Pricing Schemes in Electric Energy Markets

by

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ABSTRACT

Two thirds of the U.S. power systems are operated under market structures. A good market design should maximize social welfare and give market participants proper incentives to follow market solutions. Pricing schemes play very important roles in market design.

Locational marginal pricing scheme is the core pricing scheme in energy markets. Locational marginal prices are good pricing signals for dispatch marginal costs. However, the locational marginal prices alone are not incentive compatible since energy markets are non-convex markets. Locational marginal prices capture dispatch costs but fail to capture commitment costs such as startup cost, no-load cost, and shutdown cost. As a result, uplift payments are paid to generators in markets in order to provide incentives for generators to follow market solutions. The uplift payments distort pricing signals.

In this thesis, pricing schemes in electric energy markets are studied. In the first part, convex hull pricing scheme is studied and the pricing model is extended with network constraints. The subgradient algorithm is applied to solve the pricing model. In the second part, a stochastic dispatchable pricing model is proposed to better address the non-convexity and uncertainty issues in day-ahead energy markets. In the third part, an energy storage arbitrage model with the current locational marginal price scheme is studied. Numerical test cases are studied to show the arguments in this thesis.

The overall market and pricing scheme design is a very complex problem. This thesis gives a thorough overview of pricing schemes in day-ahead energy markets and addressed several key issues in the markets. New pricing schemes are proposed to improve market efficiency.

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Chapter 1

INTRODUCTION

1.1 Background

The electric power grid is one of the most complex engineered machines ever created. The National Academy of Engineering ranks the electrification as the greatest achievement of the 20th century (National Academy of Engineering, 2015). Electric power systems can be divided into four sub-systems: the generation, transmission, distribution, and load systems, as illustrated in Figure 1.1 (U.S.-Canada Power System, 2004).

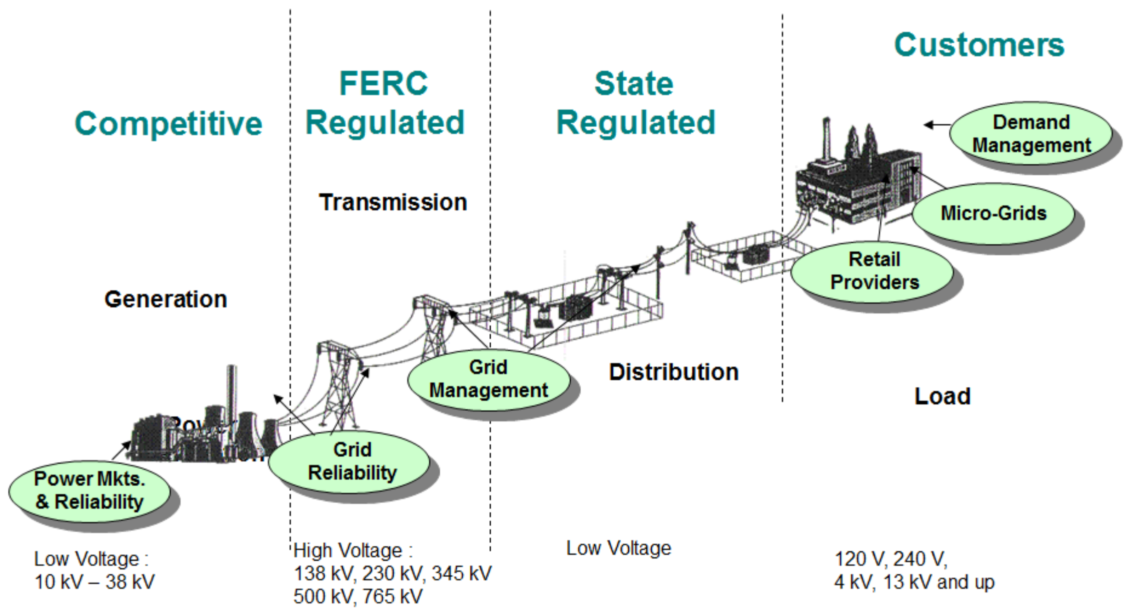

Figure 1.1: Structure of Electric Power Systems

(U.S.-Canada Power System, 2004)

Followed the Federal Energy Policy Act in 1992, the concepts of regional transmission organization (RTO) and independent system operator (ISO) were first introduced. RTO/ISOs are nonprofit independent entities and play a similar role to that of air traffic controllers in air transportation industry. RTO/ISOs operate the electric power systems in market structures while ensuring security and efficiency in power systems. Currently, two-thirds of the U.S. area is served by these independent grid operators, Figure 1.2 (California ISO, 2011) illustrates their respective service territories. There are 7 major RTO/ISOs in the U.S.: CAISO, ERCOT, ISONE, MISO, NYISO, PJM, and SPP.

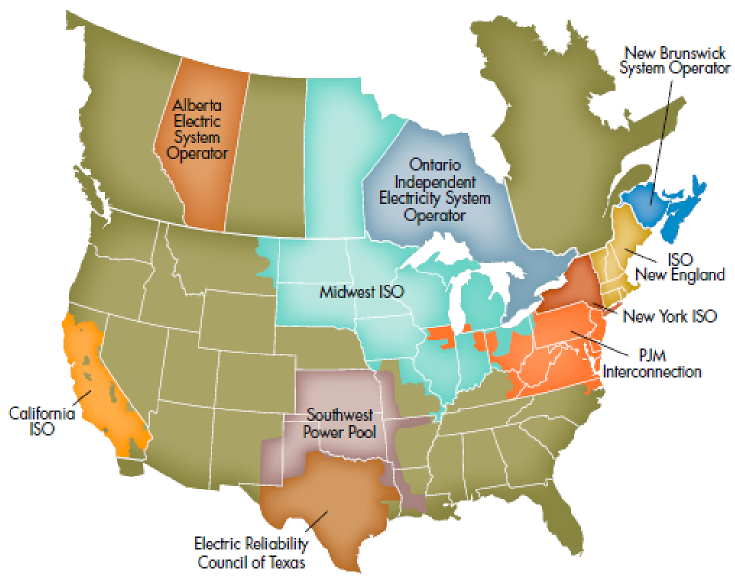

Figure 1.2: RTO/ISOs in the U.S.

(California ISO, 2011)

A good market design should induce all participants to truthfully reveal their private information; avoid strategic bidding or exercising market power; and be incentive compatible, i.e., participants have no incentive to deviate from market solutions (Federal Energy Regulatory Commission, 2014a).

The electric energy wholesale markets in the U.S. are cleared by centralized auctions. RTO/ISOs receive offers and bids from both supply and demand sides. The bidders from supply side are mainly generators and the bidders from demand side are mainly load serving entities (LSE). The offers and bids include mainly prices and capacities that the market participants would like to supply or consume. RTO/ISOs clear the energy markets by running market models based on the collected bids as model inputs.

The energy markets are multi-settlement markets including mainly day-ahead market (DAM) and real-time market (RTM). The DAM and RTM represent a forward market and a spot market. The forward (financial) market is in advance of the corresponding real-time spot (physical) market where agreements are made based on the future delivery at agreed upon forward contracts. Although different RTO/ISOs have different market clearing processes and terminologies for the processes, there is a general market clearing process describes as follows. In DAM, RTO/ISOs: a) collect bids, b) run security-constrained unit commitment (SCUC) model to determine generator commitments, c) fix commitments, run security-constrained economic dispatch (SCED) model to determine dispatch solution, d) post DAM solution and DAM prices. In RTM, RTO/ISOs: a) run SCED to balance energy supply and demand, b) determine RTM prices. Figure 1.3 (Midcontinent ISO, 2007) illustrate the DAM process in MISO.

Pricing schemes are important for market designs since market participants will make operating and investment decisions based on pricing signals (Hogan, 2014). A pricing signal is the informational value of the market clearing prices that are used to settle the markets (O'Neill, 2009). ISONE proposed three principles to evaluate pricing signals: efficiency, transparency, and simplicity (ISO New England, 2014). Efficiency evaluates whether the offered prices can maximize social welfare and all participants would like to follow market solutions. Transparency evaluates whether much is known by many, i.e., every participant knows the prices other receive. Sim-

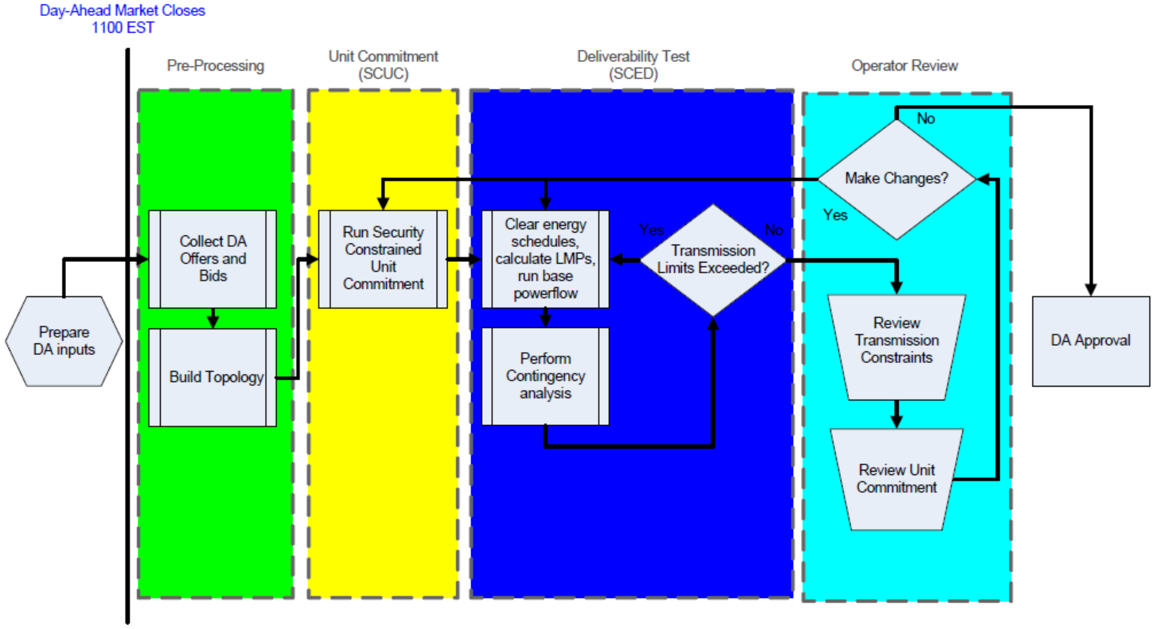

Figure 1.3: DAM Process in MISO

(Midcontinent ISO, 2007)

plicity evaluates whether the pricing scheme is simple and easy to be interpreted.

In the energy markets in the U.S., a uniform pricing scheme is adopted. The uniform pricing clears the market at the marginal unit's cost and all selected bids are paid at a uniform market clearing price. Starting form late 90s, RTO/ISOs began to switch from zonal pricing to nodal pricing for generators (Pope, 2014). Locational marginal price (LMP) is the core of pricing in all RTO/ISOs' energy markets nowadays. The LMP scheme is a uniform pricing mechanism and emphasizes the locational differences caused by the limits and losses in transmission.

Power flow problems are non-linear, non-convex problems (Wood and Wollenberg, 1996). RTO/ISOs adopt linearized power flow models to approximate the real power flow in the market models, as known as direct current optimal power flow (DCOPF) models (Federal Energy Regulatory Commission, 2011). A generalized market model is represented as follows:

$$
\begin{aligned}
\min \quad & C(\mathbf{u}, \mathbf{p}) && && (1.1) \\
\text{s.t.} \quad & (\mathbf{u}^g, \mathbf{p}^g) \in \mathbf{X}^g \quad \forall g && \text{resource-level constraints} && (1.2) \\
& K(\mathbf{p}, \mathbf{D}) \leq 0 && \text{system-level constraints} && (1.3)
\end{aligned}
$$

where decision variables are commitment status, $\mathbf{u}$, and dispatch quantities, $\mathbf{p}$. Equation (1.1) is the objective to minimize total system cost. Equation (1.2) represents a set of resource-level constraints restricting each generator's commitment status, $\mathbf{u}^g$, and generation level output, $\mathbf{p}^g$; where $\mathbf{X}^g, \forall g$, are feasible commitment and dispatch subspaces of each generator. The resource-level constraints include generation EcoMin, EcoMax constraints, ramping constraints, commitment minimum up/down constraints. Equation (1.3) represents a set of system-level constraints; where $K(\mathbf{p}, \mathbf{D})$ is linear functions of generation level output, $\mathbf{p}$, and forecasted load, $\mathbf{D}$. The system-level constraints usually include system-balance constraint (total generations equal to total loads) and network constraints (power flows are within transmission line limits). The interpretation of the LMP is the system total cost increment/decrement when increasing/decreasing one unit of power at the corresponding location. The shadow prices (dual variables) of the system-level constraints give marginal cost of supplying one more/less MWh of energy, i.e., the LMPs.

1.2 Research Focus

Ideally, the energy prices would reflect the true marginal cost of production, taking into account all physical system constraints, and these prices would fully compensate all resources for the variable cost of providing service. For competitive market participants, when they are presented with the set of market prices, but without being told their dispatch quantities for each product, they would choose to supply the same amount of each product for the dispatch as the market solution in order to maximize their profits (Federal Energy Regulatory Commission, 2014a).

LMPs are good pricing signals for single-period (short-run) dispatch marginal costs. However, the LMPs alone are not incentive compatible since energy markets are non-convex markets. The non-convexities of energy markets are a result of many reasons. The most important reason is that the commitment status is a binary decision and the EcoMin of most generators are not zero, i.e., most generators are not perfectly partially dispatchable. Moreover, minimum up/down time requirements restrict generators online/offline when they may not provide economic efficiency for the corresponding period. LMPs capture dispatch costs, but fail to capture commitment costs such as startup cost, no-load cost, and shutdown cost. In fact, the discrete nature of commitment decisions, startup costs, and no-load costs may prevent the existence of a set of incentive compatible market clearing prices in DAM since there is generally no set of market prices that would induce profit maximizing generators and loads to voluntarily follow the pricing scheme (Gribik, 2007).

In this thesis, the focus is on studying and improving the current pricing scheme, i.e., LMP scheme. First, convex hull pricing scheme is studied and extended to network-constrained model. Second, prices inconsistency between DAM and RTM is studied, and a stochastic dispatchable pricing scheme is proposed. Third, under the current energy market structure and pricing scheme, price arbitrage of electric energy storage is studied and analyzed.

1.3 Summary of Chapters

In Chapter 2, two pricing schemes in energy markets are studied, LMP scheme and convex hull pricing pricing. The effects of these two pricing mechanisms are compared with regards to the allocation of the market surplus between generators and loads. The two pricing mechanisms are also analyzed with regards to the required uplift payments. The results confirm that uplift payments are reduced under the convex hull pricing mechanism. However, convex hull pricing does not appropriately represent the marginal market clearing price for the market dispatch solution.

In Chapter 3, a stochastic dispatchable locational marginal pricing scheme is proposed to better represent the non-convexity and uncertainty in DAM markets. The advantages of the proposed pricing scheme are analyzed and two test cases are presented to compare different pricing schemes.

In Chapter 4, the impacts of electric energy storage arbitrage in energy markets are studied. The charging or discharging activities for large-scale storage units may have huge impacts on real-time LMPs. An optimization model is proposed to maximize the arbitrager's profits with the consideration of the charging and discharging impacts on the LMPs. Three charging policies are discussed to handle the uncertainty that the intermittent wind penetration brings to the power grid. Finally, an IEEE 118-bus system case study is carried out to evaluate the model and the different charging policies.

Chapter 5 concludes this thesis and discusses potential future research directions.

Chapter 2

CONVEX HULL PRICING

2.1 Introduction

The wholesale electricity markets in the U.S. are designed to promote the efficient delivery of electric power between generators and loads. The DAM solution is determined by solving SCUC and SCED problems to obtain the least-cost solution to satisfy the load, while ensuring system reliability. The pricing mechanism used within energy markets should incentivize generators and loads to follow the market solution.

Due to the non-convex nature of electricity markets, there may not exist a linear marginal pricing mechanism for electricity that properly incentivizes all market participants to follow the market solution (O'Neill *et al.*, 2005). Thus, a multi-component pricing mechanism is required to properly incentivize all market participants.

