru} & 0 & 0 & 0 & \dots & 0 \\ -\gamma_s \gamma_{ru} & -\gamma_{ru} & 0 & 0 & \dots & 0 \\ -\gamma_s^2 \gamma_{ru} & -\gamma_s \gamma_{ru} & -\gamma_{ru} & 0 & \dots & 0 \\ -\gamma_s^3 \gamma_{ru} & -\gamma_s^2 \gamma_{ru} & -\gamma_s \gamma_{ru} & -\gamma_{ru} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -\gamma_s^{T-1} \gamma_{ru} & -\gamma_s^{T-2} \gamma_{ru} & -\gamma_s^{T-3} \gamma_{ru} & -\gamma_s^{T-4} \gamma_{ru} & \dots & -\gamma_{ru} \end{bmatrix} \quad (36)$$

$$A_{rd} = \begin{bmatrix} \gamma_c \gamma_{rd} & 0 & 0 & 0 & \dots & 0 \\ \gamma_s \gamma_c \gamma_{rd} & \gamma_c \gamma_{rd} & 0 & 0 & \dots & 0 \\ \gamma_s^2 \gamma_c \gamma_{rd} & \gamma_s \gamma_c \gamma_{rd} & \gamma_c \gamma_{rd} & 0 & \dots & 0 \\ \gamma_s^3 \gamma_c \gamma_{rd} & \gamma_s^2 \gamma_c \gamma_{rd} & \gamma_s \gamma_c \gamma_{rd} & \gamma_c \gamma_{rd} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_s^{T-1} \gamma_c \gamma_{rd} & \gamma_s^{T-2} \gamma_c \gamma_{rd} & \gamma_s^{T-3} \gamma_c \gamma_{rd} & \gamma_s^{T-4} \gamma_c \gamma_{rd} & \dots & \gamma_c \gamma_{rd} \end{bmatrix} \quad (37)$$

$$S = [S_1 \quad S_2 \quad S_3 \quad \dots \quad S_T]^T \quad (38)$$

Additional inequality constraints come from the maximum charge/discharge per time period and the maximum storage capacity of the facility:

$$\begin{aligned}
0 \leq q_t^D + q_t^{RU} \leq \bar{q}^D & \quad \text{bounds on the energy discharged at time period } t \\
0 \leq q_t^R + q_t^{RD} \leq \bar{q}^R & \quad \text{bounds on the energy charged at time period } t \\
0 \leq S_t \leq \bar{S} & \quad \text{bounds on the state of charge quantity at time period } t
\end{aligned} \quad (39)$$

Since these constraints are a function of two parameters in x , the $Ax \leq b$ formulation must be employed in addition to the constraints on x , $lb \leq x \leq ub$. The upper/lower bound constraints are given by

$$lb^{4Tx1} = [0 \dots 0]^T, \quad ub^{4Tx1} = [\bar{q}^D \dots \bar{q}^D \quad \bar{q}^R \dots \bar{q}^R \quad \bar{q}^D \dots \bar{q}^D \quad \bar{q}^R \dots \bar{q}^R]^T \quad (40)$$

The constraints that are a function of two parameters in x are described below.

$$0 \leq q_t^D + \gamma_t^{RU} q_t^{RU}, \quad [-I^{TxT} \mid 0^{TxT} \mid -I^{TxT} \mid 0^{TxT}] x \leq 0^{Tx1} \quad (41)$$

$$q_t^D + \gamma_t^{RU} q_t^{RU} \leq \bar{q}^D, \quad [I^{TxT} \mid 0^{TxT} \mid I^{TxT} \mid 0^{TxT}] x \leq [\bar{q}^D]^{Tx1} \quad (42)$$

$$0 \leq q_t^R + \gamma_t^{RD} q_t^{RD}, \quad [0^{TxT} \mid -I^{TxT} \mid 0^{TxT} \mid -I^{TxT}] x \leq 0^{Tx1} \quad (43)$$

$$q_t^R + \gamma_t^{RD} q_t^{RD} \leq \bar{q}^R, \quad [0^{TxT} \mid I^{TxT} \mid 0^{TxT} \mid I^{TxT}] x \leq [\bar{q}^R]^{Tx1} \quad (44)$$

$$\text{combining } 0 \leq S_t \text{ and } S \leq A_s x \text{ yields } -A_s x \leq 0 \quad (45)$$

$$\text{combining } S \leq A_s x \text{ and } S_t \leq \bar{S} \text{ yields } A_s x \leq \bar{S} \quad (46)$$

combining the above inequalities in matrix form yields the following system of equations:

$$Ax \leq b, \text{ where } A = \begin{bmatrix} -A_d & -A_r & -A_{ru} & -A_{rd} \\ A_d & A_r & A_{ru} & A_{rd} \\ -I & 0 & -I & 0 \\ I & 0 & I & 0 \\ 0 & -I & 0 & -I \\ 0 & I & 0 & I \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ \bar{S} \\ 0 \\ \bar{q}^D \\ 0 \\ \bar{q}^R \end{bmatrix} \quad (47)$$

The financial quantities are defined by

P_t	Price of electricity (LMP) at time t
P_t^{RU}	Price of regulation up at time t
P_t^{RD}	Price of regulation down at time t
C_d	Cost of discharging at time t
C_r	Cost of recharging at time t
r	Interest rate for one period

The cost function (or revenue) that we are trying to maximize is given by:

$$J = \sum_{t=1}^T [(P_t - C_d)q_t^D + (P_t^{RU} + \gamma_{ru}(P_t - C_d))q_t^{RU} + (P_t^{RD} - \gamma_{rd}(P_t + C_r))q_t^{RD} - (P_t + C_r)q_t^R] e^{-rt} \quad (48)$$

In many areas, the net energy for regulation is settled at the real-time price. This provides an additional arbitrage opportunity between the day ahead price and the real-time price. Since this

study is primarily concerned with arbitrage and regulation revenue from the day ahead market, the price P_t represents the day ahead LMP. While this does not reflect the actual settlement process, it keeps the optimization from incorporating any arbitrage between the day ahead and the real-time market.

$$f = \begin{bmatrix} (P_1 - C_d)e^{-r} \\ (P_2 - C_d)e^{-2r} \\ (P_3 - C_d)e^{-3r} \\ \vdots \\ (P_T - C_d)e^{-Tr} \\ -(P_1 + C_r)e^{-r} \\ -(P_2 + C_r)e^{-2r} \\ -(P_3 + C_r)e^{-3r} \\ \vdots \\ -(P_T + C_r)e^{-Tr} \\ (P_1^{RU} + \gamma_{ru}(P_1 - C_d))e^{-r} \\ (P_2^{RU} + \gamma_{ru}(P_2 - C_d))e^{-2r} \\ (P_3^{RU} + \gamma_{ru}(P_3 - C_d))e^{-3r} \\ \vdots \\ (P_T^{RU} + \gamma_{ru}(P_T - C_d))e^{-Tr} \\ (P_1^{RD} - \gamma_{rd}(P_1 + C_r))e^{-r} \\ (P_2^{RD} - \gamma_{rd}(P_2 + C_r))e^{-2r} \\ (P_3^{RD} - \gamma_{rd}(P_3 + C_r))e^{-3r} \\ \vdots \\ (P_T^{RD} - \gamma_{rd}(P_T + C_r))e^{-Tr} \end{bmatrix} \quad (49)$$

Since we are trying to maximize profits and need to formulate the problem as a minimization problem, we can define a new cost function J^* that is the negative of the original cost function. Therefore, minimizing J^* maximizes the profits from the facility.

$$J^* = -f^T x \quad (50)$$

The next section applies these optimization techniques to estimate the maximum potential revenue for the Tehachapi Wind Energy storage project using historical data from 2010-2011.

4 Case Study: Tehachapi Wind Energy Storage Project

In this section we analyze 2010 and 2011 data from the CAISO (California Independent System Operator) TAP78_6_B1 node to evaluate the maximum potential arbitrage and regulation market opportunity for an energy storage device. This node in the CAISO system was selected because it is near the location of the ARRA (American Recovery and Reinvestment Act of 2009) Tehachapi Wind Energy Storage Project [10]. This project will demonstrate an 8MW, 32MWh grid-connected battery energy storage system. Southern California Edison (SCE) is leading the effort with engineering consulting from Quanta Technology. The battery developer and manufacturer is A123 Systems. CAISO is the independent system operator for the California Transmission grid.

The analysis is broken into two sections. First, the results are presented for energy arbitrage only. The subsequent section presents the results for energy arbitrage and the regulation market. The parameters of the energy storage device are listed in Table 1. Historical financial data was obtained from the CAISO OASIS (Open Access Same-Time Information System) web site [11]. This analysis focuses on the maximum potential gross revenue from two approaches: arbitrage only and arbitrage combined with the regulation market. Therefore, expenses from maintenance, facility leases, and other operational categories are ignored. The facility is also assumed to be operational 100 percent of the time. Net revenue, which must take into consideration these items, could be significantly lower than the maximum potential gross revenue figures presented in this analysis. The maximum potential gross revenue is a critical calculation because it serves as a benchmark to evaluate the performance of an existing system or to evaluate the potential performance of trading strategies for a proposed system. It is also important to note that arbitrage and regulation are only two of the proposed benefits of the Tehachapi Wind Energy storage project. The complete list of proposed benefits includes [12]

Transmission

1. Voltage support and grid stabilization
2. Decrease transmission losses
3. Diminish congestion
4. Increase system reliability
5. Defer transmission investment
6. Enhance value and effectiveness of renewable energy-related transmission

System

7. Provide system capacity/resource adequacy
8. Integrate renewable energy (smoothing)
9. Shift wind generation output

Grid

10. **Frequency regulation**
11. Spin/non-spin/replacement reserves
12. Ramp management
13. **Energy price arbitrage**

The revenue streams from each of these benefits must be accounted for when estimating the total value of this energy storage system.

4.1 Arbitrage Only

This section presents the maximum possible revenue from arbitrage for an energy storage system with the parameters in Table 1 and located near the CAISO TAP78_6_B1 node. An LP optimization was performed on historical data to determine the optimum quantities of electricity that should be purchased and sold subject to the constraints of the storage system to maximize the revenue. The price of electricity was assumed to be the Locational Marginal Price (LMP) in the day ahead market (DAM) from the CAISO OASIS system. The optimization was performed for each month during 2010 and 2011. Because the optimization was run on a monthly basis, this implies boundary conditions on the state of charge S_t . The state of charge must be 0 at the beginning and end of each month. Results of the optimization for a single week are presented in Figure 4. For the most part, the optimal strategy is to purchase energy when the price is low in the early morning hours and sell when the price is high in the late afternoon and early evening. In addition to the diurnal swing in prices, several days during this week exhibit an increase in prices in the late morning

Parameter	Value	Description
\bar{q}^D	$8MWh$	maximum quantity that can be sold/discharged in a single period
\bar{q}^R	$8MWh$	maximum quantity that can be bought/recharged in a single period
\bar{S}	$32MWh$	maximum storage capacity of the device
γ_s	1.0	storage efficiency (fraction of stored energy maintained over one period)
γ_c	0.8	conversion efficiency (fraction of input power that gets stored)
γ_{ru}	0.25	regulation up efficiency (fraction of reserve capacity that is actually employed in real-time)
γ_{rd}	0.25	regulation down efficiency (fraction of reserve capacity that is actually employed in real-time)
Δt	1 hour	Length of time in a single time period
r	0	Interest rate, continuous compounding

Table 1: Energy storage device parameters for revenue analysis.

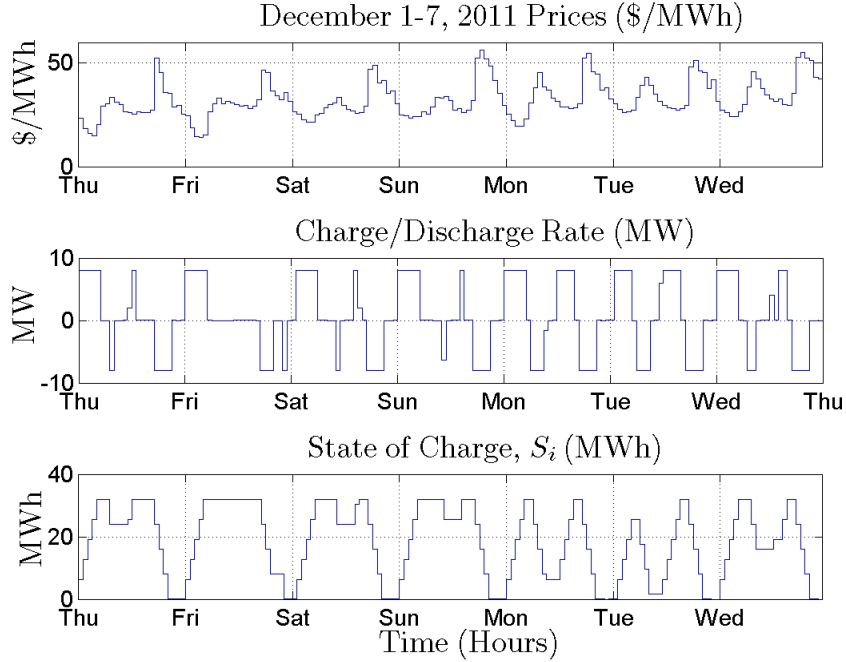


Figure 4: Example arbitrage optimization results for one week, December 1-7, 2011. CAISO TAP78.6_B1 node.

followed by a decline after lunch, which is then followed by the traditional increase in prices in the early evening. For these days, the optimal policy is to complete two charge/discharge cycles in one day (e.g. see Monday and Tuesday in Figure 4). A summary of the maximum monthly potential arbitrage revenue for 2010-2011 is listed in Table 2. The same information is presented graphically in Figure 5. Table 2 breaks down the percentage of time spent charging and discharging the system.

4.2 Arbitrage and Regulation Market

This section presents the maximum possible revenue from arbitrage and participation in the regulation market. The energy storage system parameters are the same as for the previous analysis. The device parameters are summarized in Table 1 and the location is assumed to be near the CAISO TAP78.6_B1 node. An LP optimization was performed on historical data to determine the optimum quantities of electricity that should be purchased and sold for arbitrage as well as the optimum quantities to offer into the regulation market to maximize revenue. The price of electricity was assumed to be the Locational Marginal Price (LMP) in the day ahead market (DAM) from the CAISO OASIS system. Likewise, the prices for regulation up and regulation down are from the day ahead market. The optimization was performed for each month during 2010 and 2011. This implies boundary conditions on the state of charge S_t . The state of charge must be 0 at the beginning and end of each month.

The regulation settlement process in CAISO includes a payment/charge for net energy used/supplied while performing regulation. CAISO employs the real-time price for the time period of interest in the settlement process. As mentioned previously, incorporating this real-time price into the opti-

2010		2011	
January	\$13,312.81	January	\$20,761.66
February	\$11,536.89	February	\$26,308.60
March	\$13,546.55	March	\$29,689.12
April	\$11,618.19	April	\$36,168.24
May	\$11,507.19	May	\$33,802.68
June	\$31,470.36	June	\$40,382.73
July	\$29,443.67	July	\$44,660.42
August	\$23,503.50	August	\$33,120.60
September	\$17,745.66	September	\$21,733.96
October	\$10,894.70	October	\$15,316.56
November	\$10,209.21	November	\$15,500.19
December	\$13,541.88	December	\$14,547.74
Total	\$198,330.62	Total	\$331,992.49

Year	Charge Time (%)	Discharge Time (%)
2010	20.88%	16.70%
2011	25.36%	20.29%

Table 2: Summary of arbitrage optimization results, 2010-2011. CAISO node TAP78.6_B1

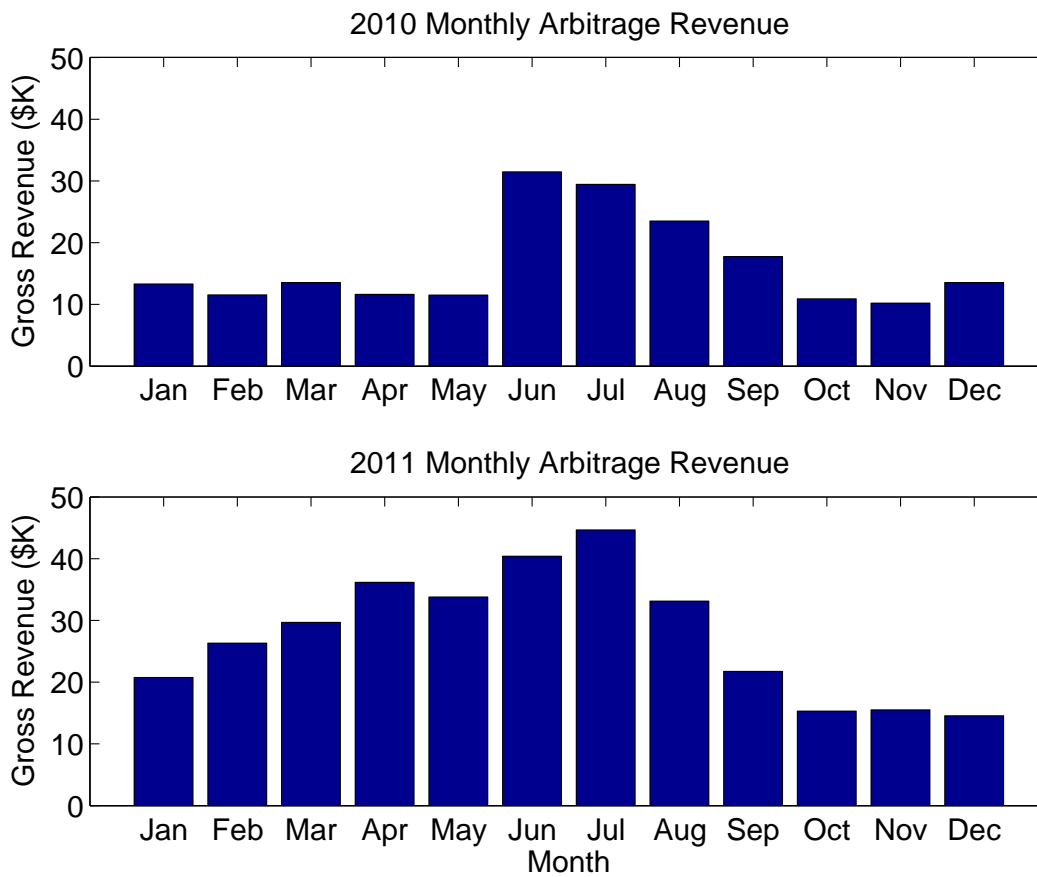


Figure 5: Summary of arbitrage optimization results. CAISO Node TAP78_6_B1.