As a result, uplift payments are paid to generators in order to provide incentives for generators to follow market solutions. Uplift payments can be categorized into two types: make whole payments (MWPs) and lost opportunity costs (LOCs) (ISO New England, 2015). MWPs are paid when a generator's revenue is not enough to cover its costs, including both commitment costs and dispatch costs. MWPs bring a generator's profit to zero, make the generator indifferent between following the market solutions and doing nothing. LOCs are paid when a generator is restricted to lower down generation level to provide reserves while the generator can make more profits if it increases the output level, since the market price is higher than the generator's marginal cost. Uplift payments distort price signals and hurt the transparency of the pricing. Uplift is a symptom rather than a cause of price formation problems. The focus should be on improving pricing efficiencies, rather than on reducing uplift payments (Pope, 2014). The uplift payment may not be eliminated due to the non-convexity of energy markets.

The current pricing mechanism found in many RTO/ISOs consists of a locational uniform price based on the LMP to deliver electric power to the location and a discriminatory uplift payment for commitment. To determine the LMPs, the UC problem is first solved to obtain the least-cost solution to satisfy the load. The binary commitment variables are then fixed to their optimal values and the LMPs are determined by the dual solution of the node-balance constraints. For the UC problem with fixed commitments, LMP provides incentives for market participants to follow the market dispatch solution; however, LMP may not properly incentivize generators to follow the market commitment solution due to the non-convex nature of electricity markets (Hogan and Ring, 2003; Gribik *et al.*, 2007). Specifically, LMP is not influenced by the fixed costs associated with commitment, such as startup and no-load costs. In order to provide proper market incentives for commitment, the RTO/ISOs provide uplifts to generators if their revenue does not cover their total costs; these uplifts are decided at the end of every day.

Currently, many RTO/ISOs pay uplift payments only to generators. The associated costs are then distributed uniformly amongst the load according to the percent of total load in order to maintain a locational uniform pricing mechanism on the load side. These uplift payments can raise load payments above their marginal bids, which can incentivize price sensitive loads to deviate from the market solution.

Convex hull pricing (CHP) scheme (Gribik *et al.*, 2007), sometimes referred as extended locational marginal pricing (ELMP), is an alternative pricing mechanism, which is the closest locational uniform price to clearing the market while also minimizing the total uplift payments required to properly incentivize market participants to follow the market solution (Hogan and Ring, 2003).

In this chapter, the effects of the LMP and CHP schemes on the allocation of the market surplus between suppliers and loads are studied. The work in this chapter is based on a joint work with Greg Thompson. Greg Thompson did literature review for the topic and I developed the rest of the work. For each pricing mechanism, the magnitude of the generation rent and load payment is determined under two different UC models and varying levels of load. The initial model builds off of the model used in (Wang *et al.*, 2012) by including generator minimum up/down time and ramp-rate constraints. The second model extends the first by including transmission constraints based on the direct current optimal power flow (DCOPF) approximation.

The organization of the chapter is as follows. Section 2.2 introduces the concepts of CHP. Section 2.3 gives the formulations of the proposed models. Section 2.4 describes the methods for calculating LMP and CHP. Section 2.5 analyzes the effects of the pricing mechanisms based on the IEEE RTS96 single zone test case. Conclusions are presented in section 2.6.

2.2 Convex Hull Pricing

With the issues of current utilized LMP (standard LMP) in non-convex energy markets, CHP scheme was proposed in Hogan and Ring (2003) and Gribik *et al.* (2007). CHP takes the dual of whole unit commitment model, sets prices as the Lagrangian multipliers of node balance constraints. Since the Lagrangian multipliers represent the slope of the convex hull of the total cost function, the pricing scheme is named as CHP scheme. CHP scheme aims at giving better pricing signals.

The Lagrangian dual of UC problem is equivalent to a problem that maximize each generator's profit given a set of market clearing prices. Hogan and Ring (2003) proved that CHP scheme minimizes uplift payment. Moreover, CHP gives a monotonically non-decreasing total cost function with respect to total load demand, in other words, higher price under higher demand.

The following example, which is modified based on examples in Gribik *et al.* (2007), is given to illustrate CHP scheme. Table 2.1 summarizes generators' bids in this example.

Table 2.1: Generator Bids

Gen	G1	G2	G3
fixed cost ($)	50	300	100
EcoMin (MW)	0	10	50
EcoMax (MW)	20	100	100
variable cost ($/MW)	40	10	20

In this example, there are three generators with different biding parameters. Figure 2.1 shows the total cost function with respect to total load demand. The blue curve represents the total cost curve under standard LMP scheme. It can be seen that this blue line is not a convex function. Moreover, it is not even a continuous function. The non-convexity is due to the discrete nature of unit commitment as discussed in the previous section. As load increases, new resource will be committed which causes the jumps in total cost function. The red curve represents the convex hull of the total cost function.

Figure 2.2 represents the corresponding energy prices. The price under standard LMP goes up and down as total loads increase, while the price under CHP is monotonically non-decreasing.

Uplift payment is required in both standard LMP and CHP schemes. Under standard LMP, for instance, when total load is 50MW, the most economic dispatch is to commit G2 only and dispatch 50MW. The total cost is $300 + 10 * 50 = 800$. However, the energy is priced at $10/MW, the revenue of the G2 is $10 * 50 = 500$. The received revenue is not enough to cover the total cost. Then, G2 has no incentive

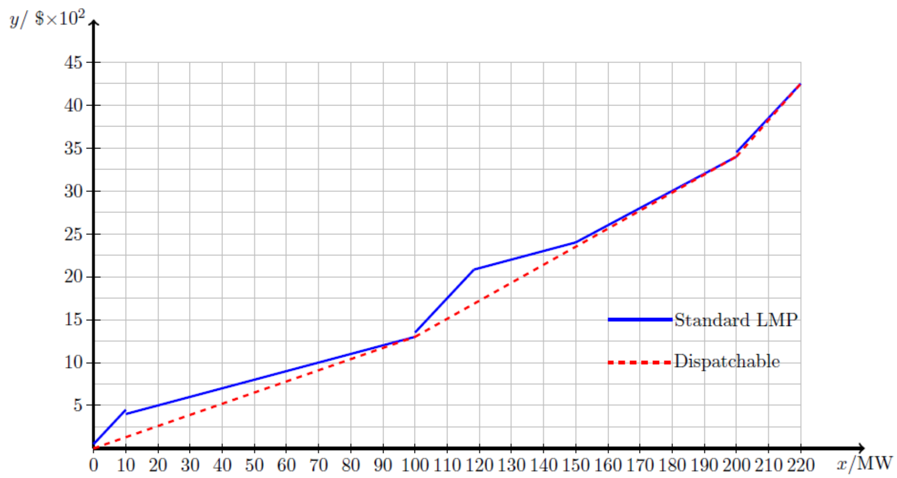

Figure 2.1: Total Cost with respect to Total Loads

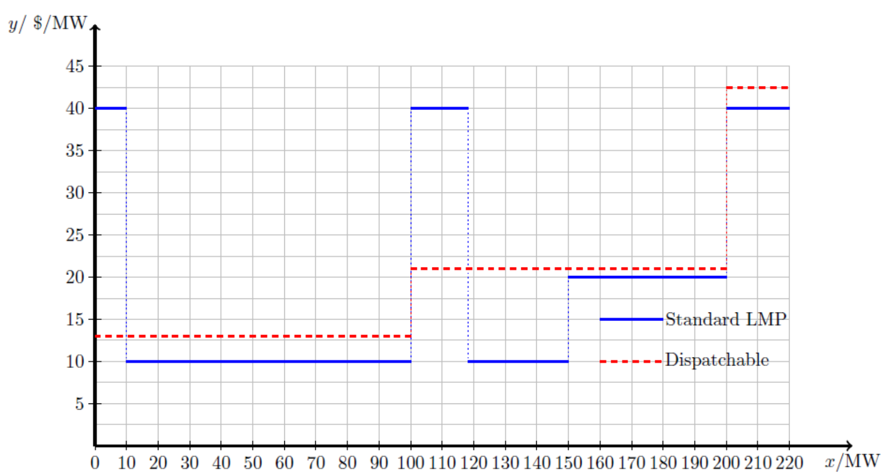

Figure 2.2: Marginal Cost with respect to Total Loads

to commit and generating power since it loses money. In order to maximize social welfare, i.e., encourage generator to stick with the most economic dispatch, RTO/ISO pays G2 $300 to bring its profit from negative to zero. Similarly, under CHP scheme, when the total load demand is 110MW, the optimal dispatch solution will be that G2 produces 100MW and G1 produces 10MW. The total cost for G1 is $50 + 10 * 40 = 450$. The energy is priced at $21/MW, thus the revenue of G1 is $10 * 21 = 210$. An uplift payment of $240 is required.

2.3 Formulation

The UC models presented here are based on Hedman *et al.* (2010). Subsection 2.3.1 gives the formulation for the ED UC model while subsection 2.3.2 gives the DCOPF UC model.

2.3.1 Economic Dispatch Unit Commitment

$$\min \quad \sum_{\forall t}\sum_{\forall g}\left(C_g^{SU} v_{gt} + C_g^{NL} u_{gt} + C_g p_{gt}\right) \tag{2.1}$$

$$\text{s.t.} \quad \sum_{\forall g} p_{gt} = \sum_{\forall n} D_{nt} \qquad \forall t \tag{2.2}$$

$$P_g^{\min} u_{gt} \leq p_{gt} \leq P_g^{\max} u_{gt} \qquad \forall g,t \tag{2.3}$$

$$v_{gt} - w_{gt} = u_{gt} - u_{g,t-1} \qquad \forall g,t \tag{2.4}$$

$$\sum_{i=t-UT_g+1}^{t} v_{gi} \leq u_{gt} \qquad \forall g,t \tag{2.5}$$

$$\sum_{i=t-DT_g+1}^{t} w_{gi} \leq 1 - u_{gt} \qquad \forall g,t \tag{2.6}$$

$$p_{gt} - p_{g,t-1} \leq R_g^{hr} u_{g,t-1} + R_g^{SU} v_{gt} \qquad \forall g,t \tag{2.7}$$

$$p_{g,t-1} - p_{gt} \leq R_g^{hr} u_{gt} + R_g^{SD} w_{gt} \qquad \forall g,t \tag{2.8}$$

$$0 \leq v_{gt}, w_{gt} \leq 1 \qquad \forall g,t \tag{2.9}$$

$$u_{gt} \in \{0,1\} \qquad \forall g,t \tag{2.10}$$

The ED UC formulation is presented below. The objective function is given by (2.1), which includes startup costs, no-load costs, and generation variable costs. Equation (2.2) gives the constraints on the system balance. The constraints on the generators' minimum and maximum production are given by (2.3). Equation (2.4) specifies the relations between the UC status variables and startup, shutdown variables. Equations (2.5) and (2.6) give the constraints on the generators' minimum up/down time, which are facet defining constraints for the u, v restriction (Rajan and Takriti, 2005). Generator ramp-rate constraints are given by (2.7) and (2.8). Equation (2.9) define the bounds on startup and shutdown variables. Equation (2.10) defines the UC status variables as binary. Note that (2.9)-(2.10), along with (2.4)-(2.6), force the startup and shutdown variables to be binary even though they are relaxed to be continuous.

2.3.2 Direct Current Optimal Power Flow Unit Commitment

The direct current optimal power flow (DCOPF) based UC model is based on the ED UC formulation; the additional constraints that are required beyond the ED UC formulation are provided below.

$$\sum_{\forall l \in \delta^+(n)} f_{lt} - \sum_{\forall l \in \delta^-(n)} f_{lt} + \sum_{\forall g \in G(n)} p_{gt} = D_{nt} \qquad \forall n, t \qquad (2.11)$$

$$f_{lt} = B_l(\theta_{nt} - \theta_{mt}) \qquad \forall l, t : l \in (m, n) \qquad (2.12)$$

$$-F_l \leq f_{lt} \leq F_l \qquad \forall, t \qquad (2.13)$$

The node-balance, power flow, and power flow limit constraints are given by (2.11)-(2.13) respectively.

2.4 Methods

The methods for calculating the LMP and CHP are presented below.

2.4.1 LMP Calculation

LMPs are obtained by first solving the model presented by (2.1)-(2.13). The integer variables are then fixed to their optimal values, thereby producing a linear program. The LMPs are then the dual solution corresponding to the node-balance constraint (2.11); note that for an ED model where there is no optimal power flow formulation, the LMPs can be considered to come from the supply equals demand constraint (2.2), which would give a single price to the entire system since the ED structure assumes that there is a single bus. An alternative linear program can be created by relaxing the integrality constraints on the commitment variables while adding equality constraints that restrict them to their optimal values (Gribik *et al.*, 2007). For either formulation, the LMPs are the dual optimal solution associated to the node-balance constraints.

2.4.2 CHP Calculation

CHPs are given by the slope of the convex hull of the total cost function within UC. To determine the CHPs, the technique based on the Wang *et al.* (2012) ELMP model is implemented. Lagrangian relaxation is applied to the node-balance constraints to form the convex hull of the total cost function. The CHPs are then given by the optimal Lagrange dual solution of the node-balance constraints.

In the following, the Lagrangian relaxation formulation is first provided; second, the Lagrangian dual problem is shown to be a concave and piecewise linear function, which allows the problem to be solved by using the subgradient algorithm; finally, the decomposition method is introduced to simplify the problem into sub-problems for each generator by relaxing the system node-balance constraints. Note that the following derivation is for the ED UC model; however, the derivation also applies to the DCOPF UC model.

Lagrangian Relaxation

Consider the ED UC model and apply Lagrangian relaxation by relaxing (2.2). Denote the resulting Lagrangian dual optimal objective value as z_{LD}, then $z_{LD} \leq z_{EDUC}$, where z_{EDUC} is the objective value of the ED UC problem (Bazaraa *et al.*, 2006). The Lagrangian dual problem is described as follows.

$$z_{LD} = \max z_{LR}(\lambda)$$

where

$$\begin{aligned} z_{LR}(\lambda) = \min & \left[\sum_{\forall g} \sum_{\forall t} \left(C_g^{SU} v_{gt} + C_g^{NL} u_{gt} + C_g p_{gt} \right) - \sum_{\forall t} \lambda_t \left(\sum_{\forall g} p_{gt} - \sum_{\forall n} D_{nt} \right) \right] \\ \text{s.t.} \quad & (2.3) - (2.10) \end{aligned}$$

Concavity

Denote the feasible set of (2.3)-(2.10) as $\{p_{gt}, u_{gt}, v_{gt}, w_{gt}\} \in Q$. Note that $conv(Q)$ is a polytope since $\{p_{gt}, u_{gt}, v_{gt}, w_{gt}\}$ are all bounded. Denote $\{p_{gt}^j, u_{gt}^j, v_{gt}^j, w_{gt}^j\}, \forall j = 1, 2, \cdots, J$ as the extreme points of $conv(Q)$, then

$$z_{LR}(\lambda) = \min\{f^j(\lambda), \forall j = 1, 2, \cdots, J\}$$

where $f^j(\lambda) = \sum_{\forall g} \sum_{\forall t} \left(C_g^{SU} v_{gt}^j + C_g^{NL} u_{gt}^j + C_g p_{gt}^j \right) - \sum_{\forall t} \lambda_t \left(\sum_{\forall g} p_{gt}^j - \sum_{\forall n} D_{nt} \right), \forall j = 1, 2, \cdots, J$, since the minimum is obtained at the extreme points of $conv(Q)$.

Proposition. *$z_{LR}(\lambda)$ is a piecewise linear concave function.*

Proof. Since, $\{p_{gt}^j, u_{gt}^j, v_{gt}^j, w_{gt}^j\}, \forall j$ are fixed parameters, $f^j(\lambda)$ is a linear function of λ. Moreover, $z_{LR}(\lambda)$ is the minimum of a finite set of linear functions $f^j(\lambda), \forall j = 1, 2, \cdots, J$, thus, $z_{LR}(\lambda)$ is piecewise linear function with finite many break points.

For any two points λ^1, λ^2, let $\lambda^3 = \alpha\lambda^1 + (1-\alpha)\lambda^2$ be a convex combination of λ^1, λ^2, where $\alpha \in (0,1)$. Without loss of generality, suppose $f^{j^*}(\lambda^3)$ is the minimum function for λ^3. Then

$$\begin{aligned} z_{LR}(\lambda^3) &= f^{j^*}(\lambda^3) \\ &= f^{j^*}(\alpha\lambda^1 + (1-\alpha)\lambda^2) \\ &= \alpha f^{j^*}(\lambda^1) + (1-\alpha) f^{j^*}(\lambda^2) \\ &\geq \alpha \min\{f^j(\lambda^1), \forall j\} + (1-\alpha)\min\{f^j(\lambda^2), \forall j\} \end{aligned}$$

That is,

$$z_{LR}(\alpha\lambda^1 + (1-\alpha)\lambda^2) \geq \alpha z_{LR}(\lambda^1) + (1-\alpha) z_{LR}(\lambda^2), \forall \alpha \in (0,1)$$

Therefore, $z_{LR}(\lambda)$ is concave. □

Corollary. *Let* $\xi_t(\bar{\lambda}) = \left(\sum_{\forall g} p^*_{gt} - \sum_{\forall n} D_{nt}\right), \forall t$, *where* $\{p^*_{gt}, u^*_{gt}, v^*_{gt}, w^*_{gt}\}$ *is the optimal solution for* $z_{LR}(\bar{\lambda})$ *subject to* $\{p_{gt}, u_{gt}, v_{gt}, w_{gt}\} \in Q$.

Then $-\xi(\bar{\lambda}) = -\left[\xi_1(\bar{\lambda}), \xi_2(\bar{\lambda}), \cdots, \xi_T(\bar{\lambda})\right]$ *is a subgradient of* $z_{LR}(\lambda)$ *at* $\lambda = \bar{\lambda}$.

Proof. By fixing $\lambda = \bar{\lambda}$, let $f^{j^*}(\bar{\lambda}) = \min\{f^j(\bar{\lambda}), \forall j\}$. Then, $z_{LR}(\lambda) = f^{j^*}(\lambda)$ at $\bar{\lambda}$. By definition, $\xi_t(\bar{\lambda}) = \left(\sum_{\forall g} p^*_{gt} - \sum_{\forall n} D_{nt}\right), \forall t$. So $\xi(\bar{\lambda}) = \left[\xi_1(\bar{\lambda}), \xi_2(\bar{\lambda}), \cdots, \xi_T(\bar{\lambda})\right]$ is the gradient of the linear function $f^{j^*}(\lambda)$.

Then $\forall \lambda$, $-z_{LR}(\lambda) \geq -f^{j^*}(\lambda) = -f^{j^*}(\bar{\lambda}) - \xi(\bar{\lambda})(\lambda - \bar{\lambda})$. Therefore, $-\xi(\bar{\lambda})$ is a subgradient of $-z_{LR}(\lambda)$ at $\bar{\lambda}$. □

Decomposition

With the corollary, the Lagrangian dual problem can be solved by subgradient algorithms on λ. In a subgradient algorithm, in each iteration, a Lagrangian relaxation problem is solved for a fixed $\bar{\lambda}$. The Lagrangian relaxation problem can be decomposed into a set of sub-problems by generator.

By re-ordering the terms in z_{LR},

$z_{LR} = \min \left[\sum_{\forall g} \sum_{\forall t} \left(C_g^{SU} v_{gt} + C_g^{NL} u_{gt} + C_g p_{gt} - \lambda_t p_{gt} \right) + \sum_{\forall t} \lambda_t \left(\sum_{\forall n} D_{nt} \right) \right]$

Denote $z_{LR} = \min \sum_{\forall g} L_g + \sum_{\forall t} \lambda_t \left(\sum_{\forall n} D_{nt} \right)$

where $L_g \equiv \sum_{\forall g} \sum_{\forall t} \left(C_g^{SU} v_{gt} + C_g^{NL} u_{gt} + C_g p_{gt} - \lambda_t p_{gt} \right)$.

The subprobelm $z_{LR_g}(\lambda), \forall g$ is defined as:

$$z_{LR_g}(\lambda) = \min \sum_{\forall g} \sum_{\forall t} \left(C_g^{SU} v_{gt} + C_g^{NL} u_{gt} + C_g p_{gt} - \lambda_t p_{gt} \right)$$

$$\text{s.t.} \quad (2.3) - (2.10)$$

2.4.3 Subgradient Algorithm

The subgradient algorithm to find the optimal solution of λ, i.e. the CHP, is described as follows.

Algorithm 1 Subgradient Algorithm

```
Initialize: i = 0, given λ^(0)
repeat
   i = i + 1
   p^(i) = solution of LR(λ^(i-1))
   ξ^(i) = solution of DR(p^(i))
   λ^(i) = λ^(i-1) + β^(i) ξ^(i)
until ||λ^(i) − λ^(i-1)|| < ε
return λ^(i)

LR(λ̄)
for g ∈ G do
   solve L_g(λ̄) get p*_gt
end for
return p

DR((p̄)
for t ∈ T do
   ξ_t = Σ_∀g p̄_gt − Σ_∀n D_nt
end for
ξ = ξ/||ξ||
return ξ
```

$\beta^{(i)}$ is the step size for iteration i, which satisfies $\sum_{i=1}^{\infty} \beta^{(i)} = \infty. \lim_{i \to \infty} \beta^{(i)} = 0$

2.5 Test Results

In this chapter, a modified version of the IEEE RTS96 single zone model is used, which consists of 24 buses, 33 generators, and 37 lines; the problem is formulated as a day-ahead UC problem with 24 periods. Additional information can be found in University of Washington (2015). The optimization is performed using IBM ILOG CPLEX version 12.4 with Concert Technology version 3.6.

First, the uplift payments are examined under two pricing mechanisms for both the ED UC and DCOPF UC models. In this chapter, the uplift payments are reserved solely for generation participants facing negative profits. The uplift payments are then socialized uniformly amongst the load according to the percent of total load.

The test results confirm that CHP reduces uplift payments compared to LMP. Table 2.2 represents the total uplift payments and the corresponding price increase for the ED UC and DCOPF UC models. Table 2.2 shows that the uplift payments under CHP are lower than with the LMP mechanism for both models. Additionally, under both pricing mechanisms, the price increase due to the uplift payments is relatively small, under \$2/MWh, compared to typical ranges for the LMP and CHP.

Table 2.2: Uplift Payment Comparison

	ED UC	DCOPF UC
uplift payment under LMP	\$90,576	\$63,969
(socialized uplift payment)	(\$1.60/MWh)	(\$1.13/MWh)
uplift payment under CHP	\$38,294	\$21,107
(socialized uplift payment)	(\$0.67/MWh)	(\$0.37/MWh)
percentage difference	-57.7%	-67.0%

In some situations, the consideration of the uplift payments into the locational prices charged to the load can reverse the relation of the locational load payments under the two pricing mechanisms; i.e., CHP > LMP but CHP + uplifts < LMP + uplifts. However, this situation rarely occurs in the test case since the socialized uplift payments are small.

Next, the total load payment, generation cost, generation revenue, and generation rent under LMP and CHP are examined for the ED UC and DCOPF UC models. Table 2.3 and Table 2.4 represent the results for the ED UC and DCOPF UC models respectively. Additionally, Table 2.4 gives the total congestion rent for the DCOPF UC model. Note that the uplift payments are included in the total load payment, generation revenue, and generation rent values calculation. The results show that the total load payment, generation revenue, and generation rent are higher under CHP than LMP for both the ED UC and DCOPF UC models. The total congestion rent in the DCOPF UC model is increased under CHP as well. It is important to note that the LMP and CHP mechanisms will not affect the operations in power systems as both pricing mechanisms are based on the same UC and ED solutions. Thus, the total generation cost and social welfare remain the same under each pricing mechanism as only the allocation of wealth differs.

Table 2.3: Load Payment and Generation Rent Comparison under ED UC

	LMP($)	CHP($)	percentage difference
total load payment	3,242,963	3,623,765	11.74%
total generation revenue	3,242,963	3,623,765	11.74%
total generation rent	2,203,858	2,584,660	17.28%
total generation cost	$ 1,039,104		

Table 2.4: Load Payment and Generation Rent Comparison under DCOPF UC

	LMP($)	CHP($)	percentage difference
total load payment	3,004,502	3,413,857	14.33%
total generation revenue	2,113,497	2,378,503	12.54%
total generation rent	999,625	1,264,631	26.51%
total congestion rent	891,005	1,056,460	18.57%
total generation cost	$ 1,113,872		

With the LMP pricing mechanism, existing simultaneous feasibility tests (SFT) guarantee revenue adequacy for the financial transmission rights (FTR) market, under a set of assumptions (Hogan, 1992); however, even with the same assumptions, the CHP pricing mechanism does not guarantee revenue adequacy for the FTR markets. There is no guarantee that the congestion rent is sufficient to compensate the FTR holders with the CHP pricing mechanism. It has been shown in Cadwalader *et al.* (2010) that the duality gap between the optimal values of the Lagrangian dual problem and the UC problem serves as an upper bound on the funds required to incentivize the market solution and includes the funds required to guarantee revenue adequacy for the FTR market.

The prices for certain nodes and certain periods under LMP and CHP, i.e., LMP + uplifts and CHP + uplifts, are examined in the following. Figure 2.3 represents the LMP + uplifts and CHP + uplifts by period for the ED UC model. As shown in Figure 2.3, for any given period, the LMP + uplifts can be higher than the CHP + uplifts and vice versa. The LMP + uplifts is higher than the CHP + uplifts for periods 1-6 and 24 while the CHP + uplifts is higher for periods 7-23. For the periods that the LMP + uplifts is higher, the average increase in price is $1.48/MWh (maximum is $2.84/MWh); in contrast, the average increase in price for the periods where the CHP + uplifts is higher is $25.02/MWh (maximum is $63.60/MWh).

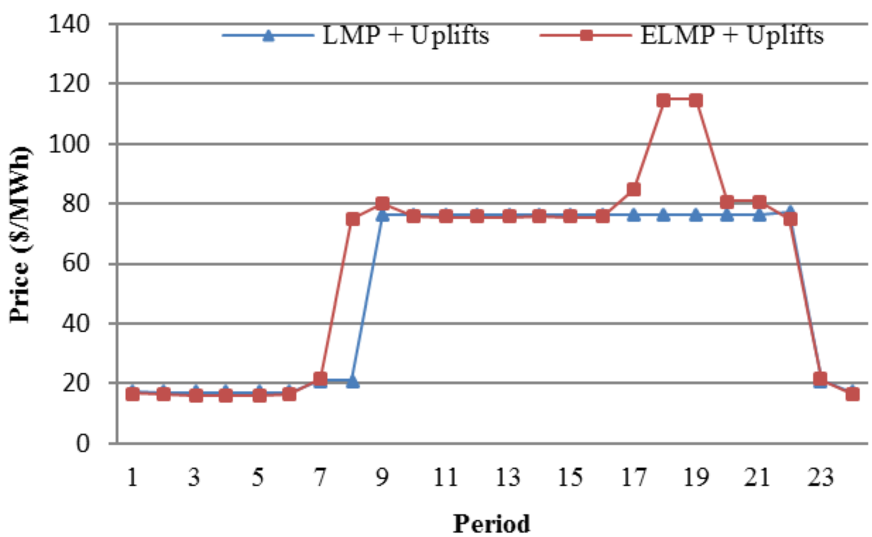

Figure 2.3: Prices Comparison by Period under ED UC

To compare the LMP and the CHP mechanisms in the DCOPF UC model, test results are examined and three representative examples are selected to illustrate the relationship between LMP + uplifts and CHP + uplifts during certain periods. Figure 2.4 displays the LMP + uplifts and CHP + uplifts at each node for period 6. As shown in Figure 2.4, for any given node, the LMP + uplifts can be higher than the CHP + uplifts and vice versa. Figure 2.5 and Figure 2.6 display the LMP + uplifts and CHP + uplifts at each node for periods 9 and 20 respectively. Figure 2.5 shows that, for all nodes, the CHP + uplifts are higher than the LMP + uplifts for period 9; Figure 2.6 shows that the LMP + uplifts are higher than the CHP + uplifts at all nodes for period 20. Additionally, for all nodes, the LMP + uplifts are higher than the CHP + uplifts for periods 10, 11, and 20; the CHP + uplifts are higher than the LMP + uplifts at all nodes for periods 9, 17-19, and 21. For the periods that the LMP + uplifts is higher, the average increase in price is \$10.07/MWh (maximum is \$13.06/MWh); in contrast, the average increase in price for the periods that the CHP + uplifts is higher is \$20.60/MWh (maximum is \$34.48/MWh).

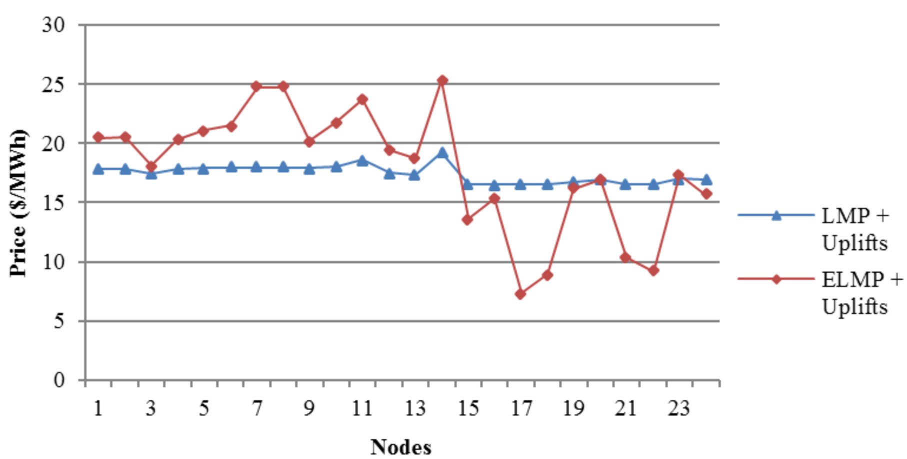

Figure 2.4: Prices Comparison for Period 6 under DCOPF UC

The above discussion shows that there is no systemic pattern between the LMP + uplifts and the CHP + uplifts for a given node or for a given period. The relations

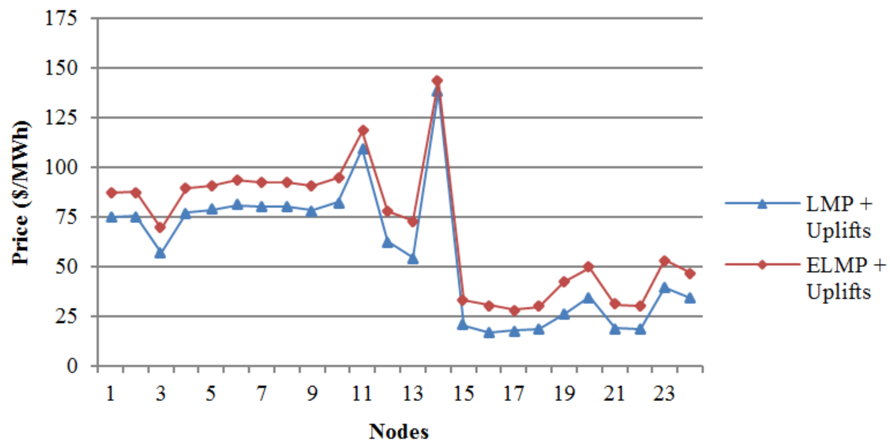

Figure 2.5: Prices Comparison for Period 9 under DCOPF UC

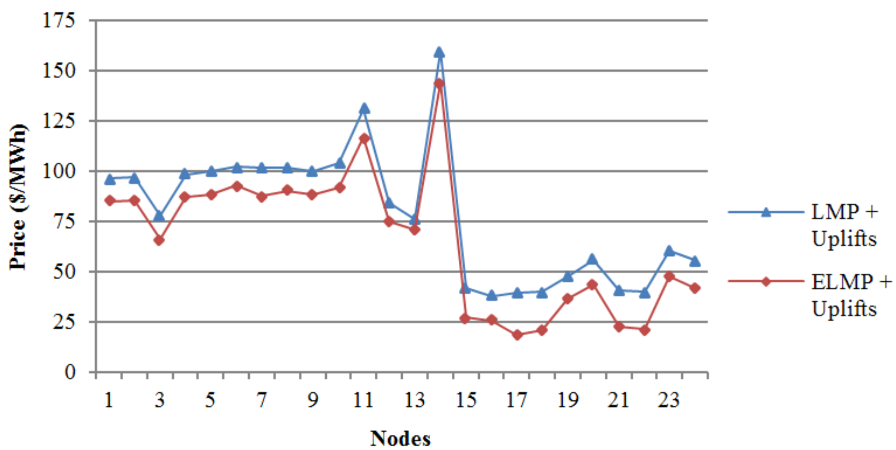

Figure 2.6: Prices Comparison for Period 20 under DCOPF UC

of the two prices vary with different nodes and different periods.