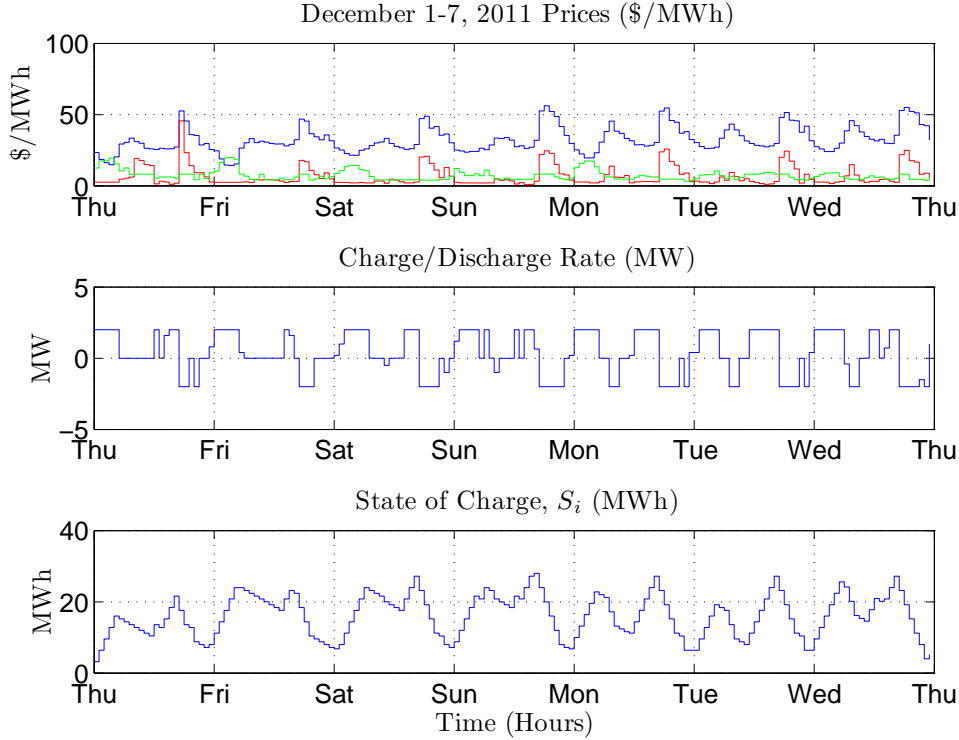


Figure 6: Example arbitrage and regulation market optimization results for one week, December 1-7, 2011. CAISO TAP78_6_B1 node. Legend for prices: blue: LMP, red: RU, green: RD.

mization would open up the opportunity to arbitrage the day ahead and real-time energy markets. Since the focus of this analysis was on the day ahead energy and regulation markets, the day ahead price was used in the regulation settlement. This forces the optimization to arrive at the optimal policy based on day ahead energy and regulation prices, while ignoring the potential opportunities to arbitrage the day ahead and real-time market. This type of arbitrage represents another potential revenue source, but the analysis is beyond the scope of this report.

Results of the optimization for a single week are presented in Figure 6. For participation in arbitrage and the regulation department the optimal behavior is significantly different than for the arbitrage only case. As seen in Figure 6, the optimal strategy is to offer into the regulation market the majority of the time with very selective participation in pure arbitrage. This is evident in Figure 7 which shows the quantity of energy purchased q_t^R , the quantity of energy sold q_t^D , the quantity offered into the regulation up market q_t^{RU} , and the quantity offered into the regulation down market q_t^{RD} for the same week in December. There was only one small purchase of energy for recharging and no selling of energy for discharging. All other transactions were executed through the regulation market. The strategy corresponds to always participating in the regulation up/down market simultaneously except for hours when electricity is very inexpensive and when the state of charge needs to be increased. During these hours, offering into the regulation down market results in some energy procurement as some fraction of the reserve capacity is employed for regulation in real-time. The purchase costs are further reduced by the capacity charge collected for regulation down. The price of regulation down is often highest when the LMP is lower (e.g. shortly after midnight).

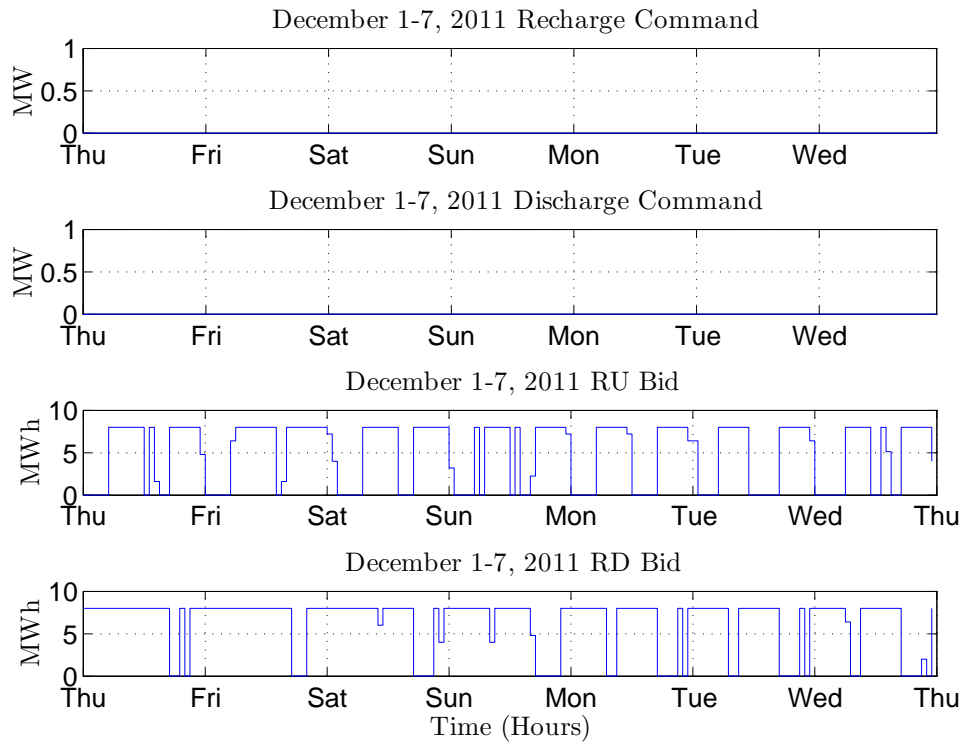


Figure 7: Example arbitrage and regulation market optimization results for one week, December 1-7, 2011. CAISO TAP78_6_B1 node.

2010		2011	
January	\$71,103.25	January	\$76,825.72
February	\$88,296.91	February	\$50,015.48
March	\$134,799.22	March	\$107,063.38
April	\$54,354.18	April	\$211,301.04
May	\$90,515.97	May	\$164,734.76
June	\$135,820.36	June	\$138,109.37
July	\$91,061.94	July	\$153,057.00
August	\$56,740.30	August	\$100,426.99
September	\$50,994.81	September	\$65,498.31
October	\$50,601.42	October	\$79,579.72
November	\$50,277.53	November	\$78,569.27
December	\$61,409.31	December	\$63,250.14
Total	\$935,975.19	Total	\$1,288,431.19

Year	Charge Time (%)	Discharge Time (%)	Regulation Up Time (%)	Regulation Down Time (%)
2010	4.71%	0.64%	81.10%	85.80%
2011	6.72%	0.78%	81.94%	79.60%

Table 3: Summary of arbitrage and regulation optimization results, 2010-2011. CAISO node TAP78_6_B1

A summary of the maximum monthly potential arbitrage and regulation revenue for 2010-2011 is listed in Table 3. The same information is presented graphically in Figure 8. The next section discusses several potential trading strategies for arbitrage only and arbitrage plus the regulation market. These strategies are then benchmarked against the maximum possible revenue numbers derived from the optimization in this section.

4.3 Trading Strategies

In this section we describe several trading strategies and compare them to the maximum potential revenue calculated via the LP optimization. All strategies are based on the day ahead market for energy and regulation. The first two strategies are for arbitrage only and the third strategy is for arbitrage and the regulation market. For the case of arbitrage, a natural strategy is to use historical data to predict when to purchase and sell energy. The mean hourly LMP's for 2010 and 2011 are shown in Figure 9. The correlation between the average hourly prices for the two years is 0.989.

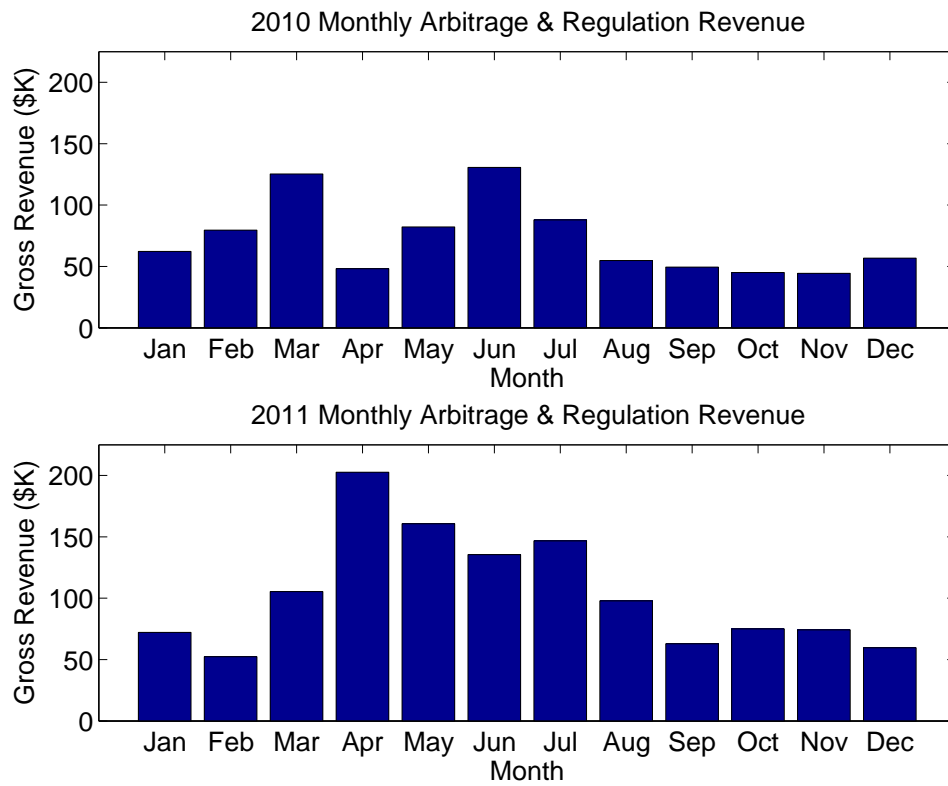


Figure 8: Summary of arbitrage and regulation optimization results. CAISO TAP78.6_B1 node.

Hour	3AM	2AM	4AM	1AM	5AM
Price (\$/MWh)	22.12	22.98	23.69	25.19	27.42
Hour	7PM	3PM	5PM	4PM	6PM
Price (\$/MWh)	41.39	41.45	41.54	41.76	42.21

Table 4: 2010 hours with the highest and lowest energy prices

Year	Maximum Revenue	Prior Year Strategy	Percent of Maximum
2011	\$331,992.49	\$218,718.48	65.88%

Table 5: Arbitrage revenue employing prior year data for predicting energy prices, 2011. CAISO TAP78.6_B1 node.

Based on this notion, the first arbitrage trading strategy is given by:

$$\text{Arbitrage Trading Strategy 1:} \left\{ \begin{array}{l} \text{Sell } \bar{S} \text{ MWh of energy during} \\ \text{the hours with the highest prices.} \\ \text{Use average prices from the prior year} \\ \text{to select the time periods.} \\ \text{Purchase } \bar{S}/\gamma_c \text{ MWh of energy during} \\ \text{the hours with the lowest price.} \\ \text{Use average prices from the prior year} \\ \text{to select the time periods.} \end{array} \right. \quad (51)$$

where \bar{S} is the energy capacity of the electricity storage system.

For the $32MWh$, $8MW$ system in our example, this corresponds to selling $8MWh$ during the four hours with the highest prices. Since the conversion efficiency $\gamma_c = 0.8$, $40MWh$ of energy must be purchased so that after the inefficiency losses the full $32MWh$ may be sold. This means that energy must be purchased during the 5 hours with the lowest energy prices. The lowest and highest energy prices for 2010 are shown in Table 4. The total arbitrage revenue for 2011 data using this trading strategy comes to \$218,718.48. From the optimization analysis in the previous section, the maximum possible arbitrage revenue in 2011 was \$331,992.49. Therefore the simple strategy of employing average data from the previous year to select the optimal purchase and sale times only harvests 65.88% of the maximum potential arbitrage profits. This information is summarized in Table 5.

The second arbitrage strategy analyzed involves using the prior 24 hour period to determine the optimal times to purchase and sell electricity for the current day. As with the first strategy,

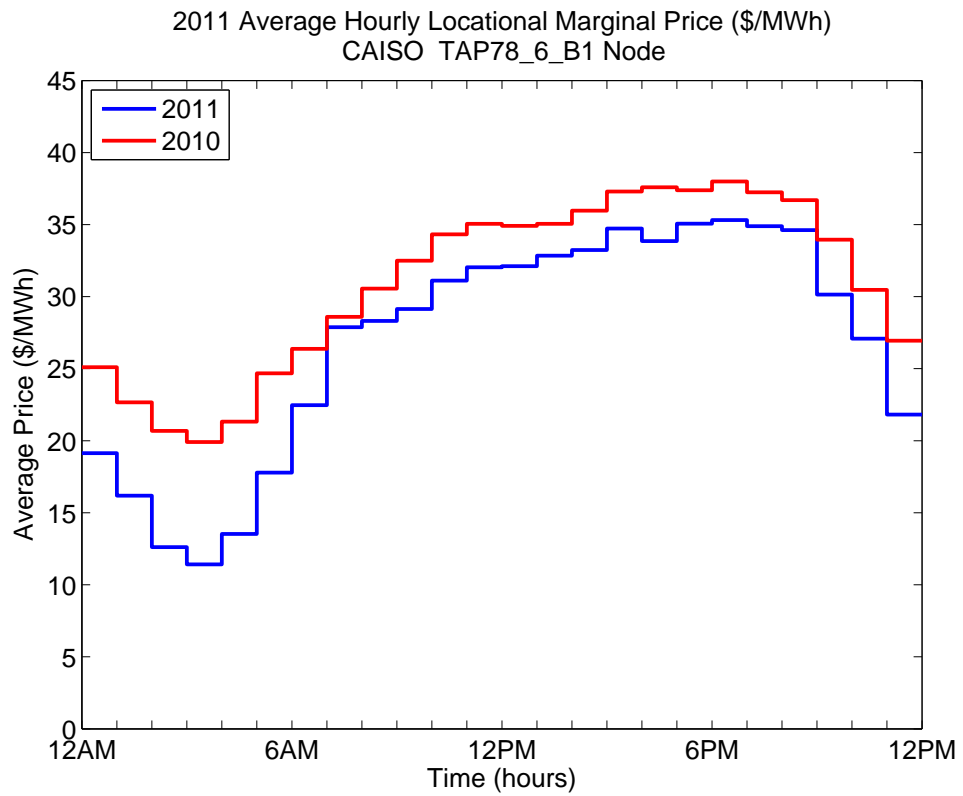


Figure 9: Average hourly locational marginal prices for CAISO node TAP78_6_B1, 2010-2011 data. Correlation $\rho = 0.989$.

Year	Maximum Revenue	Prior Day Strategy	Percent of Maximum
2010	\$198,330.62	\$162,602.55	81.99%
2011	\$331,992.49	\$285,874.36	86.11%

Table 6: Arbitrage revenue employing prior day data for predicting energy prices, 2010-2011. CAISO TAP78_6_B1 node

the full capacity of the device is sold each day and \bar{S}/γ_c is purchased each day.

$$\text{Arbitrage Trading Strategy 2:} \left\{ \begin{array}{l} \text{Sell } \bar{S} \text{ MWh of energy during} \\ \text{the hours with the highest prices.} \\ \text{Use prices from the prior 24 hours} \\ \text{to select the time periods.} \\ \text{Purchase } \bar{S}/\gamma_c \text{ MWh of energy during} \\ \text{the hours with the lowest price.} \\ \text{Use prices from the prior 24 hours} \\ \text{to select the time periods.} \end{array} \right. \quad (52)$$

The results of this trading strategy are summarized in Table 6. This strategy is more effective with 81.99% and 86.11% of the maximum revenue being recovered in the 2010-2011 time period. Although this is a significant improvement over the first strategy, this approach still falls well short of the maximum potential revenue for the time period. More sophisticated prediction algorithms would be required to attempt to recover a larger percentage, and it may not be possible to harvest the maximum potential revenue.

The third trading strategy is designed for participation in arbitrage and the regulation market and is based on the optimization results. Given the storage system parameters, the device can maintain a state of charge by participating in the regulation down market 100 percent of the time and participating in the regulation up market for the 19.2 hours when the LMP prices are highest. This strategy is summarized below and results for 2010-2011 data are shown in Table 7.

$$\text{Arbitrage/Regulation Trading Strategy 3:} \left\{ \begin{array}{l} \text{Offer } \bar{q}^R \text{ into the regulation} \\ \text{down market every hour.} \\ \text{Offer } \bar{q}^D \text{ into the regulation} \\ \text{up market 19.2 hours a day.} \\ \text{Use prices from the prior 24 hours} \\ \text{to select the time periods} \\ \text{with the highest LMP.} \end{array} \right. \quad (53)$$

4.4 Sensitivity Analysis

This section provides the results of a sensitivity analysis to price changes for both the maximum potential return and the trading strategies in the previous section. Prices were increased and decreased ten percent to calculate the sensitivity with respect to price. In addition, a sensitivity analysis was conducted to show the effects of changes in the estimate of regulation up efficiency γ_{RU} and regulation down efficiency γ_{RD} . A summary of the sensitivity analysis scenarios is listed

Year	Maximum Revenue	Prior Day Strategy	Percent of Maximum
2010	\$935,975.19	\$893,544.7	95.47%
2011	\$1,288,431.19	\$1,218,173.0	94.55%

Table 7: Arbitrage and regulation revenue employing prior day data for predicting energy prices, 2010-2011, CAISO TAP78_6_B1 node

- Arbitrage only optimization. $LMP \in \{-10\%, \textit{nominal}, +10\%\}$
- Arbitrage and regulation optimization. $\gamma_{RU}, \gamma_{RD} \in \{0\%, 25\%, 50\%\}$
- Arbitrage and regulation optimization. $LMP \in \{-10\%, \textit{nominal}, +10\%\}$
- Arbitrage and regulation optimization. Regulation up/down $\in \{-10\%, \textit{nominal}, +10\%\}$
- Trading strategy 1. $LMP \in \{-10\%, \textit{nominal}, +10\%\}$
- Trading strategy 2. $LMP \in \{-10\%, \textit{nominal}, +10\%\}$
- Trading strategy 3. $LMP \in \{-10\%, \textit{nominal}, +10\%\}$
- Trading strategy 3. Regulation up/down $\in \{-10\%, \textit{nominal}, +10\%\}$

Table 8: Summary of sensitivity analysis scenarios.

in Table 8. A summary of the different sensitivity analysis results is listed in Table 9. As expected, for the arbitrage only case the revenue is directly proportional to the LMP and thus the spread in prices. The sensitivity with respect to conversion efficiency γ_c is rather high. For a given decrease in conversion efficiency there is a greater decrease in revenue. For the 2010 data it was a twofold decrease. For the arbitrage and regulation case the expected revenue is fairly insensitive to the LMP. Since the optimal behavior in this case primarily involves participation in the regulation market, the only effect of LMP changes is to slightly increase the net energy costs from conversion efficiency losses. Changes in the regulation up/down efficiency, γ_{RU} , γ_{RD} have a small effect on revenue, but it is important to model this parameter as accurately as possible. Changes in the price of regulation have a significant effect as they are the primary source of revenue for this scenario. Reductions in conversion efficiency have an effect but less than in the arbitrage only case. As expected, the arbitrage trading strategies 1 and 2 are greatly affected by changes in the LMP. Strategy 3, which focuses on the regulation market, is not significantly affected by changes in the LMP. Changes in the price of regulation are directly correlated with the revenues from strategy 3.

The next section summarizes the algorithms and results presented in this paper.