Finally, the price sensitivity based on the change of loads is examined. The test results show that, with congestion, the CHP + uplifts is no longer a monotonically non-decreasing function with respect to the load. Figure 2.7 shows one instance at node 1 for period 17. The non-monotonicity is caused by the congestion in the network. One of the main arguments in support of the CHP is that it creates a monotonically nondecreasing function with respect to the load for economic dispatch (with unit commitment) problems, as shown in Gribik *et al.* (2007). Frequently, the marginal cost to produce a good increases as one wishes to produce more and, thus, the CHP has been argued to be a better mechanism than the LMP since the LMP is not monotonic due to the non-convexities within unit commitment.

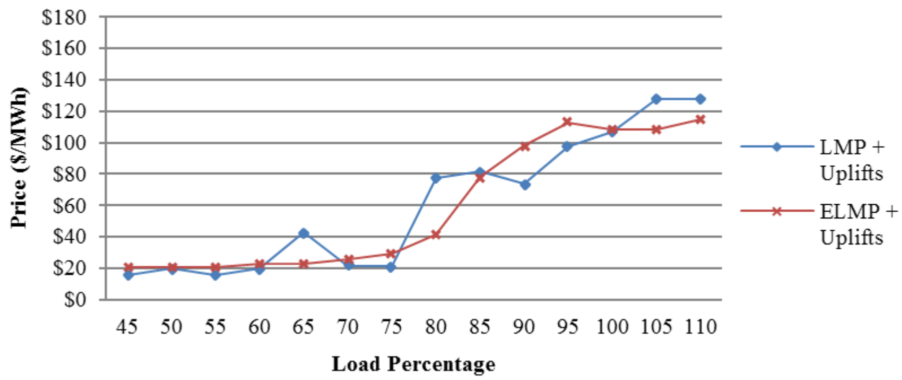

Figure 2.7: Prices Comparison with respect to Total Load Percentage

The purpose of a price is to be an economic signal to properly incentivize market behavior in order to achieve the social welfare maximizing solution. The nature of the system is not convex and not well-behaved; the desire should not be to design a settlement policy simply to produce well-behaved pricing function but to develop the best economic signal to incentivize proper market behavior and, for non-convex markets, the pricing function may not have such characteristics. Thus, the argument must first be based on the pricing mechanism's ability to achieve the desired market outcome as opposed to whether it has such characteristics. Furthermore, as shown by Figure 2.7, non-monotonicity will still occur once one introduce an optimal power flow formulation into the market structure. The final answer is that neither LMP nor CHP provide a pricing mechanism that appropriately captures all aspects of what people would desire to have as a pricing mechanism in electric energy markets.

2.6 Conclusions

In this chapter, the effects of the LMP mechanism and the CHP mechanism within wholesale energy markets are analyzed. The primary advantage of the CHP mechanism is that uplift payments are minimized. However, by incorporating fixed costs into the locational uniform price, the CHP is not a market clearing price for the market dispatch solution, which is an important advantage of the LMP mechanism. The results show that the CHPs + uplifts can be higher or lower than the LMPs + uplifts at each node. Additionally, the total load payment, generation revenue, and generation rent are increased under CHP over LMP for both the ED UC and DCOPF UC models. The total congestion rent in the DCOPF UC model is also increased under CHP. Furthermore, because CHP is not a market clearing price for the market dispatch solution, the simultaneous feasibility test does not guarantee revenue adequacy for the FTR market.

Implementing the convex hull pricing takes much more efforts since solving the dual of a mixed integer problem (MIP) is extremely hard. Few RTO/ISO have been convinced to switch to the convex hull pricing even though they understand the issues of standard LMP. Although CHP scheme minimizes the amount uplift payment, the uplift payment is not eliminated under this scheme since the duality gap of MIP.

At this time, it is difficult to conclude that CHP is outright the preferred mechanism. Further studies are needed to confirm how the CHP mechanism will affect the load payment and the generation rent as compared to the LMP pricing mechanism. A better pricing scheme is desired but it may not solve all potential issues in DAM.

Chapter 3

STOCHASTIC DISPATCHABLE PRICING

3.1 Introduction

A well-designed pricing scheme should provide a proper pricing signal and be incentive compatible. The currently utilized locational marginal price scheme releases a proper pricing signal for dispatch, but fails to capture commitment costs. Moreover, price inconsistency exists between day-ahead and real-time markets under the current deterministic pricing scheme. As more intermittent renewable resources are being introduced to power grids, the inconsistency is expected to be amplified.

Currently, two-thirds of the population in the U.S. is served by an Independent System Operator (ISO) or Regional Transmission Organization (RTO) for wholesale electricity trades. The ISO/RTOs coordinate system operations with different markets and services including but not limited to energy markets, financial transmission rights markets, capacity markets, ancillary services, and congestion management (California ISO, 2015). Those markets and services are designed with the goal of being incentive compatible (i.e., to induce all participants to truthfully reveal private information and have no incentive to deviate from market solutions) in order to bring competition and ultimately to maximize social welfare (producer surplus, consumer surplus and congestion rent). Electricity differs from ordinary products in several ways: demand is close to perfectly inelastic; supply and demand must be in balance to maintain system frequency continuously under high uncertainty; electricity travels in the power grid with very fast speed and follows Kirchhoff's laws; storage is usually considered too expensive with current technologies; most generators take some time to start up and shut down, and once they are on or off, they need to stay on or off for minimum up and down times. Due to the unique nature of the electricity commodity, pricing schemes play a very important role in electricity market design.

A well-designed pricing scheme should release proper pricing signals and induce participants' behavior to maximize social welfare. The term, pricing signal, is used to describe the forward informational value of the market clearing price that is used to settle the market.

The focus of this chapter is on pricing schemes in day-ahead energy markets (DAM). The analysis here does not consider the potential exercise of market power and assumes all participants behave non-strategically. The analysis focuses on pricing signals under different pricing schemes.

The current locational marginal pricing (LMP) scheme in DAM, referred to as restricted LMP from now on, is described as follows. The ISO/RTO first solves a security-constrained unit commitment (SCUC) problem based on the bids from both the supply and demand sides. The solution from SCUC try to ensure that enough generators will be turned on to maintain system reliability under uncertainty while keeping economic efficiency at the same time. Then, by fixing the unit commitments, a security-constrained economic dispatch (SCED) model with network constraints is solved, and LMPs are obtained as the dual variables of node-balance constraints. The dual variable represents the change in the objective (total economic surplus) when a small amount increment/decrement of power is consumed at the corresponding location. It releases a proper pricing signal for the marginal cost of dispatch.

Two issues with this restricted LMP scheme are specifically addressed in this chapter, failure to respond to non-convexity and uncertainty in energy markets.

DAM includes non-convex effects due to the discrete nature of unit commitment decisions (O'Neill *et al.*, 2005). Committing a generator will incur sunk costs such as startup cost and no-load cost. Moreover, minimum generation requirements and minimum up and down time constraints also contribute to the non-convexities. Since the restricted LMP does not take commitment costs into consideration, a generator's revenue may not be sufficient to cover all its costs. Then, the ISO/RTO pays the generator uplift payments to bring its negative net profit to zero, thereby giving the generator an incentive to commit according to the DAM schedule (O'Neill *et al.*, 2005). On the other hand, if the market price is higher than a generator's marginal cost, the generator has incentive to produce to EcoMax in order to maximize profits. If the market solution instructs the generator to dispatch under EcoMax, then lost opportunity cost uplift payment is paid to compensate the mis-incentives. Gribik *et al.* (2007) proposed a convex hull pricing (CHP) scheme, which takes the dual of the entire unit commitment model, setting prices as the Lagrange multipliers of node-balance constraints. The CHP aims at giving better pricing signals than the restricted LMP. Gribik *et al.* (2007) proved that CHP minimizes uplift payments. Moreover, it gives a monotonically non-decreasing marginal cost function with respect to total loads, whereas the restricted LMP does not. In order to calculate CHPs, the dual problem of a mixed integer programing needs to be solved, which is computationally difficult. Gribik *et al.* (2007) also discussed a dispatchable model. For a single-bus, single-period model, Gribik *et al.* (2007) showed that the prices under the dispatchable model are the same as that under CHP, by relaxing generation minimum requirement constraints and allocating fixed cost to generation variable cost. The ISO/RTOs have implemented modifications based on the restricted LMP to reduce uplift payments. Most ISO/RTOs amortize startup and no-load costs to generation variable cost to set generation marginal cost (Federal Energy Regulatory Commission, 2014a). Moreover, some ISO/RTOs allow committed inflexible fast-start generators to set energy prices although they cannot change their dispatch. Several ISO/RTOs, such as ISO-NE, NYISO, MISO, allow off-line fast-start units to set energy prices (Federal Energy Regulatory Commission, 2014a). Although many efforts have been devoted to deal with uplift payments, no method claims to eliminate uplift payments completely. In fact, Gribik (2007) states that the discrete nature of commitment decisions, startup costs, and no-load costs may prevent the existence of an efficient market clearing price in DAM since there is generally no set of market prices that would induce profit maximizing generators and loads to voluntarily follow the pricing scheme.

Standard energy markets' setup has both DAM and a real-time energy market (RTM). When designing pricing schemes for DAM, its impacts on RTM should be considered jointly. The restricted LMP adopts a deterministic model, i.e., taking expected or forecasted values of uncertain parameters as input data. Zavala *et al.* (2014) demonstrated and proved that price inconsistency exists between DAM and RTM with the restricted LMP. In other words, the expected RTM price differs from the DAM price. Market manipulation could happen if a participant sees persistent price premia between RTM and DAM, which consequently can cause problems such as revenue inadequacy (Zavala *et al.*, 2014). Therefore, a deterministic model that is based on summarizing statistics will not result in an efficient pricing scheme under high uncertainty: hence, a stochastic model is desired. Pritchard *et al.* (2010) and Morales *et al.* (2012) studied stochastic pricing schemes. The stochastic pricing scheme is usually a two-stage model, where the first stage represents DAM and the second stage simulates RTM. In the second stage, a set of plausible scenarios are included as predicted scenarios of RTM. Stochastic pricing schemes can be seen as a methodology to smooth LMP changes in DAM. Under the restricted LMP, at some load points, the LMP "jumps" dramatically. Under stochastic pricing schemes, DAM energy prices are still set as the dual variables of the node-balance constraints; however, by including plausible RTM scenarios, the returned prices are consistent with

RTM prices and price gaps are reduced.

In this chapter, a new pricing scheme in DAM is proposed by relaxing constraints that cause non-convexities and adopting a stochastic pricing formulation simultaneously. The proposed pricing scheme has the following advantages: 1) it addresses both non-convexities and uncertainty issues in DAM, and none of the existing literature has studied these two issues jointly; 2) the pricing run can be separated from unit commitments; 3) the resulting marginal price is a monotonically non-decreasing function with respect to total loads; 4) reduced uplift payments; 5) low computational complexity.

The rest of the chapter is organized as follows. Section 3.2 gives the mathematical model of the proposed new pricing scheme. Section 3.3 demonstrates two test case results. Finally, Section 3.4 concludes the chapter.

3.2 Pricing Model

In this section, the proposed pricing model is given first, followed by the explanation and analysis of the model.

3.2.1 Model Overview

$$\min \quad \sum_{\forall s:s\neq 0} \pi^s \sum_{\forall t} \left[\sum_{\forall g} (C_g^M p_{gt}^s + \delta_g \Delta p_{gt}^s) + \sum_{\forall j} (C_j w_{jt}^s + \eta_j \Delta w_{jt}^s) \right] \tag{3.1}$$

$$\text{s.t.} \quad 0 \leq p_{gt}^s \leq P_g^{\max} \qquad \forall g, t, s \tag{3.2}$$

$$0 \leq w_{jt}^s \leq W_{jt}^s \qquad \forall j, t, s \tag{3.3}$$

$$\sum_{\forall g \in G(n)} p_{gt}^0 + \sum_{\forall j \in J(n)} w_{jt}^0 - i_{nt}^0 = D_{nt} \qquad \forall n, t \qquad (\lambda_{nt}) \tag{3.4}$$

$$\sum_{\forall g \in G(n)} (p_{gt}^s - p_{gt}^0) + \sum_{\forall j \in J(n)} (w_{jt}^s - w_{jt}^0) - (i_{nt}^s - i_{nt}^0) = 0$$

$$\forall n, t, s : s \neq 0 \qquad (\pi^s \mu_{nt}^s) \tag{3.5}$$

$$\sum_{\forall n} i_{nt}^s = 0 \qquad \forall t, s \tag{3.6}$$

$$-F_l \leq \sum_{\forall n} \psi_{nl} i_{nt}^s \leq F_l \qquad \forall l, t, s \tag{3.7}$$

$$p_{gt}^s - p_{g,t-1}^s \leq R_g^{hr} \qquad \forall g, t, s \tag{3.8}$$

$$p_{g,t-1}^s - p_{gt}^s \leq R_g^{hr} \qquad \forall g, t, s \tag{3.9}$$

$$\Delta p_{gt}^s \geq p_{gt}^s - p_{gt}^0 \qquad \forall g, t, s : s \neq 0 \tag{3.10}$$

$$\Delta p_{gt}^s \geq p_{gt}^0 - p_{gt}^s \qquad \forall g, t, s : s \neq 0 \tag{3.11}$$

$$\Delta w_{jt}^s \geq w_{jt}^s - w_{jt}^0 \qquad \forall j, t, s : s \neq 0 \tag{3.12}$$

$$\Delta w_{jt}^s \geq w_{jt}^0 - w_{jt}^s \qquad \forall j, t, s : s \neq 0 \tag{3.13}$$

$$0 \leq p_{gt}^s \leq Q_g \qquad \forall g, t, s : s \neq 0 \tag{3.14}$$

$$\Delta w_{jt}^s \geq 0 \qquad \forall j, t, s : s \neq 0 \tag{3.15}$$

The problem is formulated as a 24-period day-ahead model with uncertainty. The uncertainty in this pricing model represents the intermittent wind power generation in power grids, i.e., the realized available wind generation capacity W_{jt}^s in the real-time scenarios. The model adopts a direct current optimal power flow (DCOPF) formulation. Equation (3.1) is the objective function that minimizes the expected scenario-based dispatch costs. Equation (3.2) is the generation level constraint for traditional generators. Equation (3.3) is the generation level constraint for wind farms. Equation (3.4) is the node-balance constraint for the base case. Equation (3.5) is the node-balance constraint for plausible real-time scenarios. Equation (3.6) is the total injection constraint. Equation (3.7) restricts transmission line flows. Equations (3.8) and (3.9) specify hourly ramping rate constraints. Equations (3.10)-(3.15) specify the generation deviation between base case and plausible scenarios.

3.2.2 Stochastic Pricing Framework

The proposed model is based on the stochastic pricing framework proposed in Pritchard *et al.* (2010). As described in the previous section, stochastic pricing models have two stages. The first stage corresponds to the day-ahead base case ($s = 0$) and the second stage includes a set of plausible real-time scenarios ($\forall s, s \neq 0$).

The original objective function is composed of two components: the first-stage costs and the expected second-stage re-dispatch costs. The original objective can be described in detail as follows.

$$\begin{aligned}
&\sum_{\forall t}\sum_{\forall g} C_g^M p_{gt}^0 + \sum_{\forall t}\sum_{\forall j} C_j w_{jt}^0 \\
&+ \mathbb{E}\Bigg[\sum_{\forall t}\sum_{\forall g}\left(C_g^{M+}(p_{gt}^s - p_{gt}^0)_+ - C_g^{M-}(p_{gt}^s - p_{gt}^0)_-\right) \\
&\qquad + \sum_{\forall t}\sum_{\forall j}\left(C_j^+(w_{jt}^s - w_{jt}^0)_+ - C_j^-(w_{jt}^s - w_{jt}^0)_-\right)\Bigg] \qquad (3.16)
\end{aligned}$$

where $C_g^{M+} = C_g^M + \delta_g, \forall g$; $C_g^{M-} = C_g^M - \delta_g, \forall g$; $C_j^+ = C_j + \eta_j, \forall j$; $C_j^- = C_j - \eta_j, \forall j$; $(p)_+ = \max\{0, p\}$; $(p)_- = \max\{0, -p\}$. Price deviation penalties $\delta_g, \eta_j, \forall g, j$ are introduced to avoid degeneracy in the solution (Pritchard *et al.*, 2010). They can be seen as penalty prices for the generation deviation from base case and plausible real-time scenarios. For instance, assume the planned generation for a generator is 100MW with marginal cost \$10/MWh in DAM. If there is a price penalty \$0.1/MWh, when demand is 110MW, the generator can sell 10MW more in RTM with marginal price \$10.1/MWh. If demand is 90MW, the generator buys back 10MW with marginal price \$9.9/MWh. The penalty prices help to avoid the existence of non-unique dual solutions, i.e., degenerate solutions. After simplification, the objective is equivalent to:

$$\mathbb{E}\left[\sum_{\forall t}\sum_{\forall g}\left(C_g^M p_{gt}^s + \delta_g|p_{gt}^s - p_{gt}^0|\right) + \sum_{\forall t}\sum_{\forall j}\left(C_j w_{jt}^s + \eta_j|w_{jt}^s - w_{jt}^0|\right)\right] \tag{3.17}$$

Then, by linearizing the absolute values with (3.10)-(3.13), the objective is represented as (3.1).

Price deviation penalties connect the dispatch decisions between the first-stage base case and second-stage scenarios. The DAM prices under stochastic pricing are set to be the dual variables of the node-balance constraint of the base case, i.e., the dual variable λ_{nt} of (3.4). The dual variable of (3.5) is the product of the corresponding plausible scenario's probability and LMP, μ_{nt}^s (Pritchard *et al.*, 2010). Wong and Fuller (2007) proved that μ_{nt}^s are also dual optimal for each single scenario. In other words, μ_{nt}^s are real-time LMPs for the corresponding scenarios if the plausible scenario is realized. It can be proved that $\lambda_{nt} = \sum_{\forall s}\pi^s\mu_{nt}^s, \forall n, t$ (Pritchard *et al.*, 2010). Therefore, under the stochastic pricing scheme, DAM LMPs are consistent with RTM LMPs in expectation, for the given set of plausible real-time scenarios. From another perspective, the resulting DAM LMPs under the stochastic LMP are smoother than under the deterministic pricing scheme, as the prices are averages of all plausible scenarios. The LMP function with respect to total loads is no longer a step-size function but is close to a continuous function. This result will be further discussed with test cases in the next section.

3.2.3 Dispatchable Relaxation

Current restricted LMPs are obtained by fixing unit commitment solutions and then solving the economic dispatch model. The discrete nature of unit commitment causes LMPs to change non-monotonically with respect to total loads. At some load point, a new committed unit may increase or decrease the marginal cost of dispatch. From an economic point of view, more demand should result in higher prices. The restricted LMP does not provide a good pricing signal in the sense that it results in non-monotonic prices with respect to total loads. In addition, uplift payments are required since the restricted LMP does not take commitment costs into consideration. The proposed pricing scheme aims at eliminating the non-convexity of energy markets and giving better pricing signals with the following modifications.

First, commitment costs are amortized to generation variable costs to reduce uplift payments as follows.

$$C_g^M = C_g + C_g^{NL}/P_g^{\max} + C_g^{SU}/UT_g/P_g^{\max} \tag{3.18}$$

Both no-load costs and startup costs are allocated to generation variable costs. The no-load cost is allocated to each generator up to their maximum generation levels, assuming every MW of capacity contributes to the no-load cost. Once a generator is turned on, the startup cost incurs. Then, the generator has to be on for the minimum up time. Thus, the startup cost is allocated to variable generation cost divided by minimum up time and maximum generation level. Other amortization rules may be adopted, but they are left for future study.

Next, the minimum generation levels of all units are relaxed to zero. The idea is inherited from the dispatchable model in Gribik *et al.* (2007). In this chapter, the model is extended to a multi-period model with network constraints. The dispatchable assumption modification matches current industry practice in the U.S. For instance, most ISO/RTOs relax fast-start generators' minimum generation levels to zero, thereby allowing them to set prices, and some ISO/RTOs also allow uncommitted fast start units to set the RTM price (Federal Energy Regulatory Commission, 2014a). In the proposed DAM pricing model, all units are assumed dispatchable, including committed and uncommitted fast- and slow-starting units.

There are several implications from these modifications. Firstly, by assuming all units to be dispatchable, the non-convexity issues are eliminated. The resulting LMP increases monotonically as total loads increase. Secondly, the pricing model is separated from unit commitment. Consequently, the pricing run can be carried out in parallel with SCUC and SCED. Thirdly, uplift payments are reduced. The above two modifications result in prices that are close to CHP (i.e., minimizing uplift payments). In place of theoretical justification, this chapter studies test cases and compares uplift payments under the proposed pricing model and the restricted LMP under more realistic assumptions. In the next section, test case results confirm that the uplift payments under the proposed pricing model are indeed reduced. Although uplift payments are reduced, they are not totally eliminated. When a generator dispatches under its full capacity, commitment costs may not be fully recovered. Equation (3.18) is an approximation to recover commitment costs that assumes maximum generation. As mentioned previously, the complex nature of electric power energy markets prevents the existence of prices in equilibrium where all participants will voluntarily follow dispatch instructions.

3.2.4 DAM and RTM Process

The proposed model is a pricing model to determine the energy prices in DAM. The dispatch solutions from this pricing model will possibly be different from the SCED solution since all units are relaxed to be dispatchable. However, the obtained LMPs from the pricing model are utilized for financial settlements and market surplus allocation. The DAM commitment and dispatch schedules are still determined by SCUC and SCED. This structure follows the ISO/RTOs' practice where they relax fast-start generators' minimum generation levels to zero in pricing models to set prices, though they are inflexible (i.e., the minimum generation requirement equals to the maximum generation requirement for gas turbines) Federal Energy Regulatory Commission (2014a).

In general, the current DAM clearing process can be seen as collecting bids, solving SCUC, solving SCED, solving the pricing model, adding reliability corrections (if needed), and finally settling the market. Under the proposed pricing scheme, all generators are included in the model to set energy prices. This is in contrast to the restricted LMP where only committed units can set prices. As a result of relaxing all units to be dispatchable, one advantage of the proposed pricing scheme is that the pricing run is separated from SCUC, i.e., the pricing model is independent of commitment solutions. Solving the pricing model only requires the bidding information such as commitment costs, dispatch variable costs and total capacities. Figure 3.1 represents the new DAM clearing process under the proposed pricing scheme. The pricing run is in parallel with SCUC and SCED. This structure enables ISO/RTOs to have more flexibility to solve stochastic pricing models, which generally take more time to solve.

In order to keep price consistency with the proposed DAM pricing scheme, all

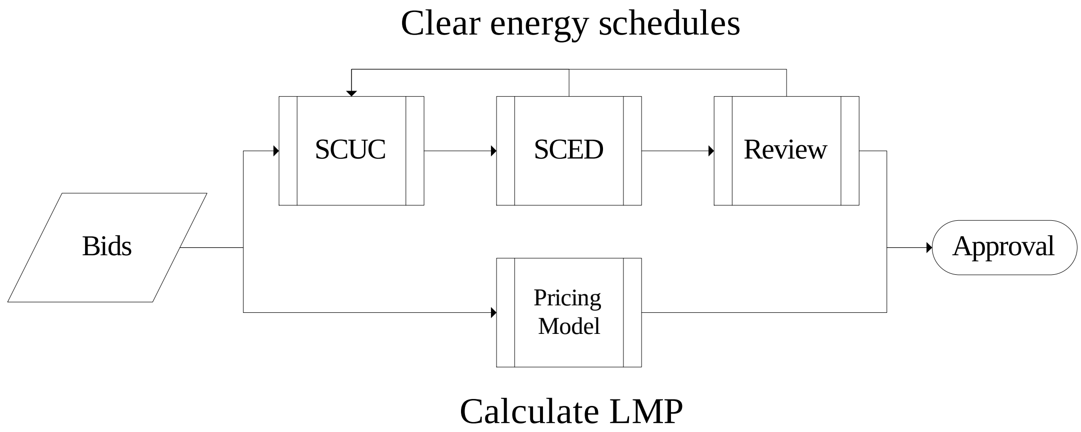

Figure 3.1: DAM Clearing Process under Proposed Pricing Scheme

units are also assumed to be dispatchable in RTM pricing models. The objective is to minimize re-dispatch cost in RTM, where the marginal costs are modified costs including the amortized commitment costs. All units' minimum generation levels are relaxed to zero, so that all units are able to set RTM energy prices as they are in DAM.

Firstly, the DAM dispatch solutions under the all-units-dispatchable assumption are obtained through the following model for each given period t. The dispatch solution from this DAM all-units-dispatchable pricing model, rather than the actual dispatch solution from DAM SCED, is used as DAM dispatch solution in RTM pricing model in order to keep price consistency.

$$\begin{aligned} \min \quad & \sum_{\forall g} C_g^M p_{gt}^0 \qquad (3.19) \\ \text{s.t.} \quad & (3.2) - (3.4) \\ & (3.6) - (3.9) \end{aligned}$$

where the index s corresponds to $s = 0$, index t corresponds to the given time period, and the optimal solution are $p^*_{gt}, \forall g, t$ and $w^*_{jt}, \forall j, t$.

In RTM, the true realization of uncertainties, i.e., available wind generation capacity $W^s_{jt}, \forall j, t$, will be revealed. ISO/RTOs solve the RTM pricing model with the revealed data to determine real-time energy prices. The RTM pricing model for each given period t is represented as follows.

$$\min \quad \sum_{\forall g}(C^M_g p^s_{gt} + \delta_g p^s_{gt}) + \sum_{\forall j}(C_j w^s_{jt} + \eta_j w^s_{jt}) \tag{3.20}$$

$$\text{s.t.} \quad (3.2) - (3.7)$$

$$(3.10) - (3.15)$$

$$p^0_{gt} = p^*_{gt} \qquad \forall g, t \tag{3.21}$$

$$w^0_{jt} = w^*_{jt} \qquad \forall j, t \tag{3.22}$$

where the index s corresponds to each real-time scenario and index t corresponds to the given time period. The ramping constraints are relaxed in the RTM pricing model since the dispatch solution from the pricing model might not be the actual dispatch solution in the real-time operation. Further discussion of the ramping constraints in the pricing model is left for future study.

3.3 Test Cases

Two test cases are presented in this section, a 6-bus system and a 118-bus system. Single-block linearized generation variable cost for thermal generation is adopted for simplicity. The startup costs, no-load costs and generation variable costs are assumed to be zero for wind power generators. The DAM schedule of unit commitment and dispatch are obtained from SCUC and SCED respectively (where the stochastic unit commitment model guarantees enough committed generator capacity for all considered scenarios). Both the SCUC and SCED formulations are based on Hedman *et al.*

(2010). 10 wind power scenarios for the 6-bus system are obtained from Wang *et al.* (2008). The available wind power scenarios for the 118-bus system are generated from normal distributions and assigned with equal probability. This is a simple assumption and alternative approaches are possible, but scenario generation and selection issues are beyond the scope of this chapter. Penalty factor δ_g is set to be \$0.1 for conventional generators and penalty factor η_j is set to be \$0.001 for wind farms, following the rule in Zavala *et al.* (2014). DAM uplift payments are paid whenever a generator's total payment is less than its total cost in 24 hours, following the convention in Federal Energy Regulatory Commission (2014b).

Four pricing schemes are compared. Let DR represent the deterministic restricted LMP scheme; SR represent the stochastic restricted LMP scheme; DA represent the deterministic all-units-dispatchable LMP scheme; and SA represent the stochastic all-units-dispatchable LMP scheme. The deterministic (D) pricing scheme does not include any real-time scenarios; the stochastic (S) pricing scheme adopts the two-stage stochastic pricing framework described in subsection III.B; the restricted (R) pricing scheme fixes commitment solutions, allows only committed units to set energy prices and uses variable generation costs (not including amortized commitment costs); the all-units-dispatchable (A) pricing scheme adopts the modifications described in subsection 3.2.3.

3.3.1 6-Bus System

The data of this system is modified from that presented in Wang *et al.* (2008). The original data can be found in University of Washington (2015). All ten scenarios in Wang *et al.* (2008) are included in the stochastic pricing scheme. The generator data is shown in Table 3.1 and Table 3.2. Gen1 is a base-load generator since it has lower generation variable cost and higher capacity. Gen2 is an expensive generator with more flexible capacity. Gen3 is a fast-start generator. Gen4 is a wind power generator.

Table 3.1: 6-Bus System Generator Basic Data

#	Gen1	Gen2	Gen3	Gen4
type	Slow	Slow	Fast	Wind
location	B1	B2	B6	B4
EcoMin (MW)	100	10	10	0
EcoMax (MW)	220	100	20	-
min up time (hr)	4	3	1	-
min down time (hr)	4	2	1	-
ramp rate (MW)	55	50	20	-

Table 3.2: 6-Bus System Generator Cost Data

#	Gen1	Gen2	Gen3	Gen4
variable cost ($/MW)	13.6	32.7	17.9	0
startup cost ($)	100	200	100	0
no-load cost ($)	177	130	137	0

First, the market allocations under different pricing schemes are compared and the results are represented in Table 3.3. Since the commitment costs are amortized on top of the generation variable cost in the all-units-dispatchable scheme, most LMPs under this scheme are increased. As expected, the all-units-dispatchable pricing scheme reduces uplift payments and increases total load payments. The total payments including load payments and uplift payments increase significantly under the two all-units-dispatchable pricing schemes. There is a distinct transfer of surplus from consumers to generators. Although the total payments under the all-units-dispatchable scheme increase, it is not necessarily negative for power systems since the ISO/RTO's goal is to maximize market surplus, i.e. not to minimize consumers' payments only. The stochastic pricing scheme also affects market allocation, but its impact is much less than that of the all-units-dispatchable pricing scheme.

Next, individual generator profit is studied. Table represents the costs, revenues, and profits of each generator. Under the restricted LMP, Gen1 loses money since in most periods its LMP is set at its generation variable cost (commitment costs are not

Table 3.3: Market Allocation Comparison

	DR	SR	DA	SA
total commitment cost	7,722			
total dispatch cost	73,416			
total load payment	150,164	153,347	186,486	191,301
total uplift payment	6,530	6,483	1,347	1,321
total payment	156,694	159,830	187,833	192,622
total generation revenue	103,416	104,606	121,128	121,108

considered). Gen1's revenue is not enough to cover generation costs and commitment costs altogether. In contrast, under all-units-dispatchable pricing, Gen1 is profitable. Gen4's (renewable) profit is increased significantly as well. This result shows that the proposed pricing scheme gives incentives to encourage investments in low-variable-cost generation technologies. In the long run, generators with high generation variable cost, such as Gen2 in this test case, will not be profitable and therefore substituted by low-variable-cost generators. This may contribute to increased social welfare from a long-term point of view.