5 Summary and Conclusions

We have developed an electricity energy storage model that can be used to evaluate the maximum potential revenue for a storage device participating in arbitrage or arbitrage and the regulation market. If parameters describing the regulation market (e.g. the fraction of reserve capacity that is actually employed for regulation in real-time) are consistent over time, both problems can be formulated as a LP optimization. The constraints on the regulation signal are not overly burdensome. Electricity storage devices have limited energy so they often require a control signal with an average value of zero or a slight charging bias to overcome losses and maintain a constant state of charge. This is especially true of devices like flywheels. The state of charge model for the electricity storage device is given by

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D + \gamma_c \gamma_{rd} q_t^{RD} - \gamma_{ru} q_t^{RU} \quad (54)$$

Scenario	Parameter	Δ or (value)	2010		2011	
			Revenue	% Change	Revenue	% Change
Arbitrage Only	LMP	+10%	\$218,163	+10.00%	\$365,192	+10.00%
		nominal	\$198,331	0%	\$331,992	0%
		-10%	\$178,498	-10.00%	\$298,793	-10.00%
	γ_c	-25% (60%)	\$102,083	-48.53%	\$228,263	-31.24%
		-12.5% (70%)	\$148,489	-25.13%	\$282,898	-14.79%
		0% (80%)	\$198,331	0%	\$331,992	0%
Arbitrage & Regulation	LMP	-10%	\$940,356	0.47%	\$1,286,236	-0.17%
		nominal	\$935,975	0%	\$1,288,431	0%
		+10%	\$932,406	-0.38%	\$1,292,028	0.28%
	γ_{ru}, γ_{rd}	-100% (0)	\$1,047,943	11.96%	\$1,372,601	6.53%
		0% (0.25)	\$935,975	0%	\$1,288,431	0%
		+100% (0.5)	\$866,488	-7.42%	\$1,244,893	-3.38%
	RU, RD	-10%	\$838,854	-10.38%	\$1,163,257	-9.72%
		nominal	\$935,975	0%	\$1,288,431	0%
		+10%	\$1,033,919	10.46%	\$1,415,011	9.82%
	γ_c	-25% (60%)	\$773,017	-17.41%	\$1,142,787	-11.30%
		-12.5% (70%)	\$860,232	-8.09%	\$1,223,966	-5.00%
		0% (80%)	\$935,975	0%	\$1,288,431	0%
Strategy 1	LMP	-10%	n/a	n/a	\$196,847	-10.00%
		nominal	n/a	n/a	\$218,718	0%
		+10%	n/a	n/a	\$240,590	10.00%
Strategy 2	LMP	-10%	\$146,342	-10.00%	\$257,287	-10.00%
		nominal	\$162,602	0%	\$285,874	0%
		+10%	\$178,863	10.00%	\$314,462	10.00%
Strategy 3	LMP	-10%	\$902,079	0.96%	\$1,223,672	0.45%
		nominal	\$893,545	0%	\$1,218,173	0%
		+10%	\$885,010	-0.96%	\$1,212,675	-0.45%
	RU, RD	-10%	\$795,656	-10.96%	\$1,090,857	-10.45%
		nominal	\$893,545	0%	\$1,218,173	0%
		+10%	\$991,434	10.96%	\$1,345,489	10.45%

Table 9: Sensitivity analysis summary. CAISO TAP78_6_B1 node.

Strategy	2010		2011	
	Maximum Revenue	Actual Revenue	Maximum Revenue	Actual Revenue
1	N/A	N/A	\$331,992.49	\$218,718.48
2	\$198,330.62	\$162,602.55	\$331,992.49	\$285,874.36
3	\$935,975.19	\$893,544.7	\$1,288,431.19	\$1,218,173.0

Table 10: Summary of trading strategies benchmarked against the maximum potential revenue.

where S_t is the state of charge, q_t^R is the quantity purchased, q_t^S is the quantity sold, q_t^{RU} is the quantity offered into the regulation up market, and q_t^{RD} is the quantity offered into the regulation down market at each time step t . γ_S is the storage efficiency (fraction of stored energy maintained over one period), γ_C is the conversion efficiency (fraction of input power that gets stored), γ_{ru} is the regulation up efficiency (fraction of regulation up offers that are accepted), and γ_{rd} is the regulation down efficiency (fraction of regulation down offers that are accepted). Using this model, it is possible to calculate the maximum potential revenue by formulating the problem as an LP optimization that maximizes

$$J = \sum_{t=1}^T [(P_t - C_d)q_t^D + (P_t^{RU} + \gamma_{ru}(P_t - C_d))q_t^{RU} + (P_t^{RD} - \gamma_{rd}(P_t + C_r))q_t^{RD} - (P_t + C_r)q_t^R] e^{-rt} \quad (55)$$

subject to the constraints of the energy storage device. P_t is the locational marginal price of electricity, P_t^{RU} is the market price for regulation up, P_t^{RD} is the market price for regulation down, C_d is the cost of discharging, C_r is the cost of recharging, and r is the interest rate for the time value of money.

Using this formulation we conducted a case study for the Tehachapi Wind Energy Storage Project, an ARRA storage demonstration project. Expected system parameters and historical data from 2010-2011 for the CAISO TAP78_6.B1 node were used to evaluate the maximum potential revenue from participating in arbitrage or arbitrage and the regulation market. For this particular node and the storage system parameters, the revenue from participating in the regulation market was approximately four times the revenue from an arbitrage-only strategy. Furthermore, a simple regulation market trading strategy (strategy 3) can recoup 95% of the theoretical maximum revenue (best possible with perfect knowledge). Not only was the arbitrage revenue lower, it was significantly more difficult to implement a simple trading algorithm that captures a large portion of the maximum possible revenue (strategy 1 and 2). A summary of three potential trading strategies benchmarked against the maximum possible revenue appear in Table 10.

One area for future research is modeling pay-for-performance features as they are implemented by various independent system operators as a result of FERC order 755. Some types of chemical storage devices that are designed for “slow” energy time shift applications often are quickly degraded if used for “fast” applications like frequency regulation. Although the life of the storage device might be reduced, if the financial benefit is great enough there would be some interest in engaging in activities that the device is not best suited for. We plan to characterize battery life as a function of discharge signal frequency content to better quantify the costs associated with low frequency versus high frequency applications. Then, using the same optimization approach presented in this report, one can estimate the “optimal” mix of activities by assigning different costs for charging/discharging

based on the activity. For example, C_d for frequency regulation might be significantly higher than C_d for energy time shifting for a specific technology.

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Appendix A - Case Study Optimization Results

Arbitrage Only

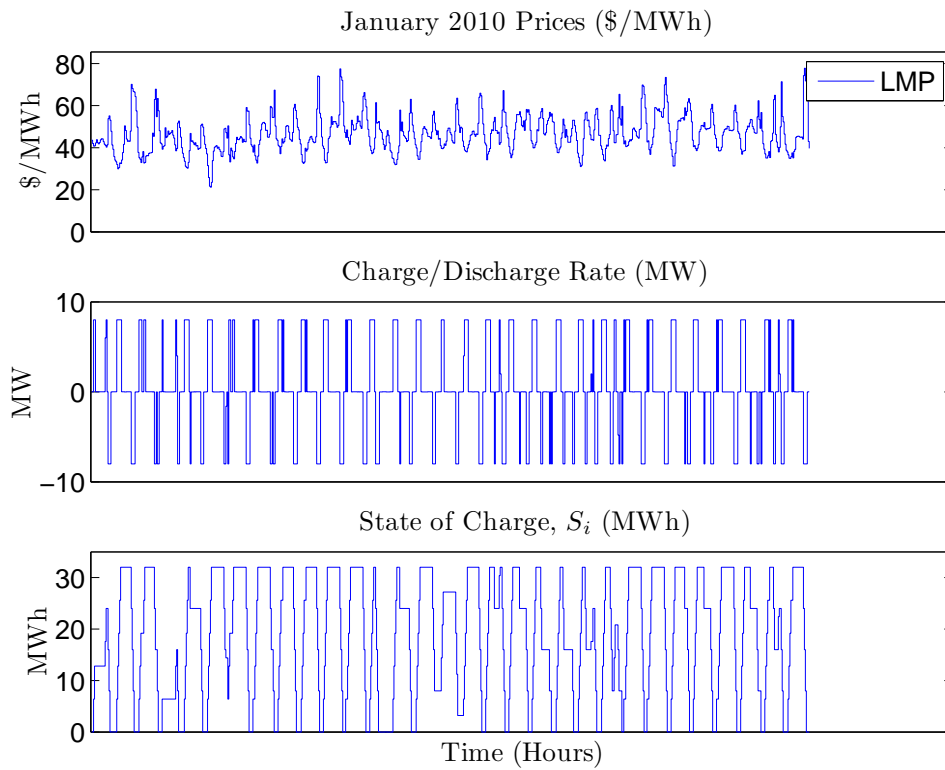


Figure 10: January 2010 arbitrage only results for node TAP78.6_B1.

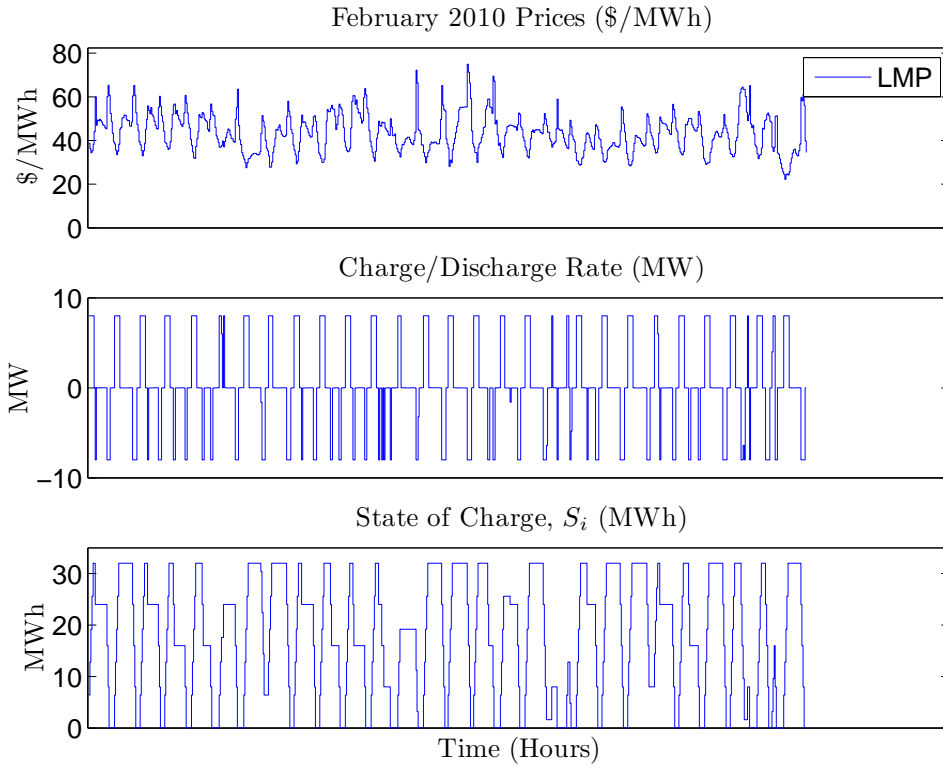


Figure 11: February 2010 arbitrage only results for node TAP78_6.B1.

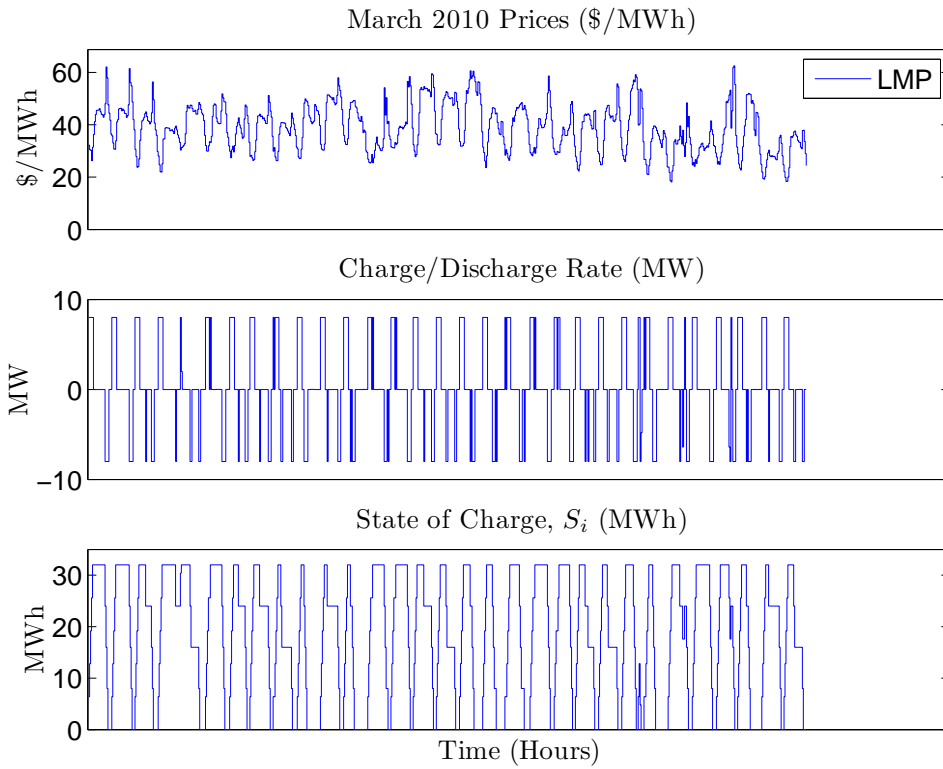


Figure 12: March 2010 arbitrage only results for node TAP78_6.B1.

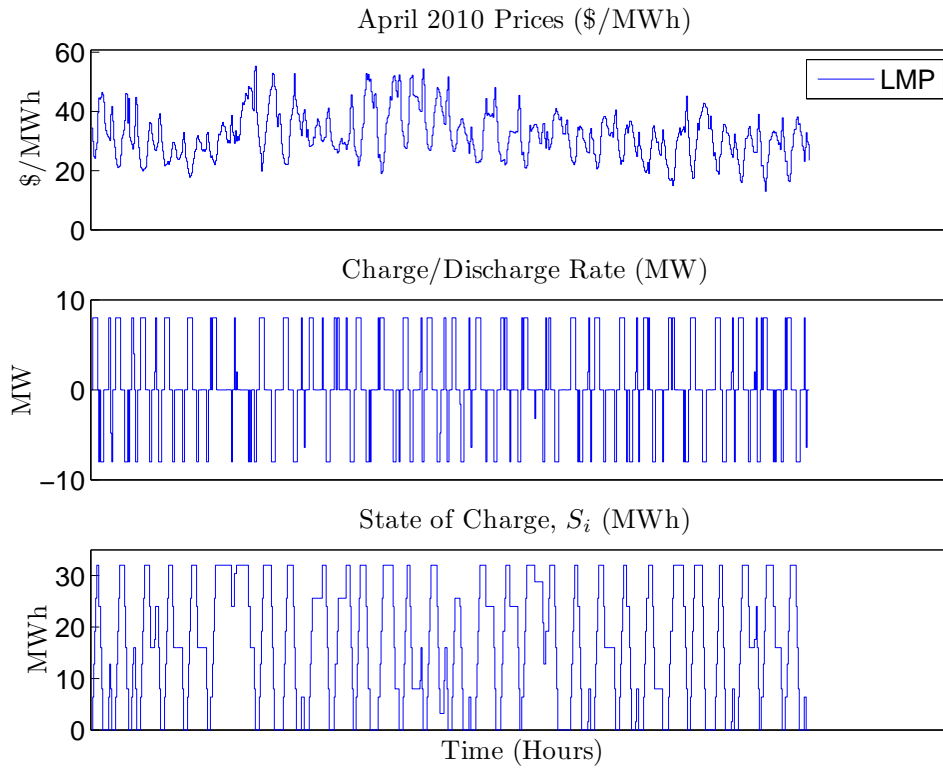


Figure 13: April 2010 arbitrage only results for node TAP78.6_B1.

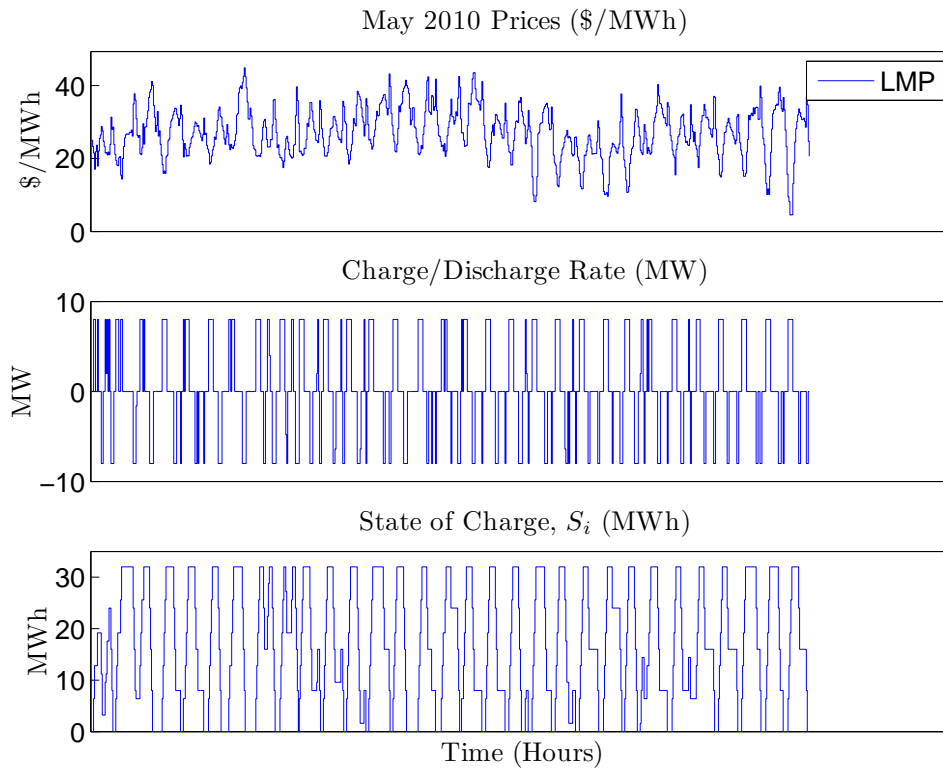


Figure 14: May 2010 arbitrage only results for node TAP78.6_B1.

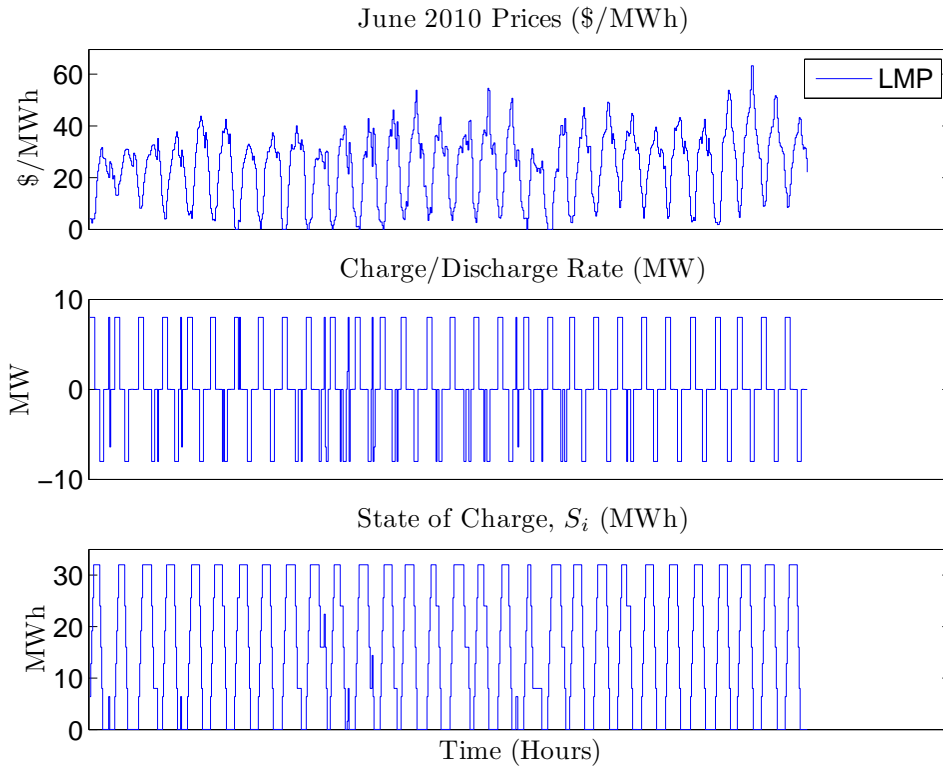


Figure 15: June 2010 arbitrage only results for node TAP78_6_B1.