Table 3.4: Generator and Wind Farm Profit Comparison

Gen1	DR	SR	DA	SA
total cost	67,273			
generation revenue	63,026	63,026	70,611	69,012
generation profit	-4,248	-4,248	3,337	1,739
Gen2	**DR**	**SR**	**DA**	**SA**
total cost	8,291			
generation revenue	6,010	6,057	6,944	6,971
generation profit	-2,282	-2,235	-1,347	-1,321
Gen3	**DR**	**SR**	**DA**	**SA**
total cost	5,573			
generation revenue	6,155	6,093	7,436	7,523
generation profit	582	520	1,863	1,949
WF	**DR**	**SR**	**DA**	**SA**
total cost	0			
generation revenue	28,225	29,430	36,137	37,603
generation profit	28,225	29,430	36,137	37,603

Finally, the pricing signals under different pricing schemes are studied. Figure 3.2 represents the LMP changes with respect to total load percentage (with respect to base case load) at a selected bus and in a selected period. It is assumed that the loads at every bus are increasing accordingly with respect to the total load percentage. The LMPs under the restricted pricing scheme go up and down as load increases. In contrast, the LMPs under the all-units-dispatchable pricing scheme show a monotonically non-decreasing property. The stochastic pricing scheme smoothens price changes. The LMPs under the stochastic all-units-dispatchable model increase almost continuously rather than jumping discontinuously.

Figure 3.3 represents the LMP comparison at different buses for the same time period. The proposed pricing scheme, i.e., the stochastic all-units-dispatchable LMP, results in a nearly continuous LMP function for every bus with respect to total loads.

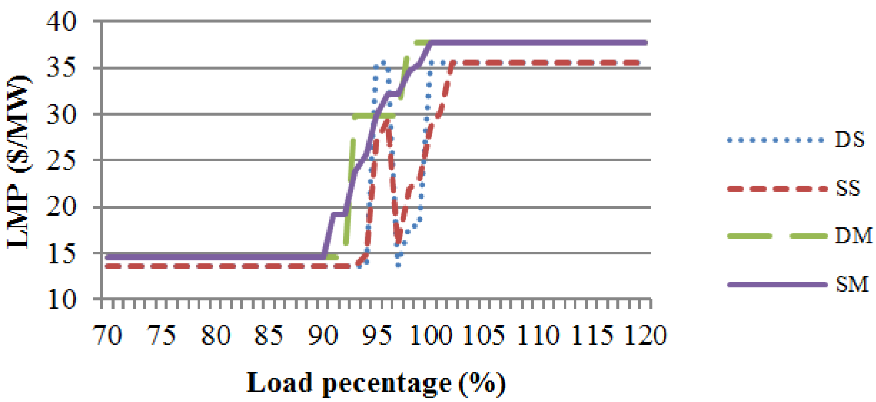

Figure 3.2: LMP with respect to Total Load at Bus 6 in Period 14

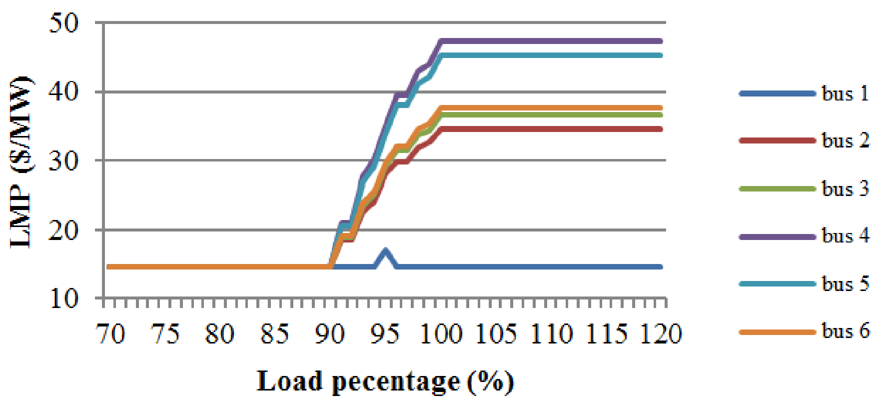

Figure 3.3: Prices with respect to Total Load in Period 14

3.3.2 IEEE 118-Bus System

In this test case, there are 118 buses, 186 transmission lines, 54 generators and 5 wind farms (University of Washington, 2015). The peak load is 4,519MW. The total generation capacity (excluding wind farms) is 5,859MW. The average wind power generation is 530MW. Table 3.5 summarizes the market allocation under different pricing schemes for a high-load day. Overall, the test results agree with the conclusions in the 6-bus system.

Table 3.5: Market Allocation Comparison for High-load Day

	DR	SR	DA	SA
total commitment cost	150,511			
total dispatch cost	747,960			
total load payment	1,826,560	1,956,710	2,355,710	2,252,460
total uplift payment	50,529	38,615	11,055	17,906
total payment	1,877,089	1,995,325	2,366,765	2,270,366
total generation revenue	1,681,040	1,802,740	2,183,630	2,087,550

Table 3.6 represents the cost data for three selected generators and Table 3.7 represents their generation cost, revenue, and profit along with a selected wind farm's profit allocation under the four pricing schemes for the same high-load day. The results show that generators with lower generation variable cost obtain more profits under the all-units-dispatchable LMP. For instance, Gen2 loses money under the restricted LMP, but makes considerable profits under the all-units-dispatchable LMP. Gen3, which has higher generation variable cost, still makes a loss under the all-units-dispatchable LMP. Therefore, the results indicate, again, that the proposed pricing scheme might incentivize investment in low-variable-cost generation.

Table 3.6: Selected Generator Data

	Gen1	Gen2	Gen3
EcoMax (MW)	350	155	12
variable cost ($/MW)	11.69	11.82	48.41
no-load cost ($)	5,500	1,173	274
startup cost ($)	379	311	80

Table 3.7: Generator and Wind Farm Profit Comparison for High-load Day

Gen1	DR	SR	DA	SA
total cost		85,646		
generation revenue	84,178	87,694	110,703	107,925
generation profit	-1,467	2,049	25,058	22,280
Gen2	**DR**	**SR**	**DA**	**SA**
total cost		21,364		
generation revenue	18,026	18,339	22,868	22,404
generation profit	-3,338	-3,025	1,504	1,040
Gen3	**DR**	**SR**	**DA**	**SA**
total cost		1,057		
generation revenue	412	439	512	488
generation profit	-646	-618	-546	-569
WF	**DR**	**SR**	**DA**	**SA**
total cost		0		
generation revenue	63,194	67,132	80,662	77,873
generation profit	63,194	67,132	80,662	77,873

Figure 3.4 and Figure 3.5 represent the LMPs across different periods at two selected buses. Generally, prices under the all-units-dispatchable LMP are higher than that under the restricted LMP. However, in some cases, such as period 3-5 in Figure 3.5, the LMPs under the restricted LMP are higher. The patterns of LMPs across time periods are similar under the four pricing schemes. It is evident again that stochastic pricing smoothens the price changes, although the impact of stochastic pricing is less prominent than the impact of the all-units-dispatchable pricing scheme.

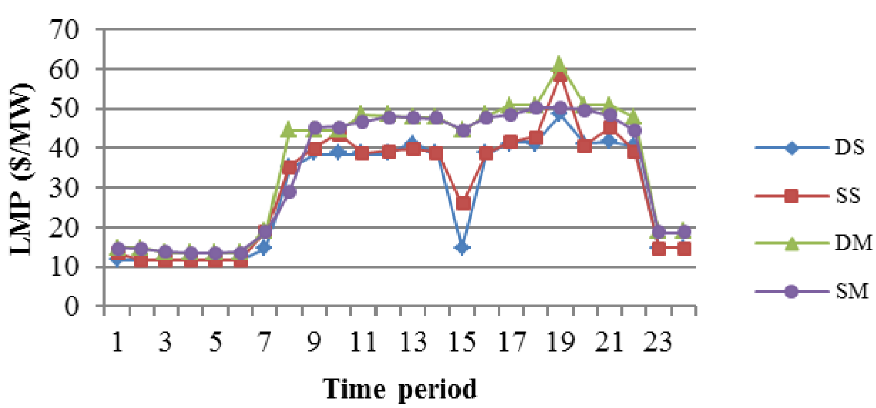

Figure 3.4: LMP Comparison across Periods at Bus 100

Table 3.8 and Table 3.9 represent the market allocation and generator profit under

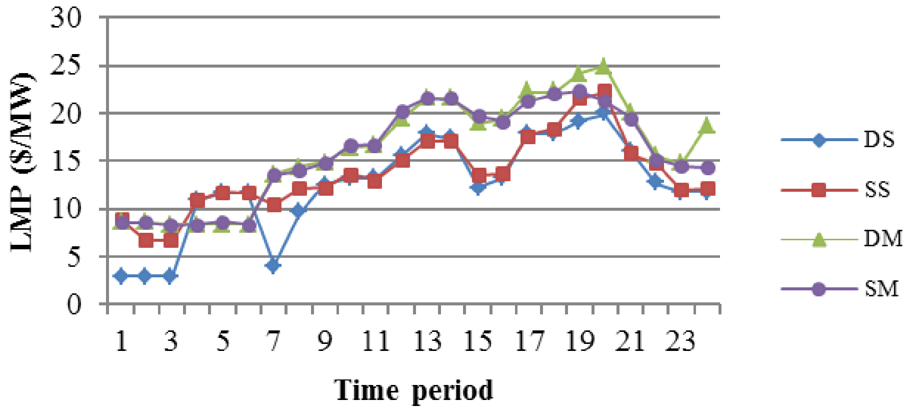

Figure 3.5: LMPs Comparison across Periods at Bus 113

a selected medium-load and low-load day for the DR and SA schemes. In the high-load day presented above, the load demand across all periods varies from 59% to 100% of the peak load. In contrast, in the medium- and low-demand days, the load demand varies from 41% to 66% and 33% to 52% of the peak load, respectively.

Table 3.8: Market Allocation under Different Load Profiles

	Medium-load		Low-load	
	DS	SA	DS	SA
total commitment cost	67,800		46,283	
total dispatch cost	289,037		177,521	
total load payment	600,894	762,248	304,107	435,156
total uplift payment	27,059	10,973	48,462	15,293
total payment	627,953	773,221	352,569	450,449
total generation revenue	578,397	728,503	280,657	394,653

From the test results, the stochastic all-units-dispatchable LMP has similar results under the medium-load day and the low-load day as for the previous high-load day. The results are consistent under different load levels. Finally, the price consistency between DAM and RTM are studied. Twenty scenarios are generated to be included in the stochastic pricing as plausible scenarios (P). 10 more scenarios are generated from the same distribution as testing scenarios (T). The price discrepancies are represented in Table 3.10.

From the test results, under the deterministic restricted pricing scheme, the price

Table 3.9: Generator and Wind Farm Profit Comparison

	Medium-load		Low-load	
Gen1	DR	SA	DR	SA
total cost	86,318		66,284	
generation revenue	81,139	104,080	43,452	60,991
generation profit	-5,179	17,762	-22,832	-5,293
Gen2	DR	SA	DR	SA
total cost	25,634		7,607	
generation revenue	24,060	30,733	4,537	5,634
generation profit	-1,574	5,099	-3,070	-1,973
Gen3	DR	SA	DR	SA
total cost	0		0	
generation revenue	0	0	0	0
generation profit	0	0	0	0
WF	DR	SA	DR	SA
total cost	0		0	
generation revenue	11,515	20,163	6,319	8,042
generation profit	11,515	20,163	6,319	8,042

Table 3.10: LMP Differences between DAM and RTM Comparison

	DR		DA		SA	
scenario sets	P	T	P	T	P	T
average LMP diff.	1.78	2.2	0.43	0.46	0	0.35
max LMP diff.	18.5	21.05	12.64	13.32	0.01	2.67
max accumulated LMP diff. all through 24 periods for a single bus	81.37	101.31	17.81	19.68	0.17	12.39
max accumulated LMP diff. all through 118 buses for a single period	1,052.98	1,265.28	579.97	614.06	1.18	135.77

inconsistency between DAM and RTM is significant. The maximum difference can be as high as \$21.05. This inconsistency may lead to arbitrage opportunities and revenue inadequacy as discussed before. The all-units-dispatchable scheme can alleviate the inconsistency to some extent, but some inconsistency still exists since it is under a deterministic pricing scheme. Under the proposed scheme, i.e., the stochastic all-units-dispatchable pricing scheme, the prices between DAM and RTM are more consistent. The results confirm that the DAM price converges to the plausible RTM scenario prices in expectation. Furthermore, the price inconsistency of the proposed pricing scheme for the testing scenarios is much smaller than for the other two schemes.

3.4 Conclusions

The proposed stochastic dispatchable pricing scheme addresses both the non-convexity and uncertainty issues in the day-ahead energy market. Electricity markets are non-convex so that a perfect equilibrium market clearing price may not exist, but the proposed pricing scheme amortizes commitment costs into generation variable costs and relaxes all units to be dispatchable to set energy prices. The scheme gives a monotonically non-decreasing marginal cost function with respect to total loads. Test results show that uplift payments are reduced and the generators with low generation variable costs obtain higher profits in the energy market under the proposed pricing scheme. The price changes are further smoothened by incorporating a set of scenarios and using a stochastic pricing framework to set DAM energy prices. Test results show that price jumps are alleviated by introducing the stochastic pricing framework, but the impacts are less prominent than the ones from the dispatchable scheme.

In general, the test results indicate that the proposed stochastic all-units-dispatchable LMP scheme gives better pricing signals and reduced need for uplift payments compared to the currently utilized restricted LMP. In the short-term, the proposed pricing scheme will result in a transfer of surplus from consumers to producers in the energy market due to higher prices. However, other transfers could adjust for this in aggregate, e.g., through reduced need for capacity payments, without changing incentives on the margin. The proposed stochastic pricing scheme also leads to more price consistency between day-ahead and real-time markets, leading to improved incentives for market participants, which may change their bidding behavior accordingly. In the long run, the proposed pricing scheme may incentivize investments in technologies with low-variable-cost generation, such as renewable energy, potentially leading to higher social welfare. Future studies are needed to analyze the long-term implications and confirm this hypothesis. The impact of the proposed pricing scheme on other markets such as the financial transmission rights market, the ancillary services market, and the capacity market, are also left for future study.

Chapter 4

ARBITRAGE IN ENERGY MARKETS

4.1 Introduction

The electric power industry is an $840-billion industry in the U.S., which represents approximately 3 percent of real gross domestic product (Edison Electric Institute, 2013). Each year, electric utilities spend roughly 200 billion in their planning and operations (Energy Information Administration, 2015). Unlike other commodities in markets, the demand of electric power is considered to be very close to perfectly inelastic. Thus, the imbalance between supply and demand can cause severe issues in power grids. Consequently, one of the most challenging problems in electric power scheduling is the uncertainty. Generally, the uncertainties in electric power scheduling can be categorized as discrete or continuous uncertainties. Discrete uncertainties include the failure of a single generator or transmission line, also known as an N-1 contingency. Continuous uncertainties include the loads and renewable energy variations with respect to their predicted levels. Nowadays, more and more renewable energy resources (mainly wind and solar farms) are being built to provide electric power in order to lower generation costs and reduce environmental pollutions. According to the California Renewables Portfolio Standard (RPS) (California Public Utilities Commission, 2015), eligible renewable energy resources in California will be increased to % of total production by 2020, compared to the current 12% nationwide renewable generation (Energy Information Administration, 2014).

While it brings many benefits both economically and environmentally, on the other hand, the high penetration of intermittent renewables also complicates power scheduling due to the uncertain nature of the renewable energy. With high renewable penetration in the power grid, electric energy storage (EES) is one way to assist handling resource uncertainties (Sandia National Laboratories, 2013). The technologies of EES are widely discussed in literature (Sandia National Laboratories, 2013; Beaudin *et al.*, 2010; Świerczynski *et al.*, 2010; Ruggiero and Heydt, 2013; Divya and Østergaard, 2009; Wade *et al.*, 2010). Pumped hydro storage (PHS), which pumps and discharges water from different reservoirs to store and release electric energy, is the most common and well-developed form of energy storage, representing approximately 3% of the world's total installed power capacity, and 97% of the total storage capacity (Beaudin *et al.*, 2010). PHS is popular for its high round-trip charging efficiency (65-85%), large power capacity (100-1000MW), large energy storage capacity (12+ hours), long life (30-60 years), and low cycle cost; however, PHS is limited by its high capital cost ($100 million - $3 billion), long project lead time (typically ten years), environmental damages, and its unique geographical requirements (Beaudin *et al.*, 2010). Compressed air energy storage (CAES) is another currently suitable technique other than PHS for large-scale EES. CAES compresses the air into large storage reservoirs using cheaper off-peak electric power instead of expensive gas and releases the air for the conventional gas turbine cycles during peak hours (Ruggiero and Heydt, 2013). CAES shares many of the same attractive characteristics of PHS, but has significantly lower capital cost and little environmental impact since the storage is underground (Beaudin *et al.*, 2010). Nevertheless, there are only two CAES plants in the world, one in Germany built in 1978 and another in Alabama, U.S. built in 1991 (Beaudin *et al.*, 2010). A variety of batteries have also been developed for EES including, but not limited to, lead-acid, nickel-cadmium, sodium-sulfur, lithium-ion, sodium-nickel-chloride, zinc-bromine, vanadium-redox and polysulphide-bromide batteries. Their characteristics are discussed in (Sandia National Laboratories, 2013;

Beaudin *et al.*, 2010; Świerczynski *et al.*, 2010; Ruggiero and Heydt, 2013; Divya and Østergaard, 2009; Wade *et al.*, 2010). Other technologies such as flywheels, capacitors and super-capacitors, hydrogen storage, superconducting magnetic energy storage (SMES), and solar thermal energy storage have been developed or are under development for various EES purposes (Sandia National Laboratories, 2013; Beaudin *et al.*, 2010; Świerczynski *et al.*, 2010; Ruggiero and Heydt, 2013; Divya and Østergaard, 2009; Wade *et al.*, 2010).