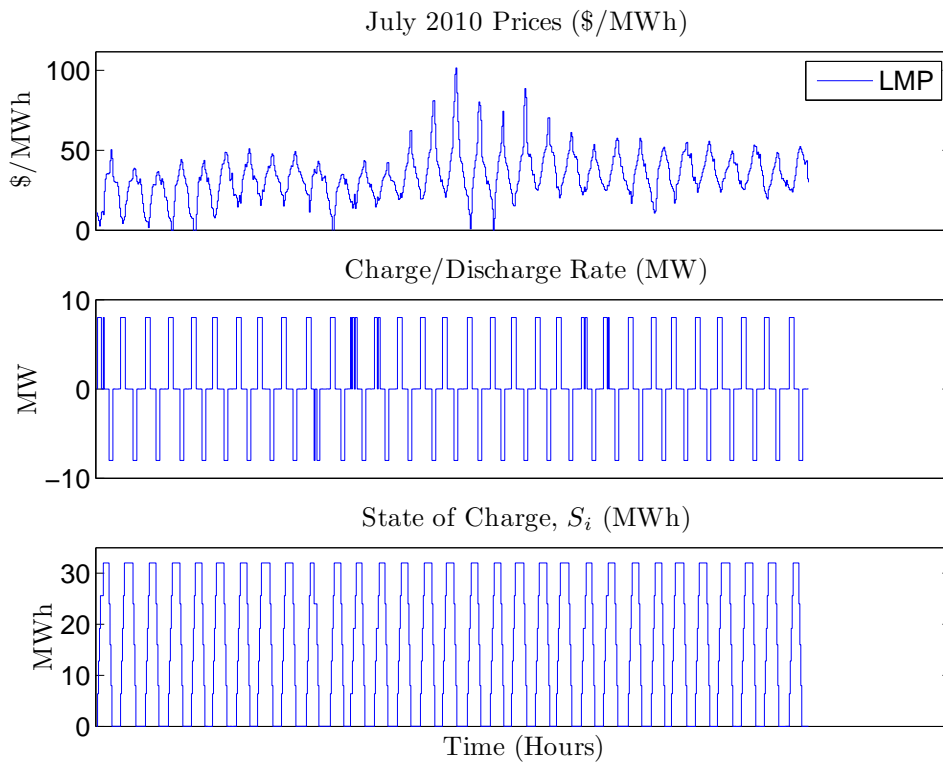


Figure 16: July 2010 arbitrage only results for node TAP78_6_B1.

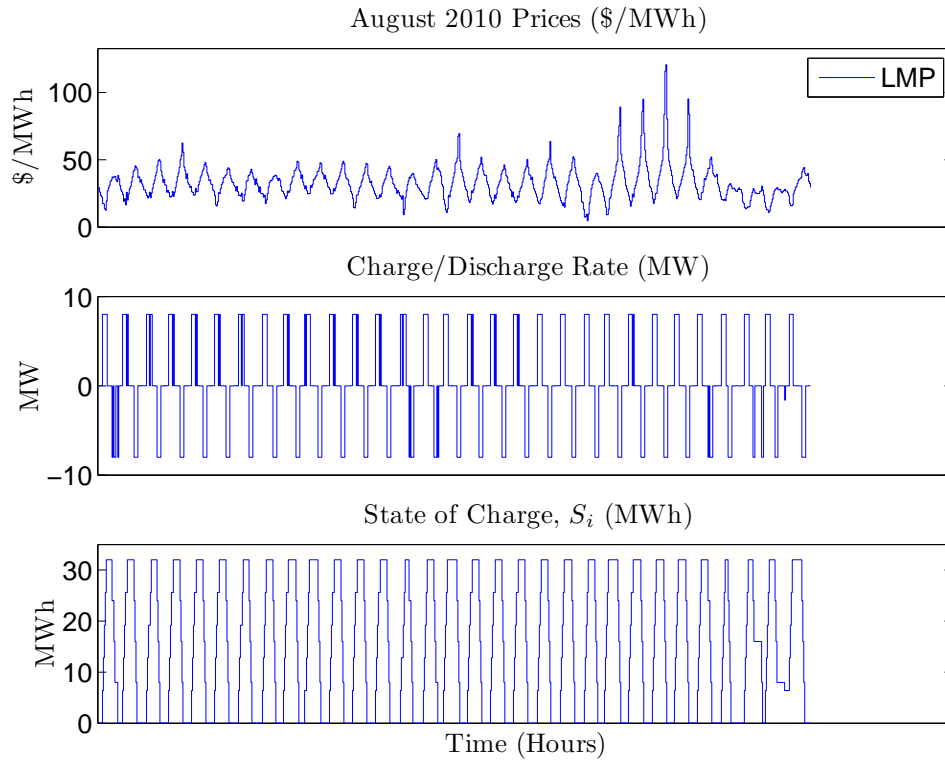


Figure 17: August 2010 arbitrage only results for node TAP78.6_B1.

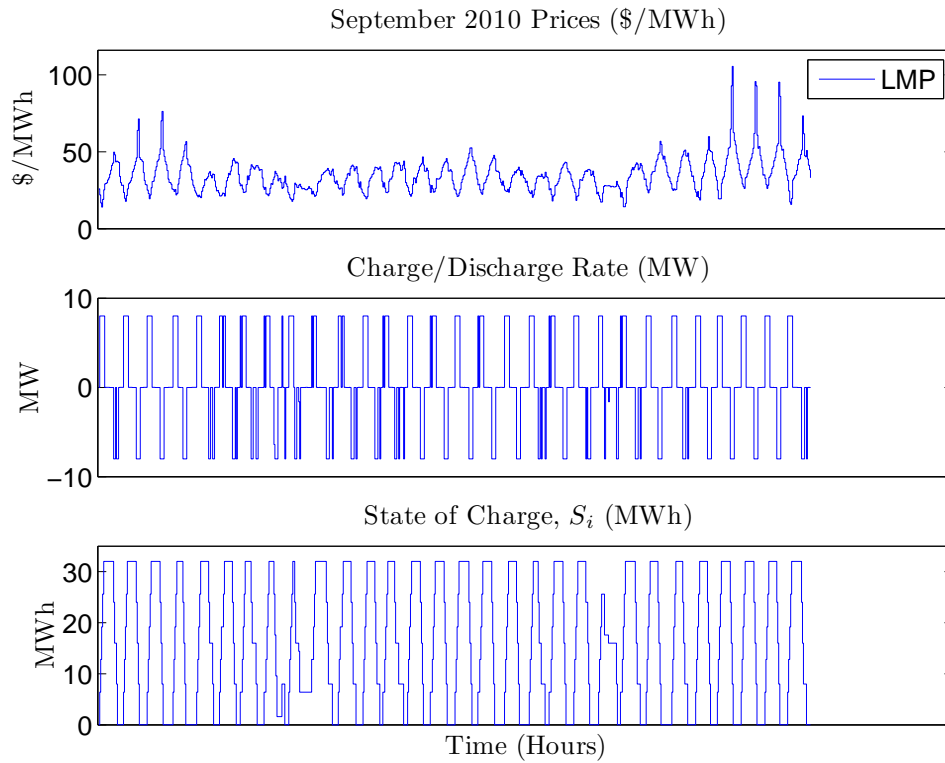


Figure 18: September 2010 arbitrage only results for node TAP78.6_B1.

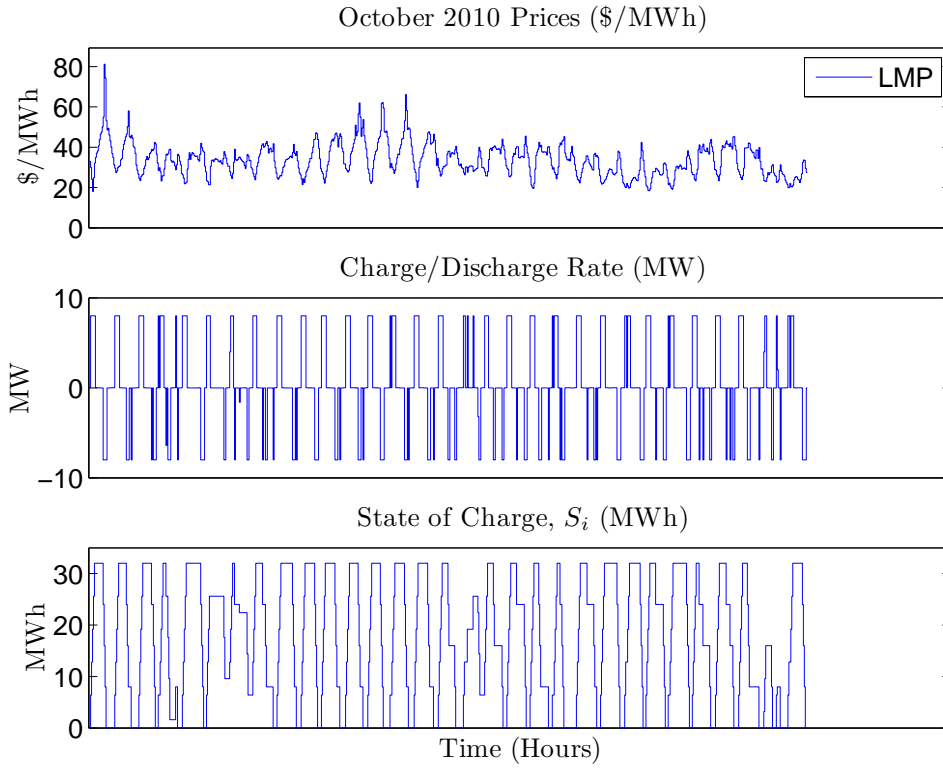


Figure 19: October 2010 arbitrage only results for node TAP78.6_B1.

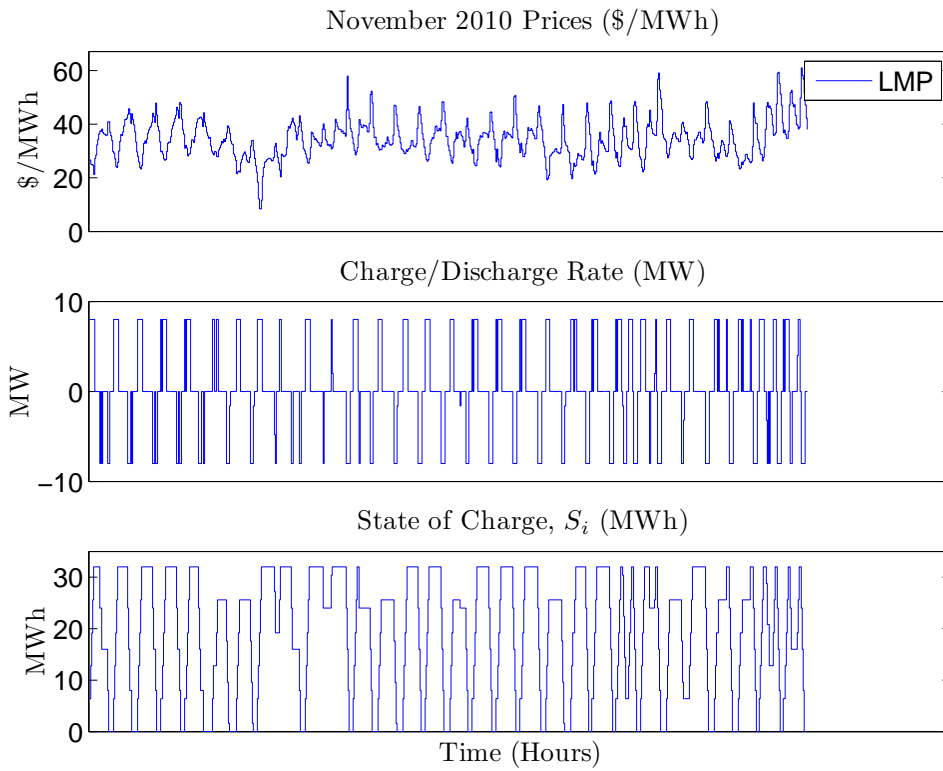


Figure 20: November 2010 arbitrage only results for node TAP78.6_B1.

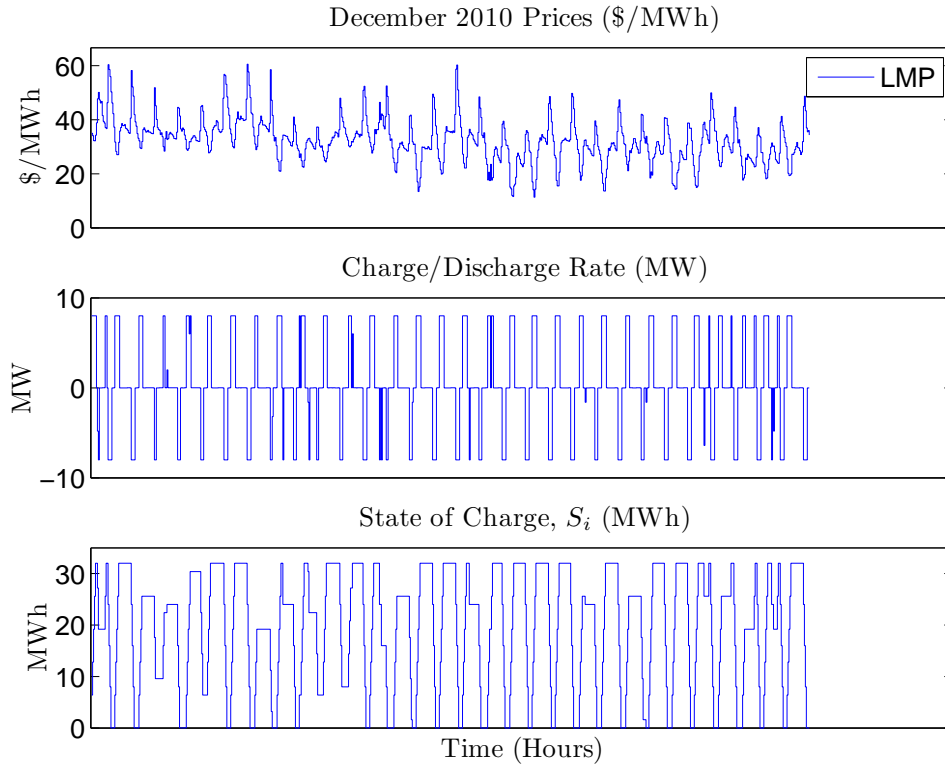


Figure 21: December 2010 arbitrage only results for node TAP78.6_B1.

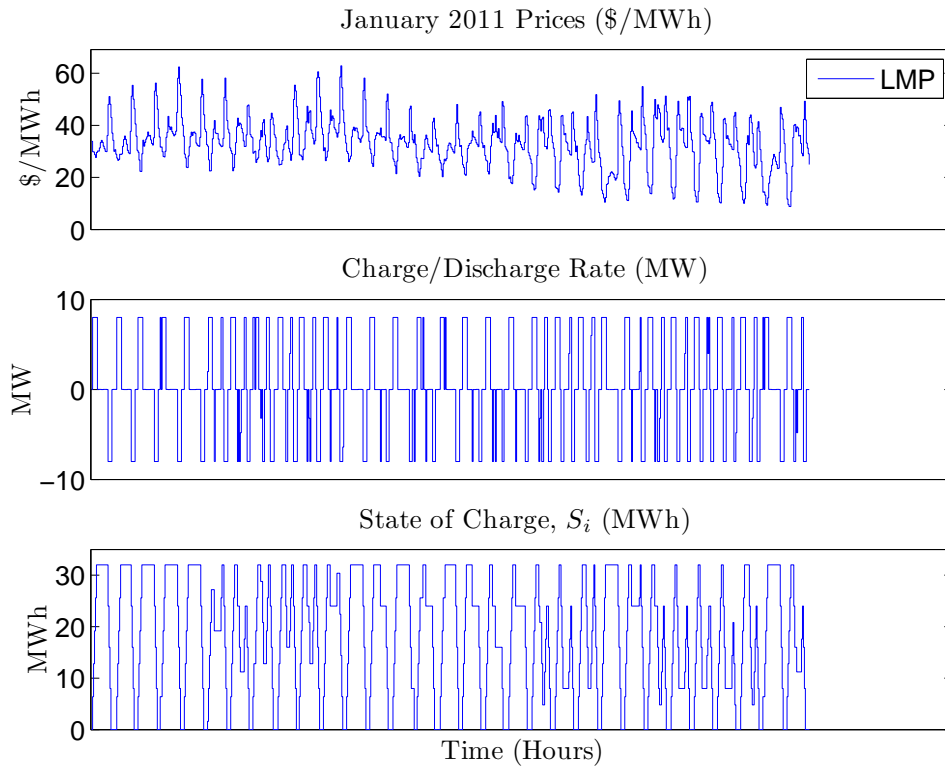


Figure 22: January 2011 arbitrage only results for node TAP78.6_B1.

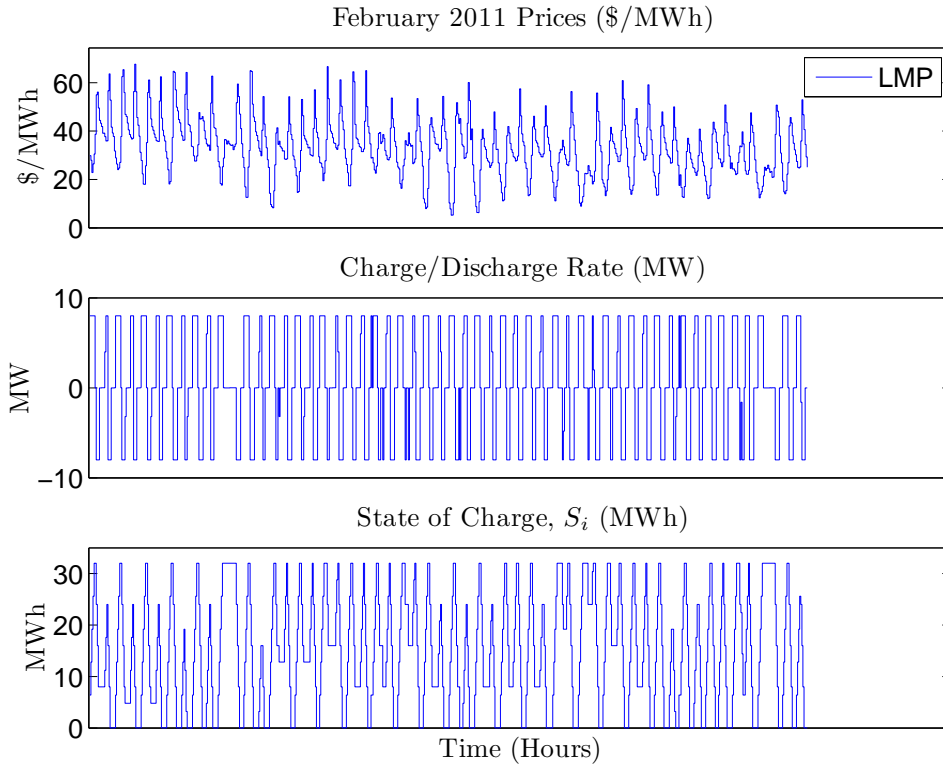


Figure 23: February 2011 arbitrage only results for node TAP78_6.B1.

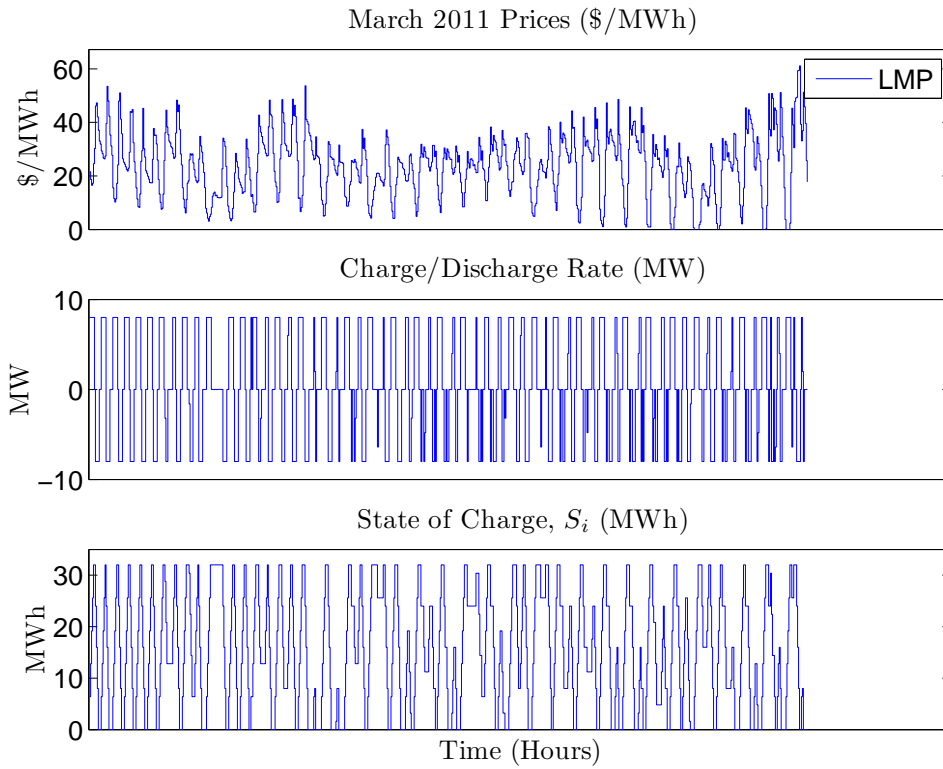


Figure 24: March 2011 arbitrage only results for node TAP78_6.B1.

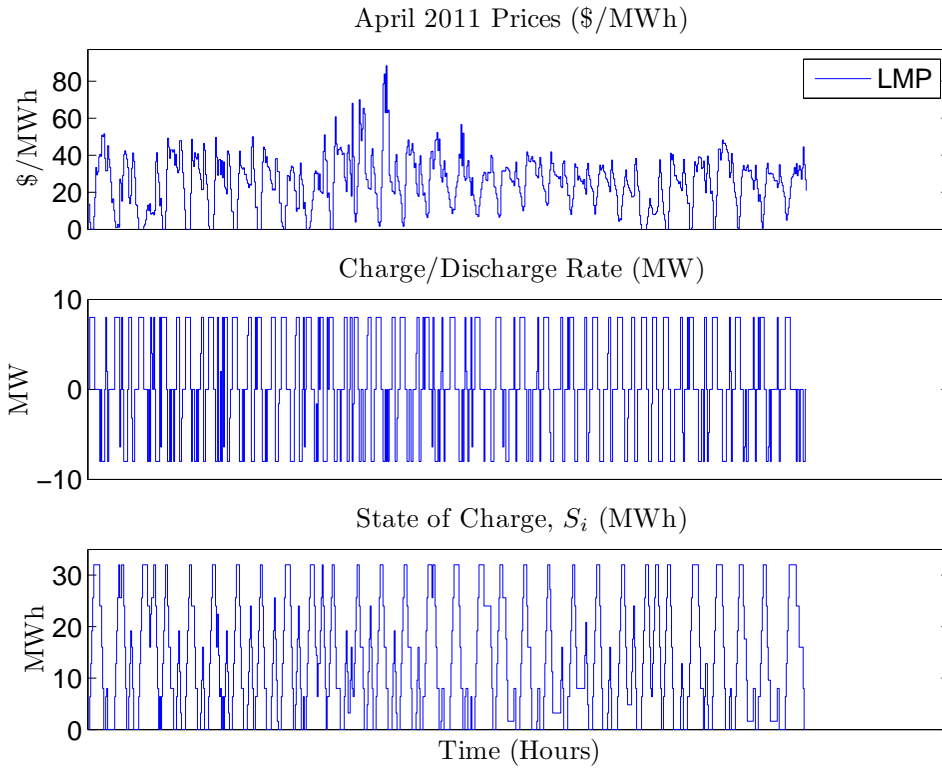


Figure 25: April 2011 arbitrage only results for node TAP78.6_B1.

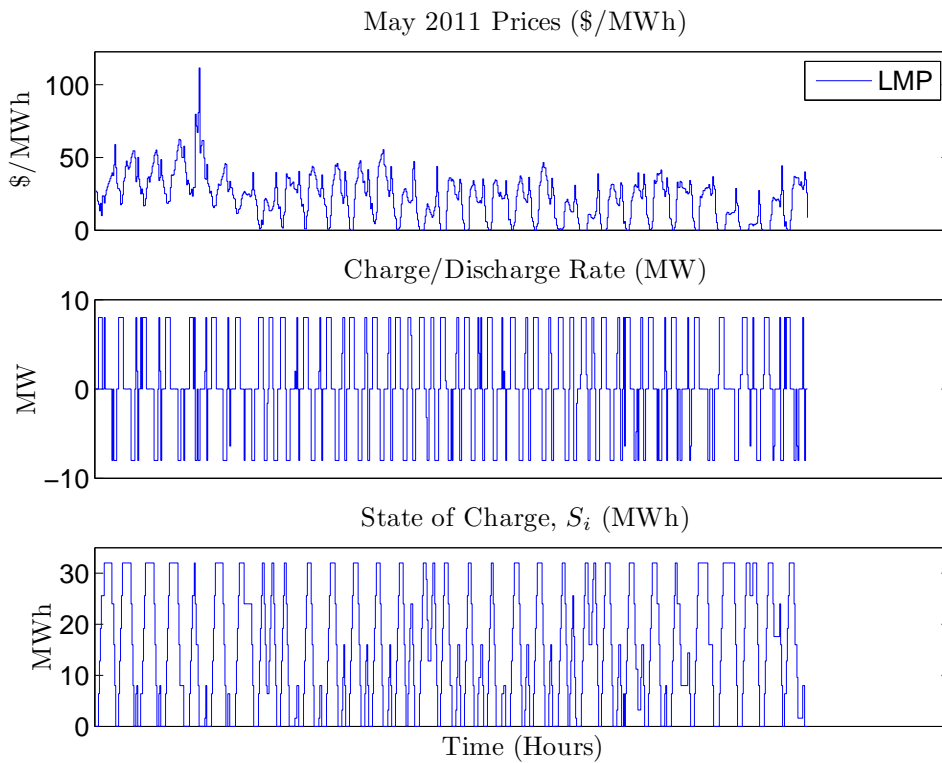


Figure 26: May 2011 arbitrage only results for node TAP78.6_B1.

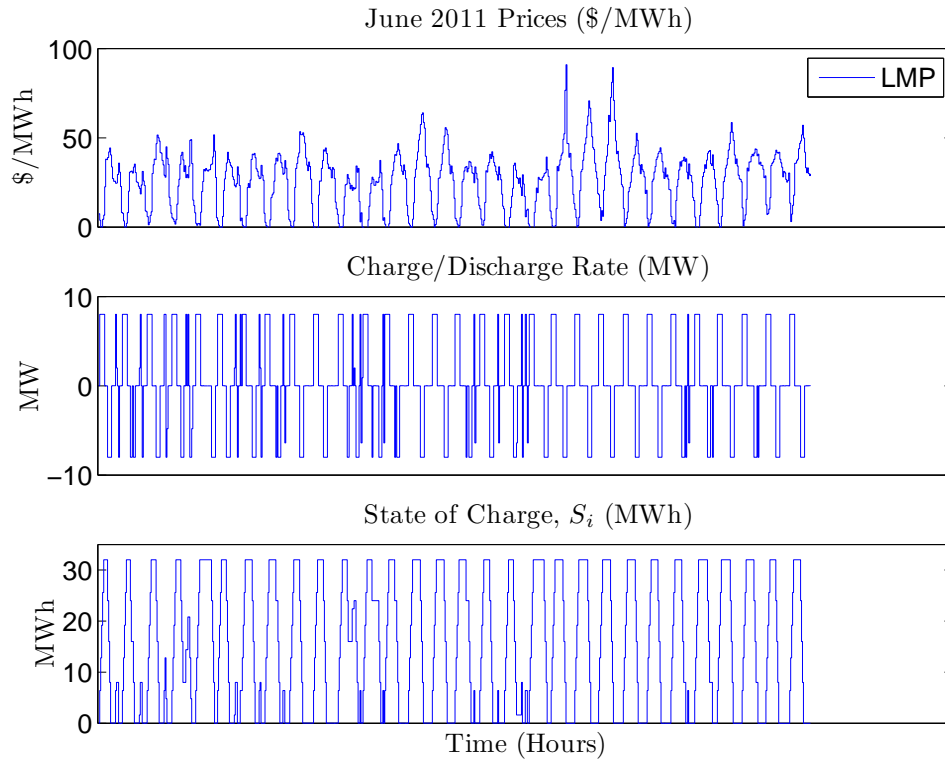


Figure 27: June 2011 arbitrage only results for node TAP78_6_B1.

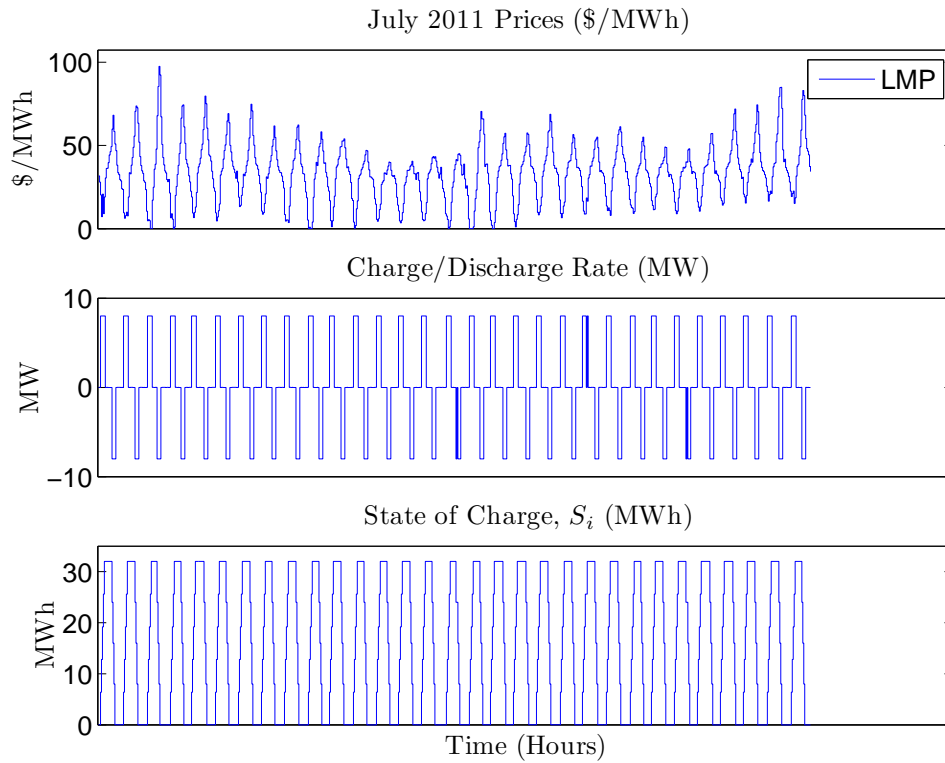


Figure 28: July 2011 arbitrage only results for node TAP78_6_B1.

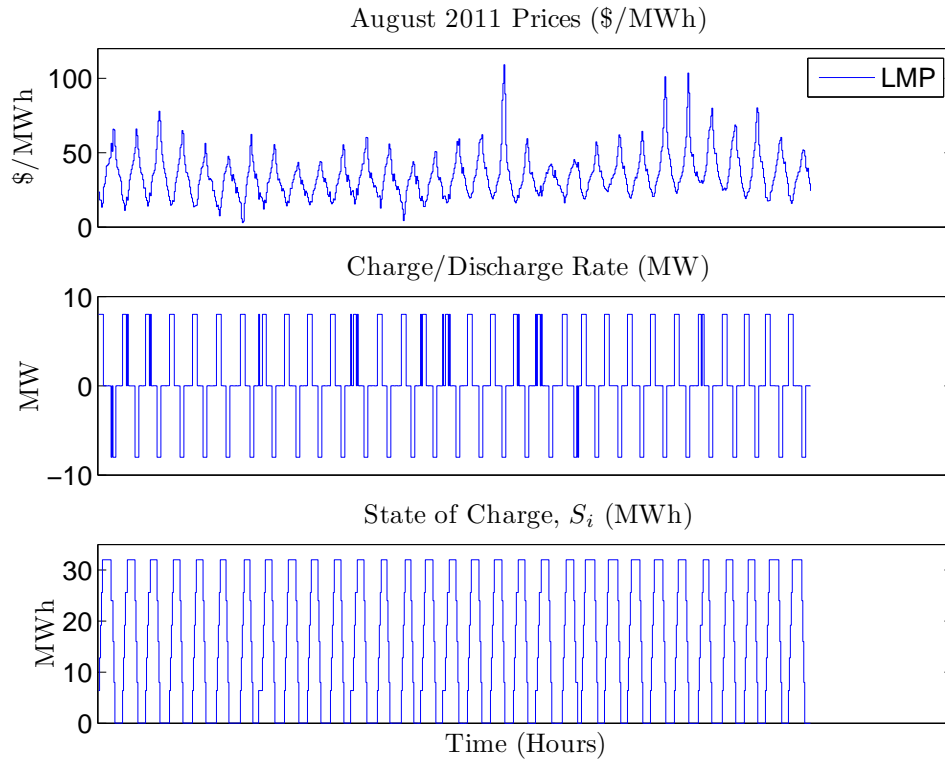


Figure 29: August 2011 arbitrage only results for node TAP78.6_B1.

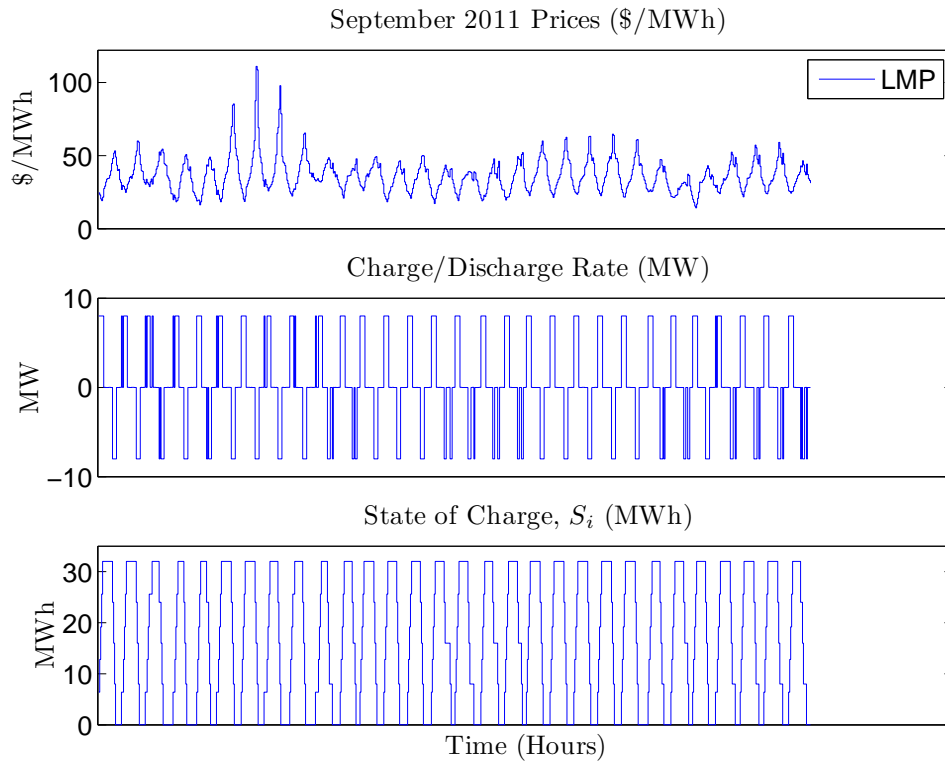


Figure 30: September 2011 arbitrage only results for node TAP78.6_B1.

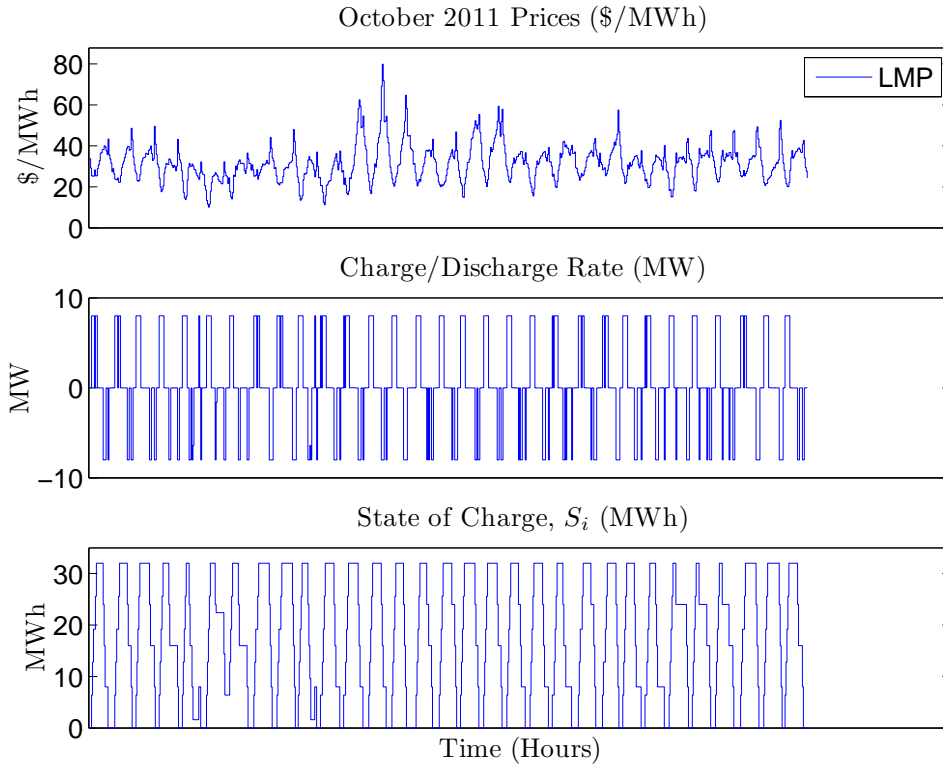


Figure 31: October 2011 arbitrage only results for node TAP78.6_B1.