As for arbitrage in electric power market, EES owners buy the energy during the off-peak hours with low price and sell it in the peak hours with higher price in order to make profits. Therefore, EES devices should have higher power capacity (20+MW is desired) and higher energy storage capacity (4+ hours is desired). Currently, only PHS, CAES, sodium-sulfur battery and lead-acid battery are suitable for arbitrage in the markets.

In addition to responding to the intermittent renewable resources, introducing EES to the power grid can benefit the system in several ways. Large-scale EES was initially studied focusing on the peak load shaving effects. Social welfare can be improved by moving the peak load to the off-peak periods by utilizing EES and, as a result, the electricity price variability is typically reduced. Moreover, introducing EES can defer facility investments (Sioshansi *et al.*, 2009). While such benefits exist, such welfare benefits may not be captured by the private investor of EES. As the private investors, they gain profits relying on pricing arbitrage. Since large-scale EES will smooth load and reduce price variance in different periods, the diminished value of arbitrage can be expected, which contradicts the investors' motivation of investing in EES facilities. Therefore, despite the benefits that EES will bring to power systems, the current market settings give limited incentives for the private investors to build EES facilities. The ownerships of EES facilities, contracts for EES in the markets, and government subsidies have been discussed but not yet implemented (Sioshansi *et al.*, 2009). An enhanced market design that is conducive to EES is left for future study.

The remainder of this chapter is organized as follows: Section 4.2 gives the mathematical formulations. Section 4.3 discusses three charging policies to hedge uncertainty for the arbitrager. Section 4.4 carries out a case study on the IEEE 118-bus system and shows the computational results. Finally, Section 4.5 draws the conclusions.

4.2 Mathematical Formulations

In the models in this chapter, a power transfer distribution factor (PTDF) based direct current optimal power flow model (DCOPF) is adopted, which is a linear approximation of real power flow with a set of simplifying assumptions (Wood and Wollenberg, 1996; Stott *et al.*, 2009).

4.2.1 Location Selection Model

Since most energy markets in the U.S. now have a nodal market settlement structure, the location of EES will play an important role. The EES location selections depend on whether the owner of EES is a vertically-integrated utility or a for-profit private entity. For vertically-integrated utilities, the objective should be to minimize the total costs. Then the EESs are preferred at the locations where the whole system will benefit. On the other hand, in regards to for-profit private entities, the EES facilities are preferred at the locations where the owner can maximize the individual profits by arbitrage. The following model gives the optimal locations for minimizing total costs, the perspective of the vertically-integrated utility. Generally, these locations are not the optimal locations from a for-profit EES owner's point of view.

Arbitrage profits and market allocations will be compared when the EES facility is located at different buses.

$$\min \quad \sum_{\forall t}\sum_{\forall g} C_g p_{gt} + \sum_{\forall n} B_n z_n \tag{4.1}$$

$$\text{s.t.} \quad i_{nt} = \sum_{\forall g \in G(n)} p_{gt} + o^-_{nt}\alpha_n - o^+_{nt}/\alpha_n - D_{nt} \qquad \forall n, t \tag{4.2}$$

$$\sum_{\forall n} i_{nt} = 0 \qquad \forall t \tag{4.3}$$

$$-F_l \le \sum_{\forall n} \psi_{nl} i_{nt} \le F_l \qquad \forall l, t \tag{4.4}$$

$$0 \le p_{gt} \le P^{\max}_g \qquad \forall g, t \tag{4.5}$$

$$e_{nt} = e_{n,t-1} + o^+_{n,t-1} - o^-_{n,t-1} \qquad \forall n, t \tag{4.6}$$

$$E^{\min}_n z_n \le e_{nt} \le E^{\max}_n z_n \qquad \forall n, t \tag{4.7}$$

$$0 \le o^+_{nt}, o^-_{nt} \le U_n \qquad \forall n, t \tag{4.8}$$

$$\sum_{\forall n} z_n \le K \tag{4.9}$$

$$z_n \in \{0, 1\} \qquad \forall n \tag{4.10}$$

Equation (4.1) is the objective that minimizes the total dispatch costs and investment costs. Equations (4.2) and (4.3) restrict the relationship of power injections. When EES is charging, since the efficiency is not 100%, o^+_t/α_n unit energy is required in order to store o^+_t unit energy in EES. In contrast, when EES is discharging o^-_t unit energy, only $o^-_t\alpha_n$ unit energy can be utilized by the power grid. Equation (4.4) restricts the transmission line ratings. Equation (4.5) restricts the generation bounds. Equation (4.6) describes the EES energy balance relations. Equations (4.7) and (4.8) specify the energy and power capacity respectively. Equation (4.9) restricts the total number of EES facilities that can be built.

4.2.2 SCUC and SCED

In DAM, the operators solve SCUC model to obtain unit commitment solutions. Then, they run SCED model and calculate LMPs. The basic procedure in DAM is described in Figure 4.1 (Midcontinent ISO, 2007). The load $D_{nt}, \forall n, t$, and the wind power generation $W_{nt}, \forall n, t$, are treated as deterministic based on predicted values.

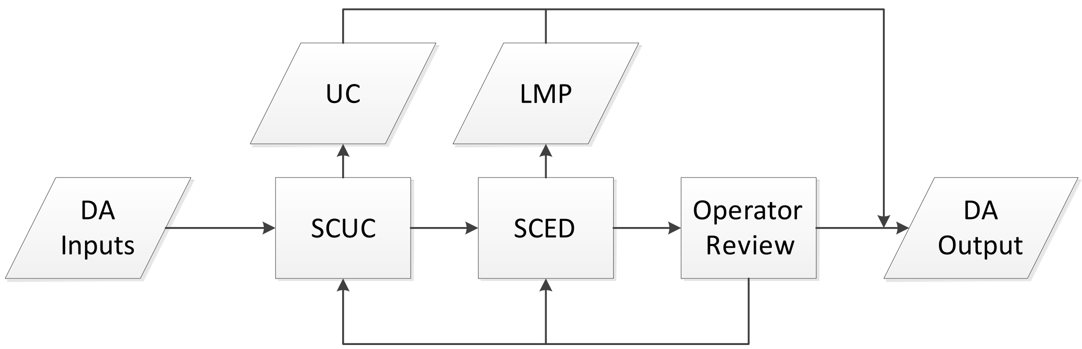

Figure 4.1: DAM Structure

The SCUC model is described as follows.

$$\min \quad \sum_{\forall t}\sum_{\forall g}\left(C_g^{SU}v_{gt} + C_g^{NL}u_{gt} + C_g p_{gt}\right) \tag{4.11}$$

$$\text{s.t.} \quad p_{gt} + r_{gt} \le P_g^{\max} u_{gt} \qquad \forall g,t \tag{4.12}$$

$$p_{gt} \ge P_g^{\min} u_{gt} \qquad \forall g,t \tag{4.13}$$

$$w_{nt} \le W_{nt} \qquad \forall n,t \tag{4.14}$$

$$\sum_{\forall g} r_{gt} \ge 3\% \sum_{\forall n} D_{nt} + 5\% \sum_{\forall n} W_{nt} \qquad \forall t \tag{4.15}$$

$$p_{gt} - p_{g,t-1} \le R_g^{hr} u_{g,t-1} + R_g^{SU} v_{gt} \qquad \forall g,t \tag{4.16}$$

$$p_{g,t-1} - p_{gt} \le R_g^{hr} u_{gt} + R_g^{SD}(v_{gt} - u_{gt} + u_{g,t-1}) \qquad \forall g,t \tag{4.17}$$

$$v_{gt} \ge u_{gt} - u_{g,t-1} \qquad \forall g,t \tag{4.18}$$

$$\sum_{i=t-UT_g+1}^{t} v_{gi} \le u_{gt} \qquad \forall g,t \tag{4.19}$$

$$\sum_{i=t+1}^{t+DT_g} v_{gi} \le 1 - u_{gt} \qquad \forall g,t \tag{4.20}$$

$$i_{nt} = \sum_{\forall g \in G(n)} p_{gt} + w_{nt} - D_{nt} \qquad \forall n,t \tag{4.21}$$

$$\sum_{\forall n} i_{nt} = 0 \qquad \forall t \tag{4.22}$$

$$-F_l \le \sum_{\forall n} \psi_{nl} i_{nt} \le F_l \qquad \forall l,t \tag{4.23}$$

$$u_{gt} \in \{0,1\} \qquad \forall g,t \tag{4.24}$$

$$0 \le v_{gt} \le 1 \qquad \forall g,t \tag{4.25}$$

$$w_{nt}, r_{gt} \ge 0 \qquad \forall n,g,t \tag{4.26}$$

The SCUC formulates the problem in 24 periods, where each period is one hour. Equation (4.11) is the objective to minimize the total costs including startup costs, no-load costs, and dispatch costs. While prior work approximates the generator cost curve as a quadratic function, the presented model assumes a piecewise linear formulation, which is consistent with existing market structures. Since the market model is non-convex, uplift payments may be required to ensure a non-confiscatory market. Equations (4.12) and (4.13) restrict the generation upper bound and lower bound. When the generator is not committed, i.e., $u_{gt} = 0$, the generation (p_{gt} and r_{gt}) is forced to be zero. Equation (4.14) restricts the wind power injection to be less than the maximum power that the wind farm can provide. Although the marginal cost of the wind power is zero, it is not always the case that dispatching all available wind power is beneficial. Due to transmission congestion and due to ramping limitations, it is at times cheaper to spill wind as opposed to displacing fossil fuel based production. Equation (4.15) specifies the system reserves in order to handle uncertainties. The ad-hoc 3+5 requirement rule, which requires the reserves to be more than 3% of the total predicted load and 5% of the total predicted wind power, is adopted (Papavasiliou *et al.*, 2011). Equations (4.16) and (4.17) restrict the hourly ramping up and ramping down constraints. Equation (4.18) specifies the relation between the unit commitment status and the startup status. Equations (4.19) and (4.20) impose the minimum up and down time constraints, which states that if a generator is turned on, it cannot be turned down in the next UT_g hours; similarly, if it is turned off, it cannot be turned on in the next DT_g hours. Equations (4.21) and (4.22) define the bus injection. Equation (4.23) imposes the transmission line rating. The generation shift factors are results from Kirchhoff's laws. Equations (4.24)-(4.26) specify the variable restrictions. The startup variable is relaxed to be continuous but is guaranteed to be either 0 or 1, since (4.18)-(4.20) form the facet-defining constraint of u, v projection Rajan and Takriti (2005).

The SCED is described as follows.

$$\min \quad \sum_{\forall t} \sum_{\forall g} C_g p_{gt} \tag{4.27}$$

$$\text{s.t.} \quad P_g^{\min} \bar{u}_{gt} \leq p_{gt} \leq P_g^{\max} \bar{u}_{gt} \qquad \forall g, t \tag{4.28}$$

$$0 \leq w_{nt} \leq W_{nt} \qquad \forall n, t \tag{4.29}$$

$$i_{nt} = \sum_{\forall g \in G(n)} p_{gt} + w_{nt} - D_{nt} \qquad \forall n, t \tag{4.30}$$

$$\sum_{\forall n} i_{nt} = 0 \qquad \forall t \tag{4.31}$$

$$-F_l \leq \sum_{\forall n} \psi_{nl} i_{nt} \leq F_l \qquad \forall l, t \tag{4.32}$$

$$p_{gt} - p_{g,t-1} \leq R_g^{hr} \bar{u}_{g,t-1} + R_g^{SU} \bar{v}_{gt} \qquad \forall g, t \tag{4.33}$$

$$p_{g,t-1} - p_{gt} \leq R_g^{hr} \bar{u}_{gt} + R_g^{SD} (\bar{v}_{gt} - \bar{u}_{gt} + \bar{u}_{g,t-1}) \qquad \forall g, t \tag{4.34}$$

In the SCED with network constraints model, the objective (4.27) only minimizes the dispatching costs. Equations (4.28)-(4.34) are the same as (4.12)-(4.14), (4.21)-(4.23), (4.16)-(4.17), with the exceptions: one, for simplicity, the real-time market is modeled as an energy-only market; two, the unit commitment variables and the startup variables are fixed. The LMPs are the dual variables of (4.30).

4.2.3 Arbitrage Model

In the following arbitrage models, it is assumed that the decision maker is a private investor who maximizes their arbitrage profits. EES is located at a single location k.

Prior work frequently assumes that the arbitragers are price-takers, i.e., the participation of EES has little impact on the real-time LMPs and charging or discharging decisions are made based on the predicted LMP (Sioshansi *et al.*, 2009; Walawalkar *et al.*, 2007; Connolly *et al.*, 2011). Due to the generally small size of EES, this assumption is valid.

The EES owner runs the following model to maximize profits.

$$\max \quad \sum_{\forall t} \lambda_{kt}(o_t^- \alpha_k - o_t^+/\alpha_k) \tag{4.35}$$

$$\text{s.t.} \quad e_t = e_{t-1} + o_t^+ - o_t^- \qquad \forall t \tag{4.36}$$

$$E_k^{\min} \leq e_t \leq E_k^{\max} \qquad \forall t \tag{4.37}$$

$$0 \leq o_t^+, o_t^- \leq U_k \qquad \forall t \tag{4.38}$$

Equation (4.35) maximizes the profit with the predicted LMPs, λ_{kt}, as a fixed constant. Equation (4.36) restricts the energy balance constraint and (4.37)-(4.38) specify the energy and power capacities respectively.

The price-taker assumption may not be true if the charging and discharging have a strong influence on its LMP. In this chapter, the focus is on how the LMP changes induced by the charging or discharging may affect the optimal schedule for EES. Actually, the LMPs λ_{kt} become a function of charging or discharging decisions o_t^+, o_t^-, i.e., the λ_{kt} will change as the o_t^+, o_t^- changes. Therefore, EES owner needs to consider this relation while making their charging decision to maximize profits. The following arbitrage model solves the optimization problem and returns the optimal charging and discharging decisions. The model is described in six parts: objective, primal constraints, dual constraints, strong duality constraint, linearizing constraints, and EES constraints. The model is described as follows.

Objective

$$\max \quad Q_k \sum_{\forall t} \sum_{\forall j} (\eta_{jt}^- \alpha_k - \eta_{jt}^+/\alpha_k) \tag{4.39}$$

Equation (4.39) is the objective to maximize the investor's profits. In (4.35), when λ_{kt} is the function of o_t^+, o_t^-, λ_{kt} also becomes the variable in the optimization problem.

Then $\lambda_{kt}o_t^+$ and $\lambda_{kt}o_t^-$ become bi-linear terms, which causes the formulation to be non-linear and non-convex. Variable η_{jt} is introduced to linearize the bi-linear term. First, we assume that charging and discharging can be divided into several segments and each segment has to be fully charged or discharged. For instance, if an EES has power capacity of 100MW, then it can charge or discharge from 10MW, 20MW, 30MW, and up to 100MW. Each segment is 10MW in this case. Then the decision becomes whether to charge or discharge the j^{th} segment. The decision involves binary variables and when the bi-linear term consists of one continuous variable and one binary variable, the big-M method can be used to linearize the bi-linear term.