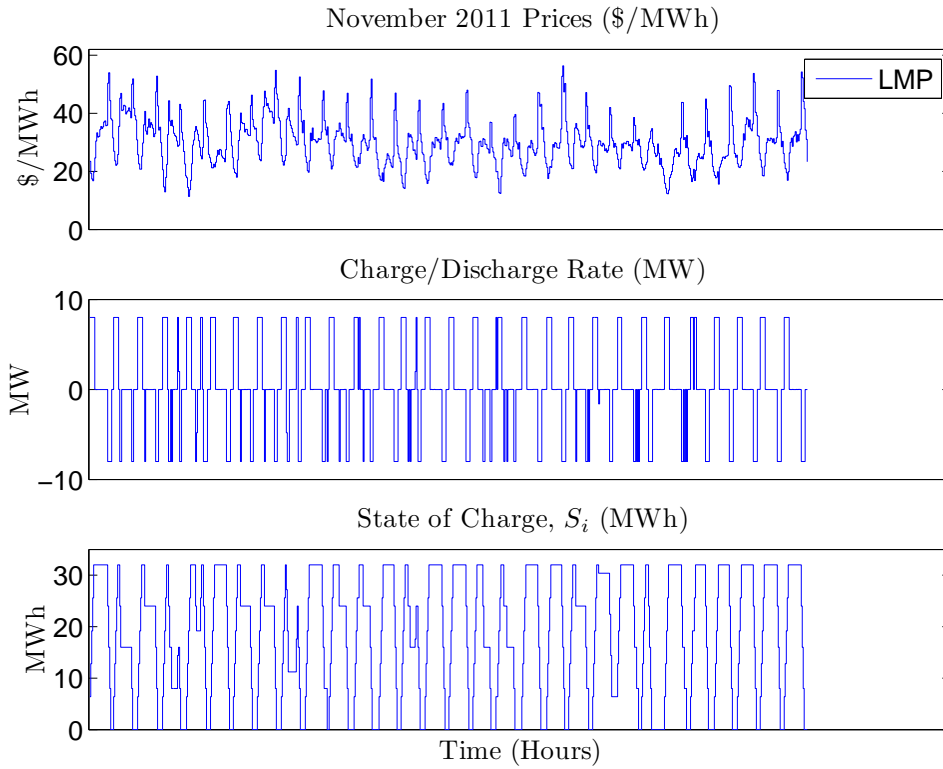


Figure 32: November 2011 arbitrage only results for node TAP78.6_B1.

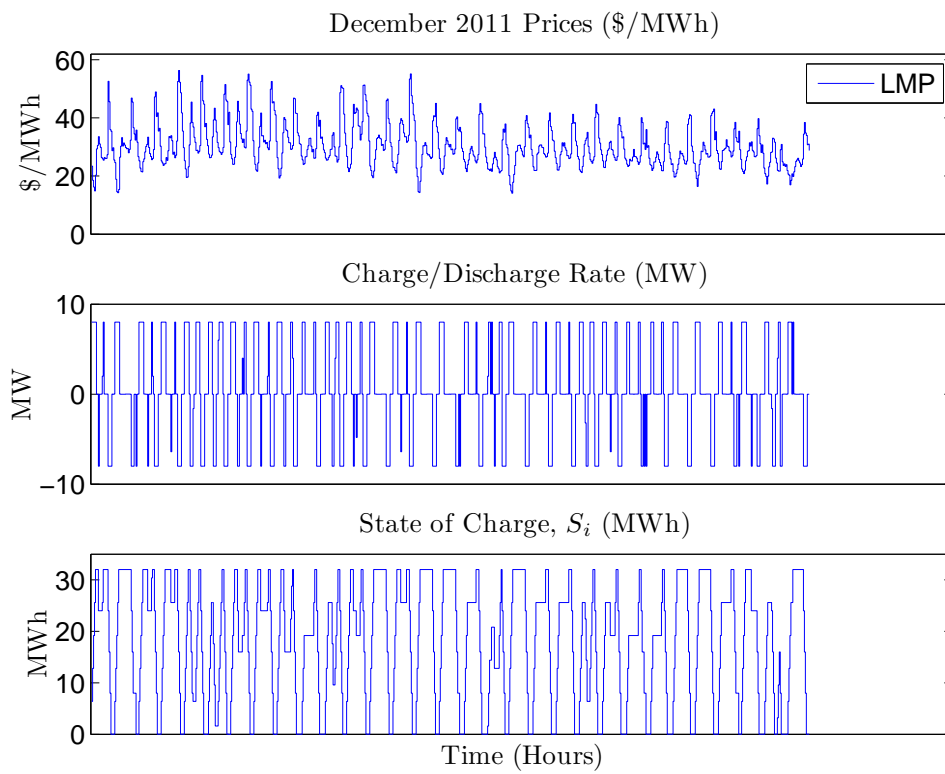


Figure 33: December 2011 arbitrage only results for node TAP78_6_B1.

Arbitrage and Regulation

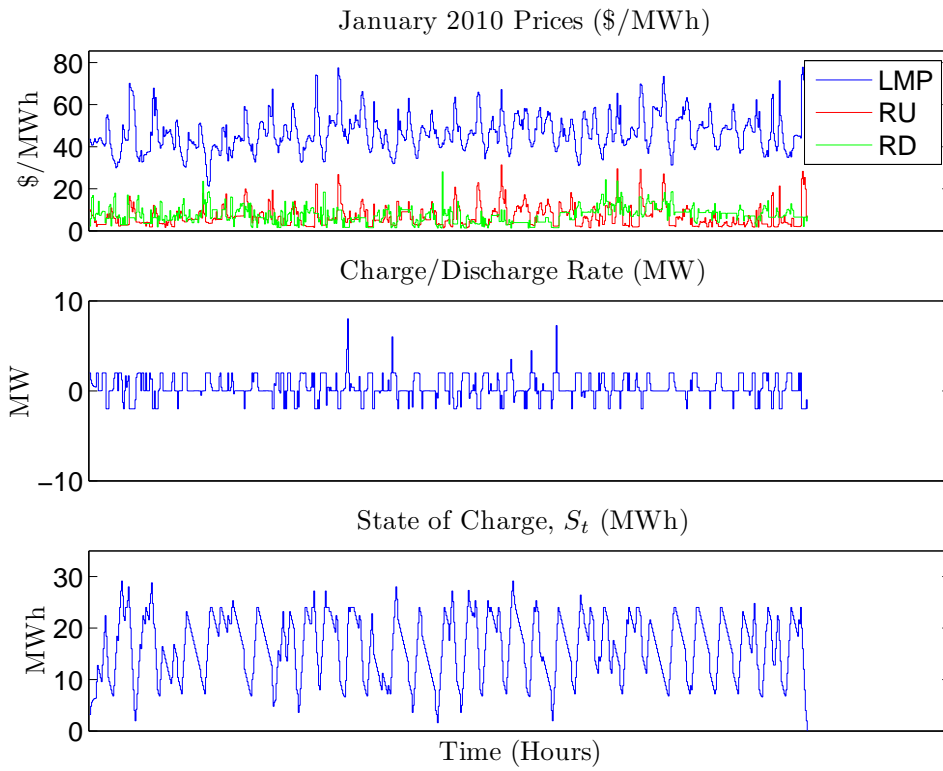


Figure 34: January 2010 arbitrage and regulation results for node TAP78.6_B1.

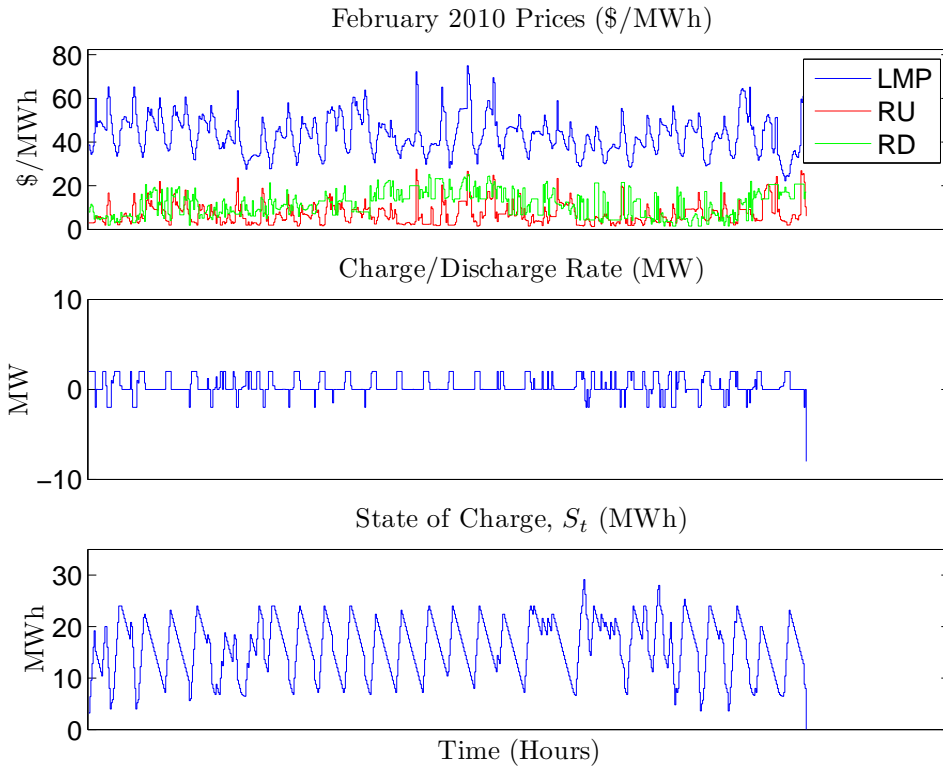


Figure 35: February 2010 arbitrage and regulation results for node TAP78_6_B1.

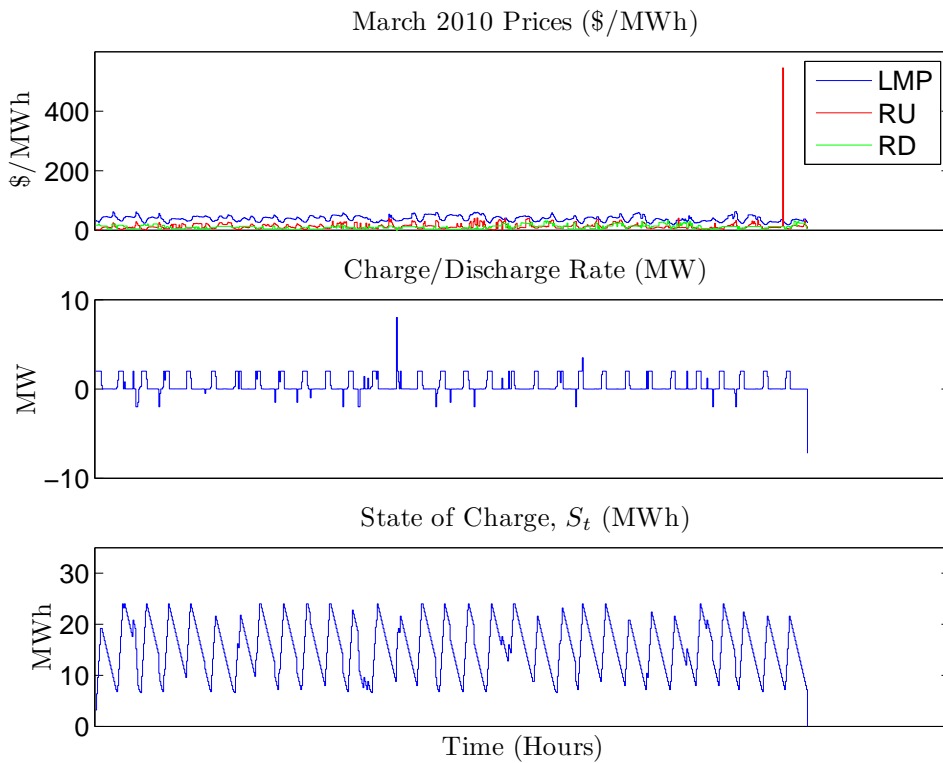


Figure 36: March 2010 arbitrage and regulation results for node TAP78_6_B1.

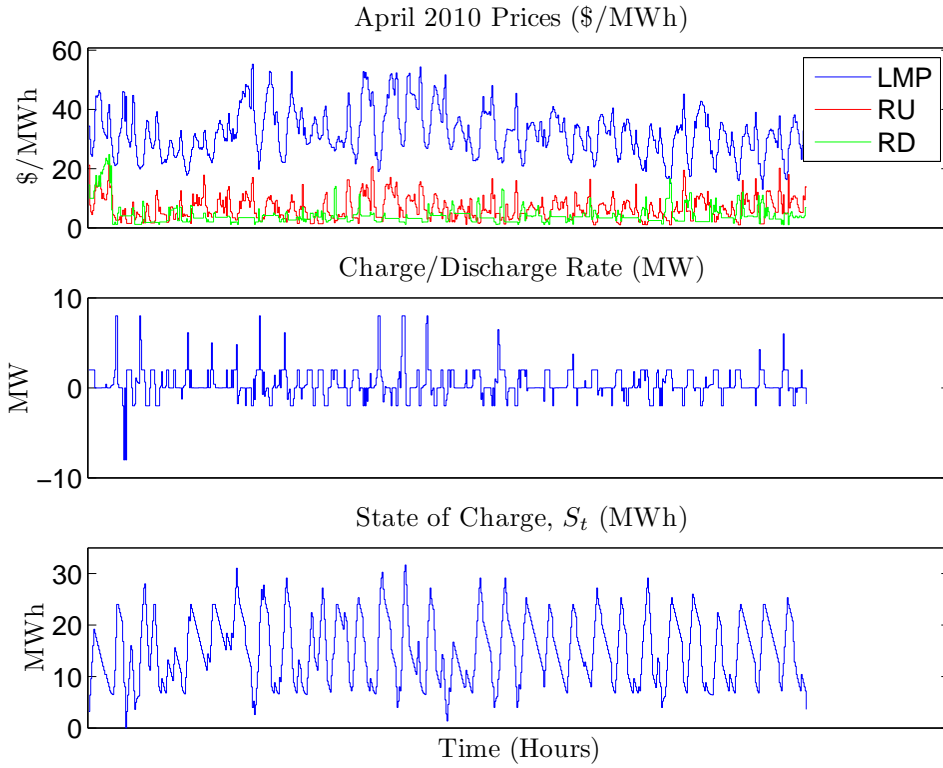


Figure 37: April 2010 arbitrage and regulation results for node TAP78.6_B1.

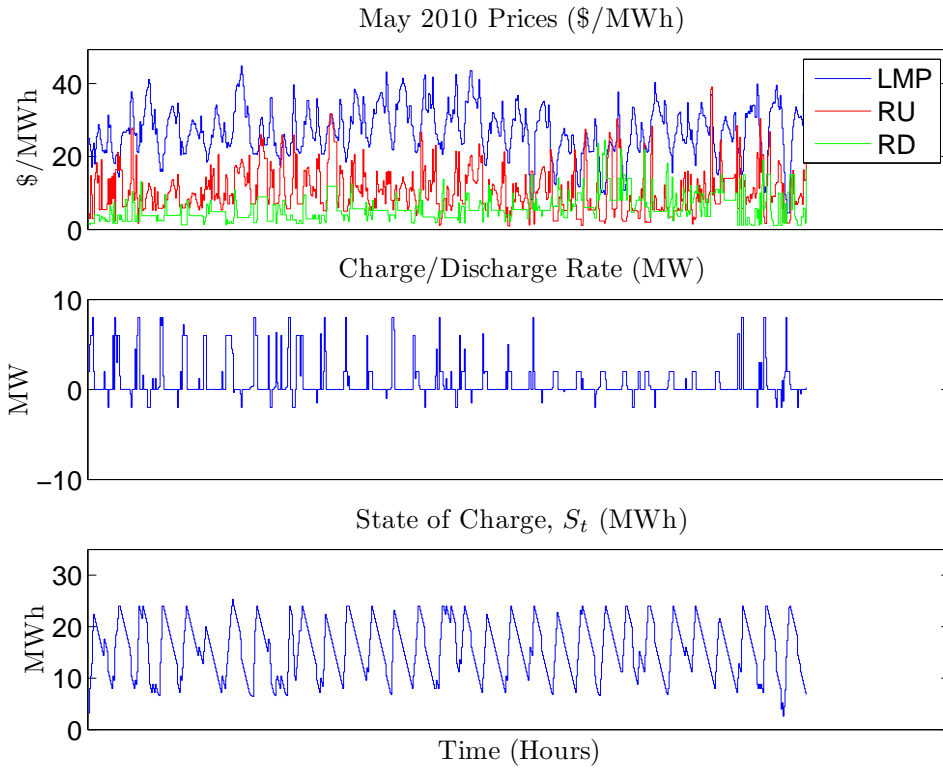


Figure 38: May 2010 arbitrage and regulation results for node TAP78.6_B1.

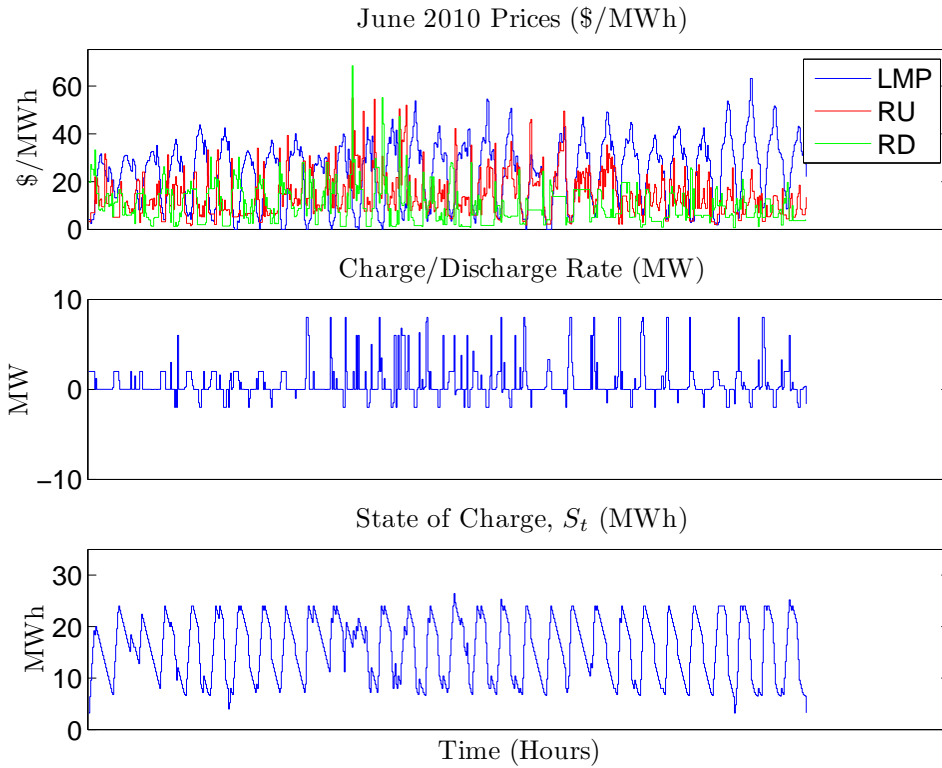


Figure 39: June 2010 arbitrage and regulation results for node TAP78_6_B1.

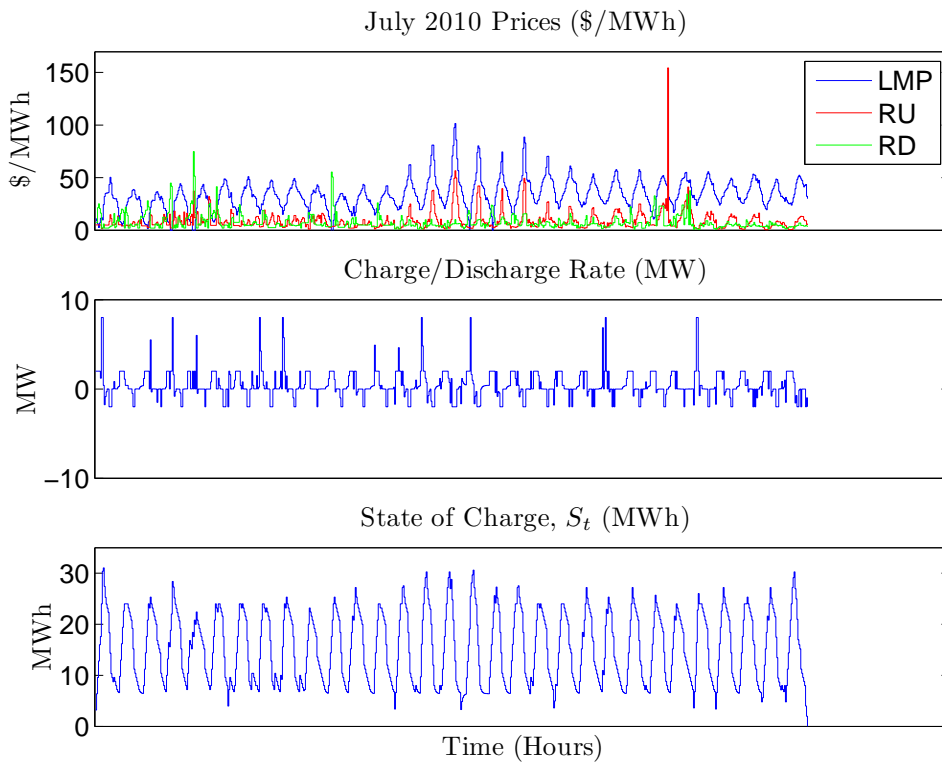


Figure 40: July 2010 arbitrage and regulation results for node TAP78_6_B1.

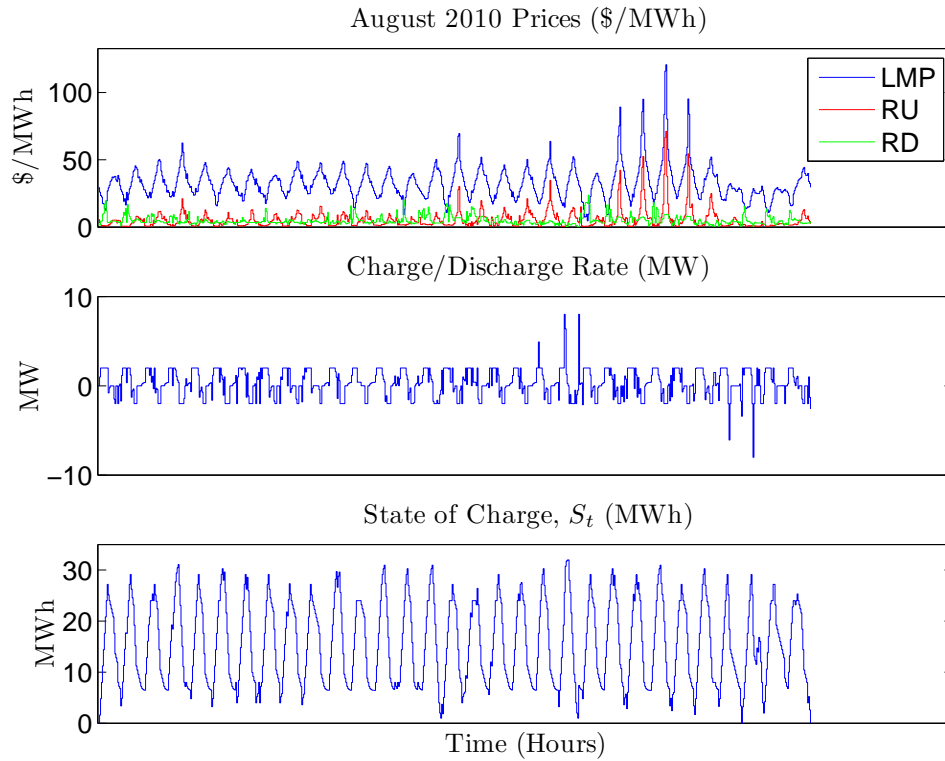


Figure 41: August 2010 arbitrage and regulation results for node TAP78_6_B1.



Figure 42: September 2010 arbitrage and regulation results for node TAP78_6_B1.

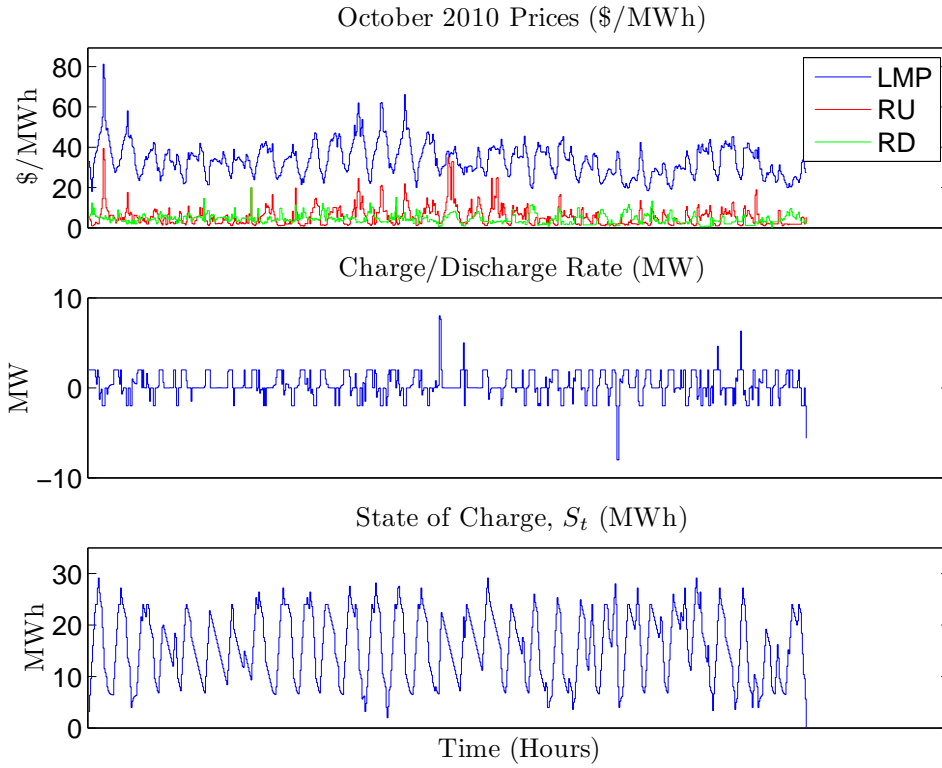


Figure 43: October 2010 arbitrage and regulation results for node TAP78.6_B1.

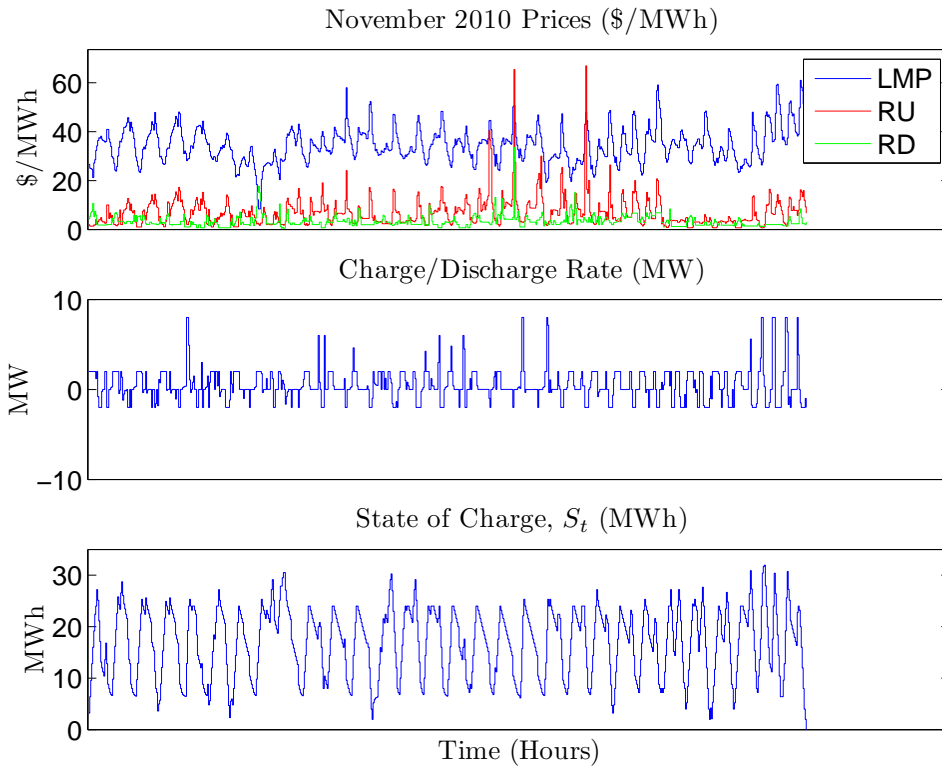


Figure 44: November 2010 arbitrage and regulation results for node TAP78.6_B1.

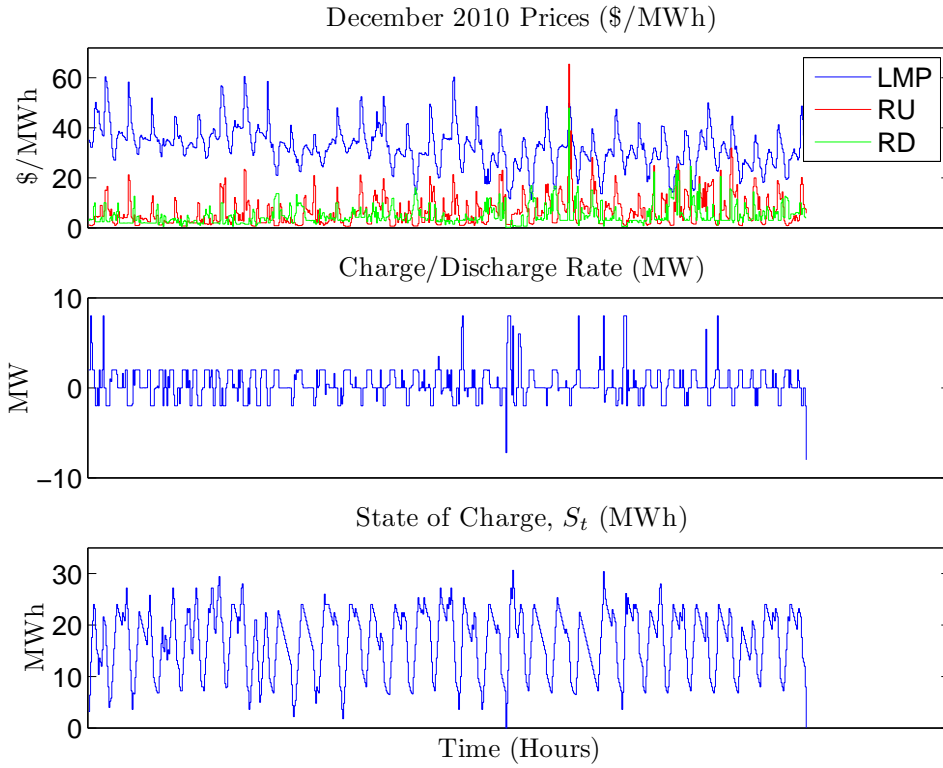


Figure 45: December 2010 arbitrage and regulation results for node TAP78.6_B1.

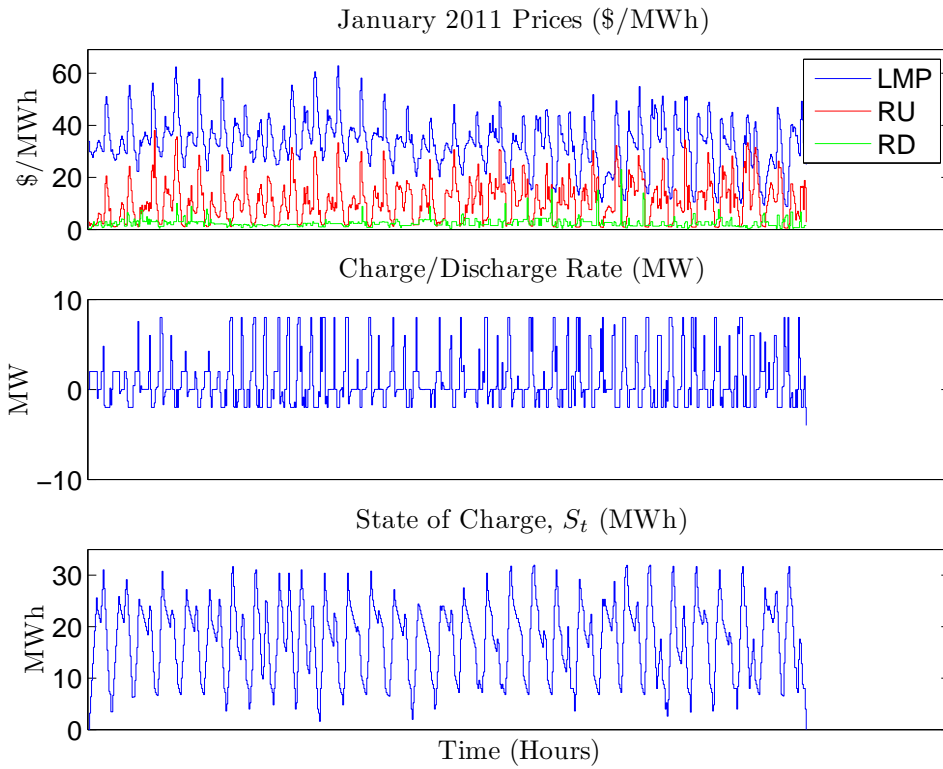


Figure 46: January 2011 arbitrage and regulation results for node TAP78.6_B1.



Figure 47: February 2011 arbitrage and regulation results for node TAP78_6.B1.

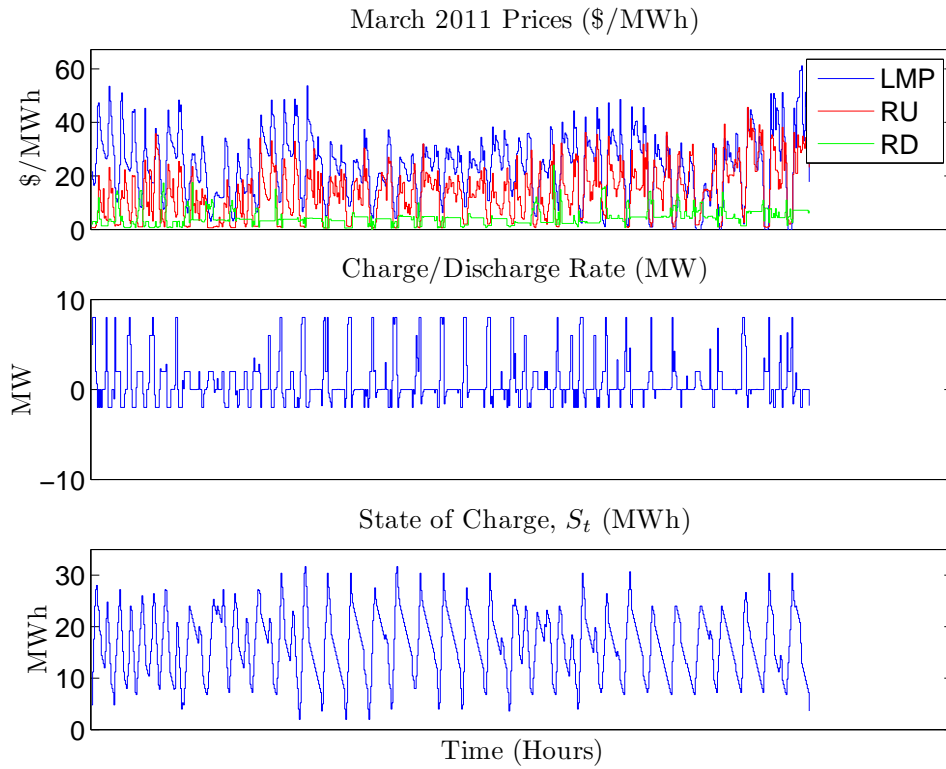


Figure 48: March 2011 arbitrage and regulation results for node TAP78_6.B1.

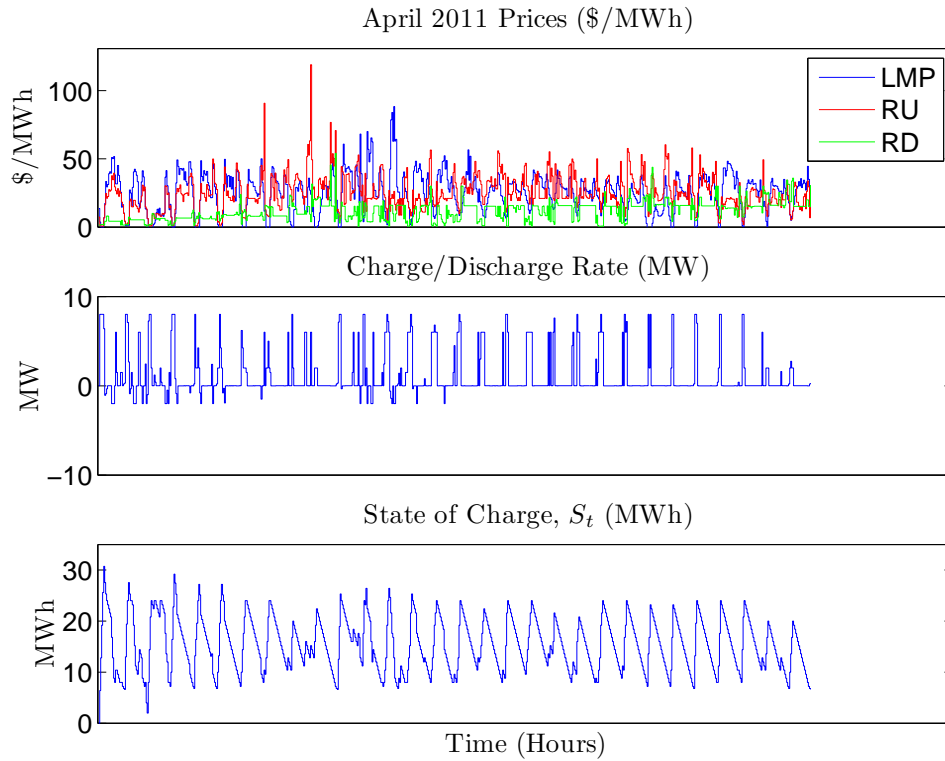


Figure 49: April 2011 arbitrage and regulation results for node TAP78.6_B1.

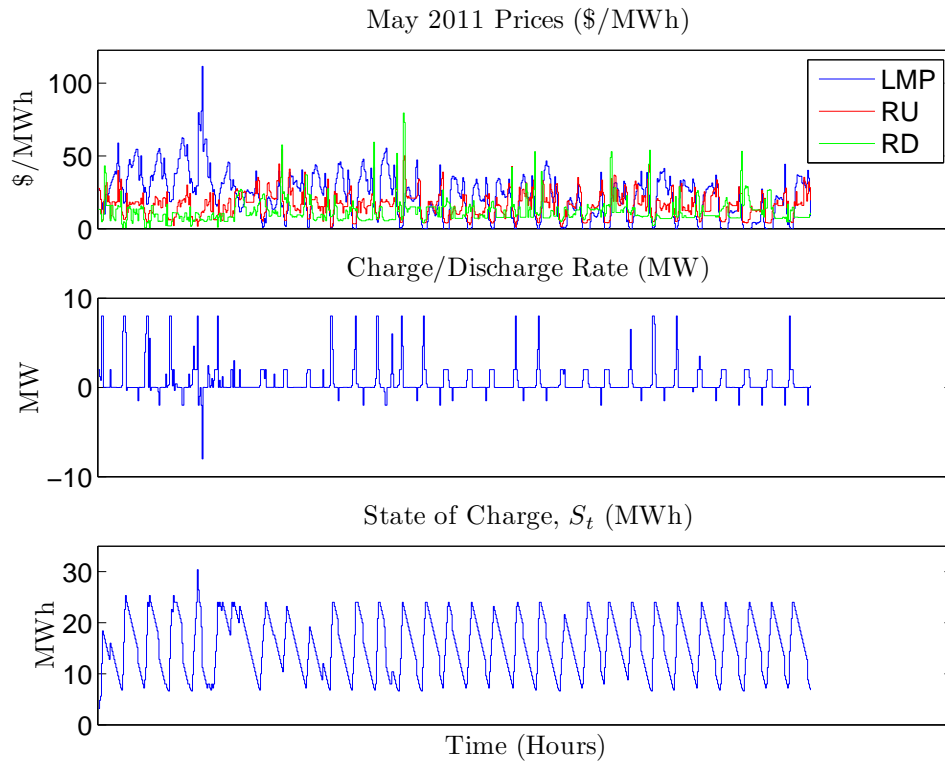


Figure 50: May 2011 arbitrage and regulation results for node TAP78.6_B1.

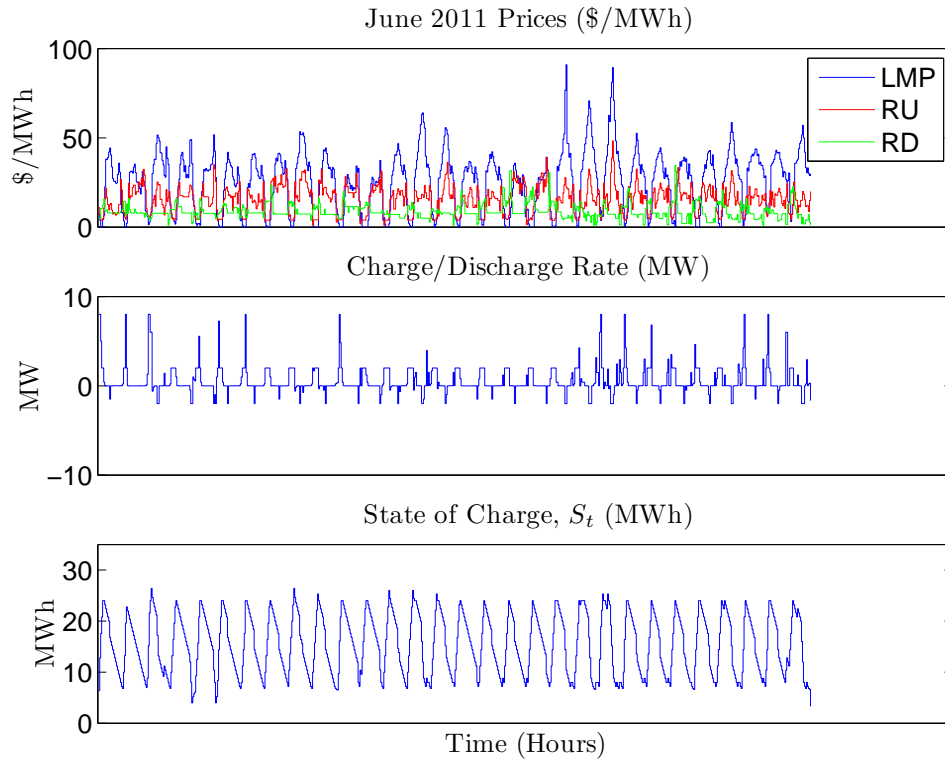


Figure 51: June 2011 arbitrage and regulation results for node TAP78_6_B1.

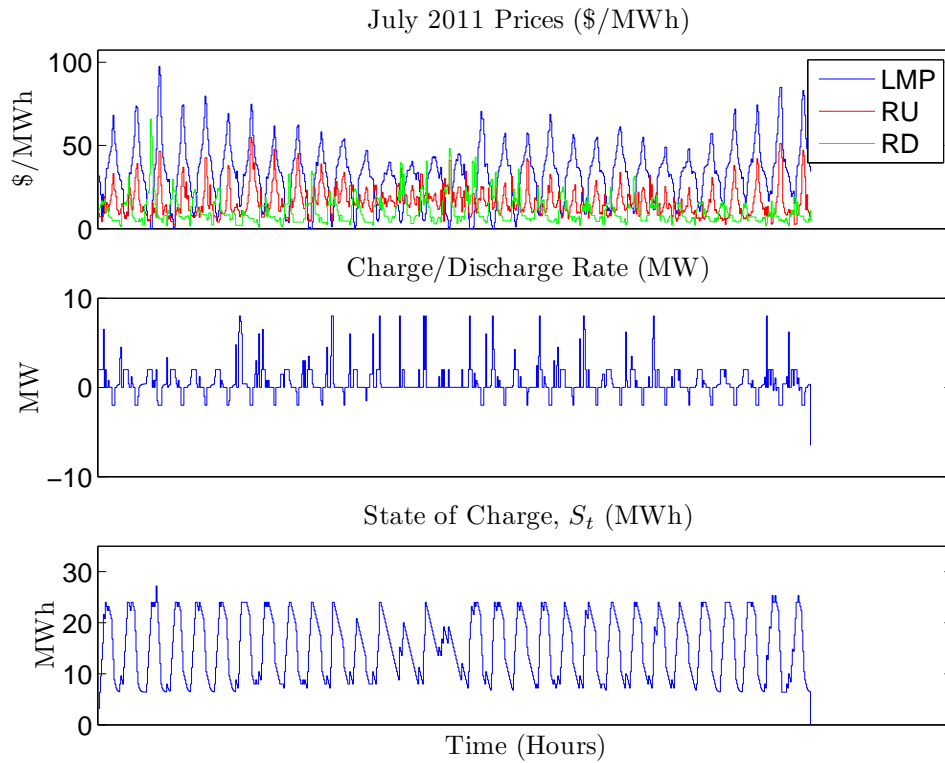


Figure 52: July 2011 arbitrage and regulation results for node TAP78_6_B1.

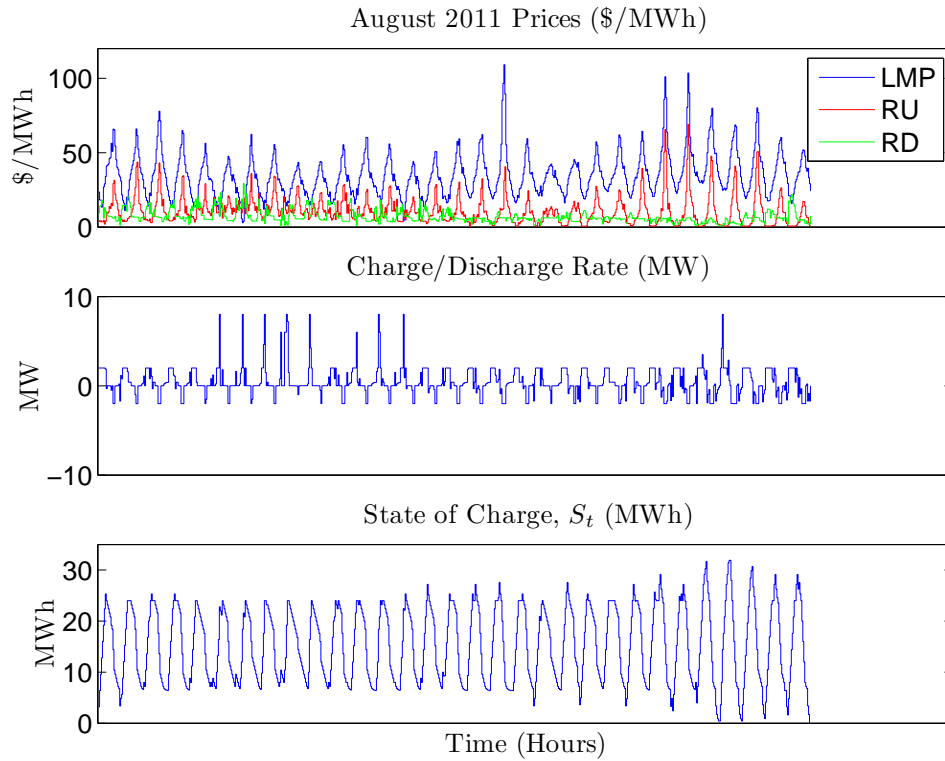


Figure 53: August 2011 arbitrage and regulation results for node TAP78.6_B1.

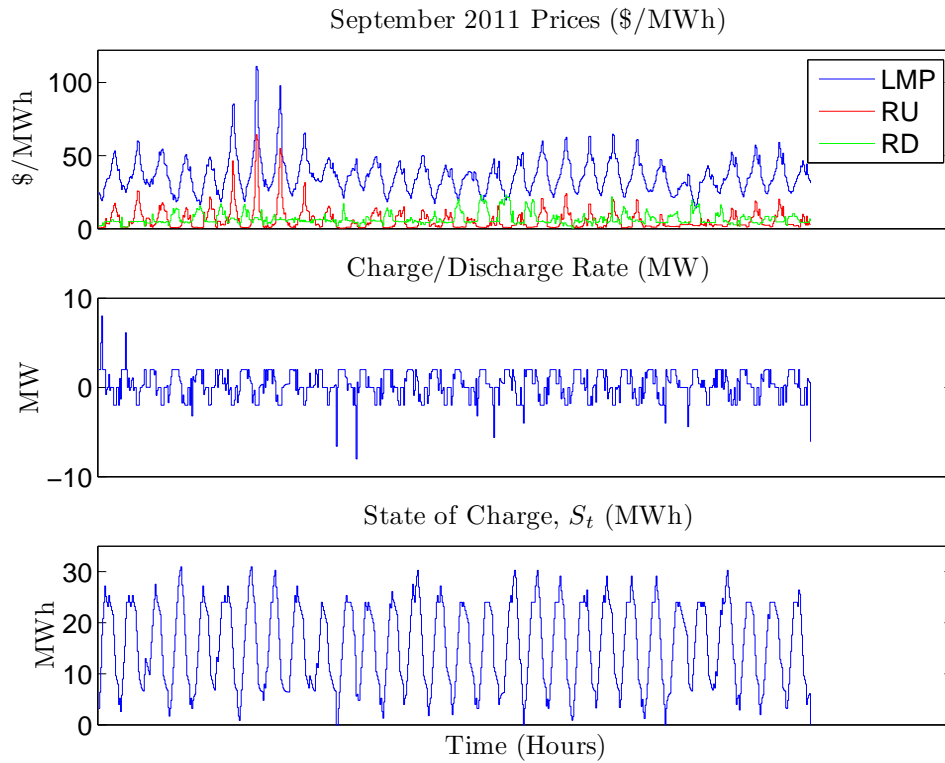


Figure 54: September 2011 arbitrage and regulation results for node TAP78.6_B1.

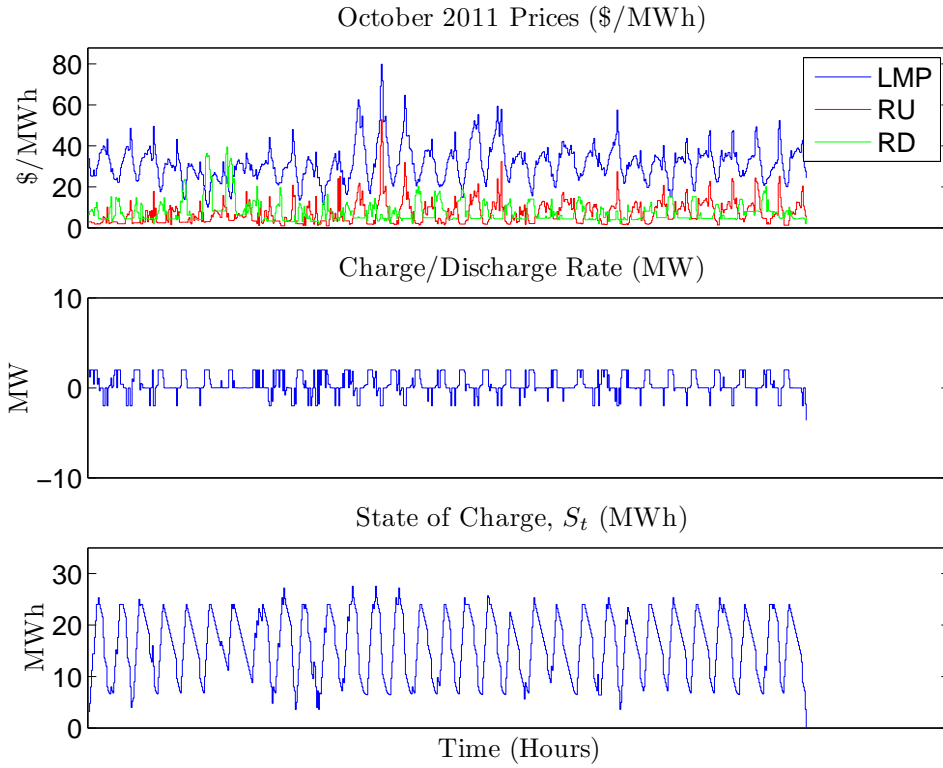


Figure 55: October 2011 arbitrage and regulation results for node TAP78.6_B1.

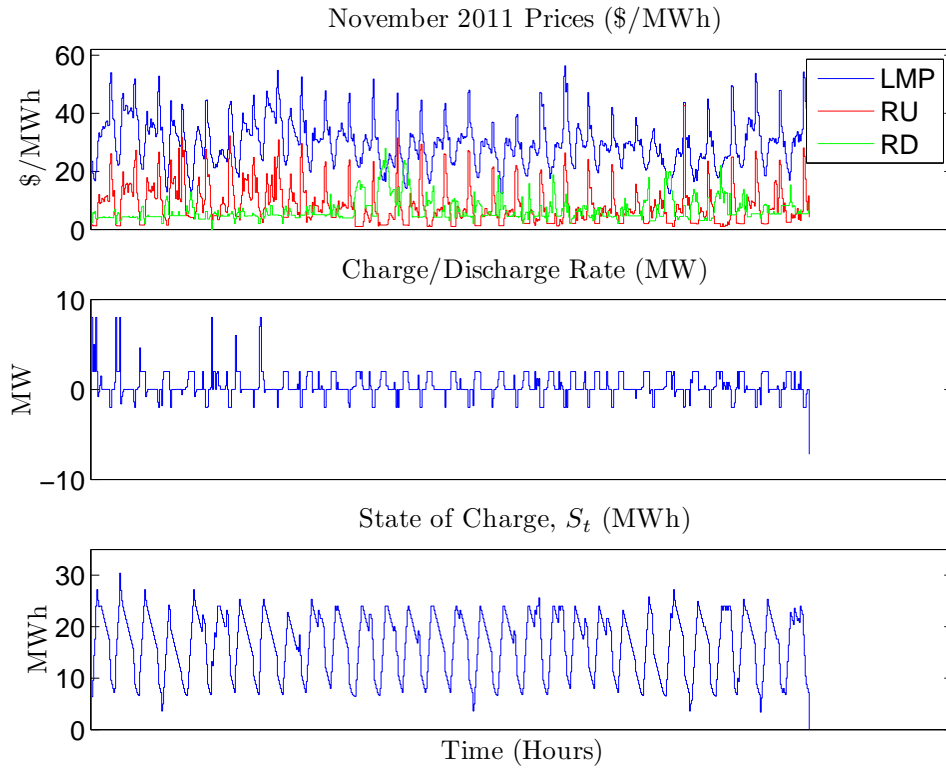


Figure 56: November 2011 arbitrage and regulation results for node TAP78.6_B1.

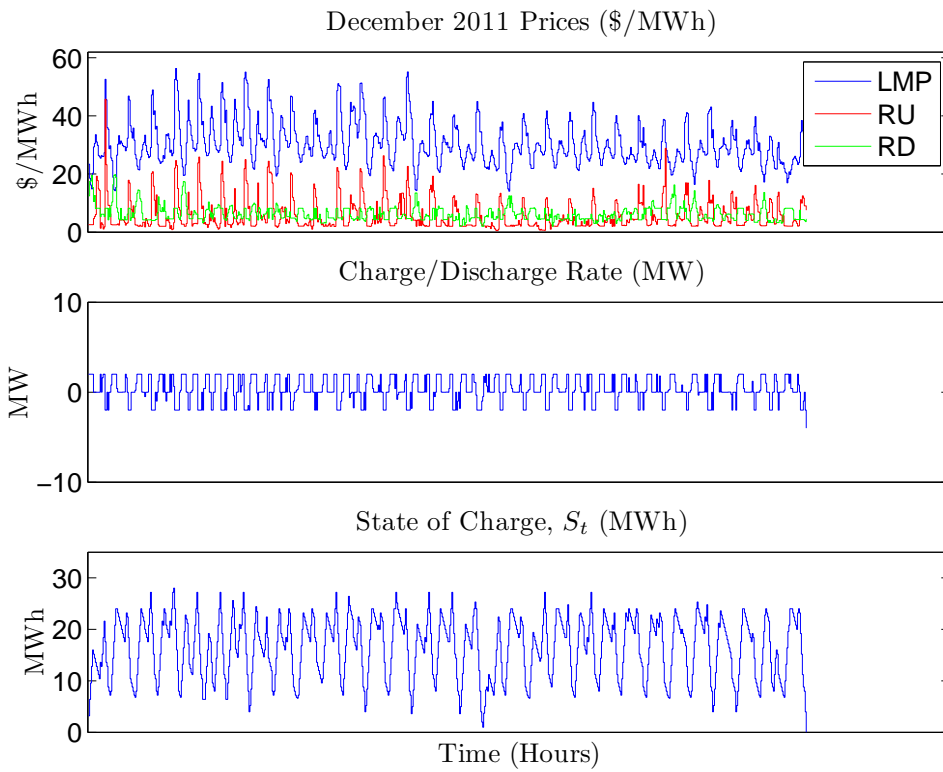


Figure 57: December 2011 arbitrage and regulation results for node TAP78.6_B1.

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