Primal Constraints

$$P_g^{\min}\bar{u}_{gt} \leq p_{gt} \leq P_g^{\max}\bar{u}_{gt} \qquad \forall g,t \qquad (4.40)$$

$$\begin{aligned} i_{nt} = &\sum_{\forall g \in G(n)} p_{gt} + w_{nt} - D_{nt} \\ &+ Q_k\alpha_k\left(\sum_{\forall j} x_{jt}^-\right) - Q_k/\alpha_k\left(\sum_{\forall j} x_{jt}^+\right) \end{aligned} \qquad n = k, \forall t \qquad (4.41)$$

$$i_{nt} = \sum_{\forall g \in G(n)} p_{gt} + w_{nt} - D_{nt} \qquad \forall n : n \neq k, t \qquad (4.42)$$

$$-F_l \leq \sum_{\forall n} \psi_{nl} i_{nt} \leq F_l \qquad \forall l,t \qquad (4.43)$$

$$\sum_{\forall n} i_{nt} = 0 \qquad \forall t \qquad (4.44)$$

$$0 \leq w_{nt} \leq W_{nt} \qquad \forall t \qquad (4.45)$$

$$p_{gt} - p_{g,t-1} \leq R_g^{hr}\bar{u}_{g,t-1} + R_g^{SU}\bar{v}_{gt} \qquad \forall g,t \qquad (4.46)$$

$$p_{g,t-1} - p_{gt} \leq R_g^{hr}\bar{u}_{gt} + R_g^{SD}(\bar{v}_{gt} - \bar{u}_{gt} + \bar{u}_{g,t-1}) \qquad \forall g,t \qquad (4.47)$$

Equations (4.40)-(4.47) are the SCED primal constraints, the repeat of equation (4.28)-(4.34). The only change is (4.41), which includes the charging and discharging events at bus k.

Dual Constraints

$$-\phi_{gt}^{+}+\phi_{gt}^{-}+\lambda_{g(n),t}-\rho_{gt}^{+}+\rho_{g,t+1}^{+}-\rho_{g,t+1}^{-}+\rho_{gt}^{-}=C_g \qquad \forall g,t \qquad (4.48)$$

$$\lambda_{nt}-\omega_{nt}\leq 0 \qquad \forall n,t \qquad (4.49)$$

$$-\lambda_{nt}-\sum_{\forall l}\psi_{nl}(\mu_{lt}^{+}-\mu_{lt}^{-})+\tau_t=0 \qquad \forall n,t \qquad (4.50)$$

$$\phi_{gt}^{+},\phi_{gt}^{-},\rho_{gt}^{+},\rho_{gt}^{-},\mu_{lt}^{+},\mu_{lt}^{-},\omega_{nt}\geq 0 \qquad \forall g,l,n,t \qquad (4.51)$$

Equations (4.48)-(4.51) are the SCED dual constraints. When taking the dual, the charging and discharging decisions are treated as known constants. The variables are generation level p_{gt}, dispatched wind power w_{nt}, and bus injection i_{nt}. Each constraint of (4.48)-(4.50) is one-to-one corresponding to the three variables and equation (4.51) specifies the sign restriction of each variable.

Strong Duality Constraints

$$\begin{aligned}\sum_{\forall t}\sum_{\forall g}C_g p_{gt}=&\sum_{\forall t}\sum_{\forall n}(D_{nt}\lambda_{nt}+W_{nt}\omega_{nt})\\&-\sum_{\forall t}\sum_{\forall g}\bar{u}_{gt}(P_g^{\max}\phi_{gt}^{+}-P_g^{\min}\phi_{gt}^{-})\\&-Q_k\sum_{\forall t}\sum_{\forall j}(\eta_{jt}^{-}\alpha_k-\eta_{jt}^{+}/\alpha_k)\\&-\sum_{\forall t}\sum_{\forall l}F_l(\mu_{lt}^{+}+\mu_{lt}^{-})\\&-\sum_{\forall t}\sum_{\forall g}(R_g^{hr}\bar{u}_{g,t-1}+R_g^{SU}\bar{v}_{gt})\rho_{gt}^{+}\\&-\sum_{\forall t}\sum_{\forall g}\left[R_g^{hr}\bar{u}_{gt}+R_g^{SD}(\bar{v}_{gt}-\bar{u}_{gt}+\bar{u}_{g,t-1})\right]\rho_{gt}^{-}\end{aligned} \qquad (4.52)$$

Equation (4.52) equals the SCED primal objective to the dual objective. Based on the strong duality theorem, for a linear programming (LP), the primal feasible solution will have an objective that equals a dual feasible solution's objective if and only if both the primal and dual are optimal. Therefore, by combining the primal constraints, the dual constraints, and the strong duality constraint together, this set of linear equations guarantees that the solution will be optimal if such a solution exists. Then the λ_{nt} will be the true LMP at each bus in each period.

Linearizing Constraints

$$\eta^+_{jt} \leq M^+ x^+_{jt} \qquad \forall j, t \tag{4.53}$$

$$\eta^+_{jt} \geq M^- x^+_{jt} \qquad \forall j, t \tag{4.54}$$

$$\eta^+_{jt} \leq \lambda_{kt} - M^-(1 - x^+_{jt}) \qquad \forall j, t \tag{4.55}$$

$$\eta^+_{jt} \geq \lambda_{kt} - M^+(1 - x^+_{jt}) \qquad \forall j, t \tag{4.56}$$

$$\eta^-_{jt} \leq M^+ x^-_{jt} \qquad \forall j, t \tag{4.57}$$

$$\eta^-_{jt} \geq M^- x^-_{jt} \qquad \forall j, t \tag{4.58}$$

$$\eta^-_{jt} \leq \lambda_{kt} - M^-(1 - x^-_{jt}) \qquad \forall j, t \tag{4.59}$$

$$\eta^-_{jt} \geq \lambda_{kt} - M^+(1 - x^-_{jt}) \qquad \forall j, t \tag{4.60}$$

Equation (4.53)-(4.60) linearize the bi-linear term using big-M method. First, assume $\lambda_{nt} \in (M^-, M^+)$. The goal is to equal η_{jt} to $\lambda_{kt} x_{jt}$. Now only look at the charging decisions. When $x^+_{jt} = 0$, (4.53) and (4.54) force $\eta^+_{jt} = 0$; while the right hand side of (4.55) is positive, the right hand side of (4.56) is negative. When $x^+_{jt} = 1$, (4.55) and (4.56) force $\eta^+_{jt} = \lambda_{kt}$ while (4.53) and (4.54) are relaxed. By introducing the linearizing constraints, the original non-linear optimization problem is transformed to a mixed integer linear program (MILP) and commercial software, such as CPLEX, can solve this kind of problem very efficiently.

As described, the big-M value should be the lower and upper bound of the LMPs. The selection of the big-M value will affect the solution time of the MILP. In general, the tighter the big-M value is, the better the formulation will be. If the big-M value is chosen to be too big, then CPLEX, which uses branch and bound combined with cutting plane algorithms, will generate many cuts and, thus, will lead to a long solution time. The big-M value can be assigned based on historical LMPs; improvements to the big-M value selection are left for future work.

EES Constraints

$$e_t = e_{t-1} + Q_k \left(\sum_{\forall j} x^+_{j,t-1} \right) - Q_k \left(\sum_{\forall j} x^-_{j,t-1} \right) \qquad \forall t \qquad (4.61)$$

$$E^{\min}_k \leq e_t \leq E^{\max}_k \qquad \forall t \qquad (4.62)$$

$$x^+_{j+1,t} \leq x^+_{jt} \qquad \forall j, t \qquad (4.63)$$

$$x^-_{j+1,t} \leq x^-_{jt} \qquad \forall j, t \qquad (4.64)$$

$$x^+_{j+1,t}, x^-_{j+1,t} \in \{0, 1\} \qquad \forall j, t \qquad (4.65)$$

Equation (4.61) restricts the energy storage balance constraint and (4.62) restricts the energy storage capacity. Equations (4.63)-(4.65) specify the relation and space of charging and discharging decisions. Q_k, the segment power capacity, can be assigned the value $U_k/|J|$, where U_k is the total power capacity and $|J|$ is the number of segments.

The entire arbitrage model combines (4.39)-(4.65); by solving this model, the optimal charging decision can be obtained with the consideration of the charging and discharging impacts on LMPs.

4.3 Electric Energy Storage Charging Policies

In the previous section, all models are deterministic models, i.e., the loads and the wind power are fixed at their predicted values. However, due to uncertainty, real-time LMPs will deviate away from their predicted values, which leads to sub-optimal arbitrage decisions, which can also cause negative profits. Three charging policies are discussed in this section. SCUC is first solved to obtain the unit commitment solution for the next 24 hours. Then the arbitrage model is solved under different polices to obtain the charging and discharging solutions. Finally, in the real-time market, the EES owner participates in the market based on the obtained charging schedule. The procedure is described in Figure 4.2.

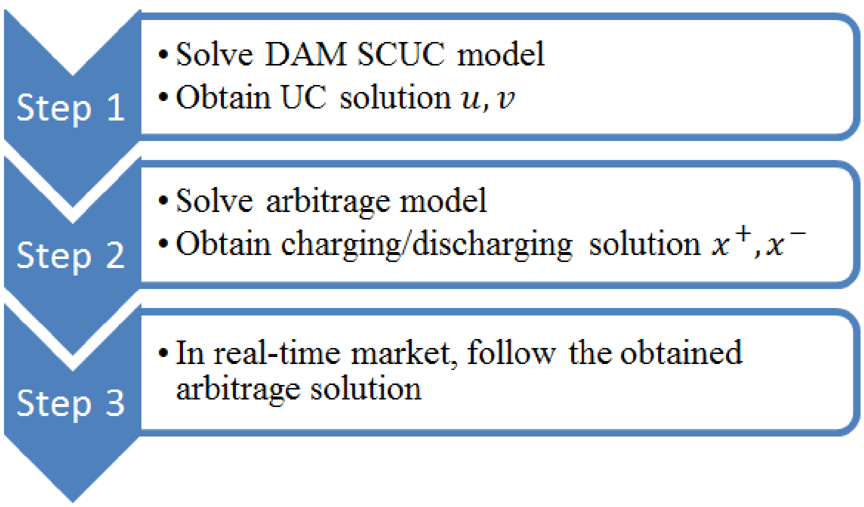

Figure 4.2: EES Charging/Discharging Decision Procedure

4.3.1 Forecasting-belief Policy

In this policy, the EES owner makes the decision based on the day-ahead forecasting loads and wind power assuming that they are the true value in the real-time. The arbitrage model is run with the predicted loads and wind power. Once the EES owner obtains the charging solutions, they stick to the charging and discharging schedule in the real-time market for the next 24 hours.

4.3.2 Robust Policy

In this robust policy, the EES owner first simulates several scenarios using Monte Carlo simulations. Then, they run the arbitrage model to estimate the best charging decision, the LMPs, and the total profits for each simulated scenario. Finally, they make the final charging decision based on these generated scenario solutions. Specifically, this policy calculates the lower and upper bound for the LMPs. Then the EES owner uses the maximum LMP when buying energy and the minimum LMP when selling the energy. In such manner, they hedge the risk of LMP variation that the wind and load uncertainty may bring to the power grid.

4.3.3 Dynamic Policy

The wind power is highly related to the wind speed. In practice, the wind speed is usually predicted first and the wind power is calculated with some static nonlinear function with respect to the wind speed (Papavasiliou and Oren, 2013). A better wind speed prediction can be obtained when the predicted period is close to the current period. In this dynamic policy, the EES owner updates their charging decision periodically. Standing at the current hour, the EES owner can have a better wind speed prediction of the following few hours. At each period, they run the arbitrage model for the next 24 hours and they keep adjusting the charging decision dynamically. This policy takes the advantage of the better prediction of the wind power and more accurate real-time LMPs. Figure 4.3 describes the procedure of the dynamic policy.

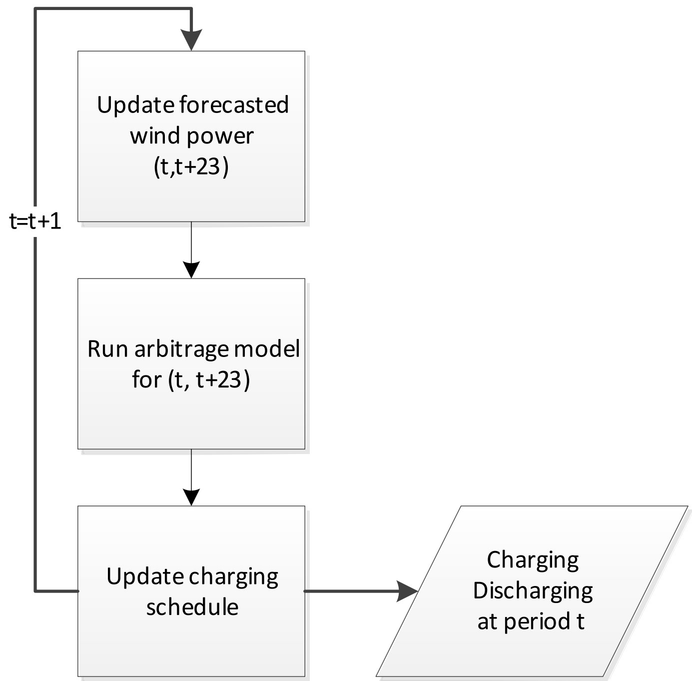

Figure 4.3: Dynamic Policy Procedure

4.4 Case Study and Computational Results

In this case study, IEEE 118-bus test case is tested. There are 118 buses, 186 transmission lines. 54 generators and five wind farms are located at different buses as suggested in Usaola (2010). The total peak load is 4519MW. The average hourly wind power is 530MW, 11.73% of the peak load. A single EES facility is considered at a single certain bus, with power capacity 100MW and 12+ hour energy storage capacity.

First, the charging or discharging impacts on LMPs are examined. Table 4.1 and Table 4.2 show the LMP with and without consideration of charging or discharging inputs.

"DA-LMP" stands for the day-ahead LMP, which is the LMP without considera-

Table 4.1: LMP Comparison under 100MW Power Capacity

Period	DA-LMP	RT-LMP	Charging	Discharging
1	11.36	11.48	1	0
2	10.65	11.36	1	0
3	11.36	11.36	1	0
4	**0**	**11.36**	1	0
5	10.65	10.65	1	0
6	10.65	10.65	1	0
7	13.35	13.35	1	0
8	31.78	31.78	0	0
9	35.32	35.32	0	0
10	35.37	35.37	0	0
11	35.37	35.37	0	0
12	35.68	35.68	0	1
13	37.54	35.68	0	1
14	35.90	35.90	0	1
15	35.68	35.68	0	0
16	35.37	35.37	0	1
17	37.40	37.32	0	1
18	37.62	37.54	0	1
19	37.62	37.54	0	1
20	37.40	37.32	0	1
21	**38.49**	**35.37**	0	1
22	38.48	38.48	0	0
23	14.38	14.57	1	0
24	12.62	14.35	1	0

tion of the charging or discharging. "RT-LMP" stands for the real-time LMP, which takes the charging or discharging into consideration. From Table 4.1, the LMP in period 4 changed dramatically when charging is taken into consideration. Originally, the day-ahead LMP was $0 without the consideration of charging impact. However, since the charging increases the load, the LMP increased to $11.36. Similarly, in period 21, the LMP dropped from $38.49 to $35.37. In period 22, the day-ahead LMP was $38.48; even still, charging does not occur in this period. It can be conjectured that if charging occurs, the real-time LMP would drop and make the arbitrage less profitable.

From Table 4.2, it can be seen that the LMP change is more frequent among 24 hours; especially in periods 4, 5, and 14, the LMPs change dramatically. Therefore, large amount of EES injection will affect the real-time LMP, which is expected.

Table 4.2: LMP Comparison under 150MW Power Capacity

Period	DA-LMP	RT-LMP	Charging	Discharging
1	11.36	11.20	0	0
2	11.36	11.03	1	0
3	11.36	11.03	1	0
4	**0**	**11.20**	1	0
5	**0**	**11.21**	1	0
6	10.65	11.13	1	0
7	10.76	13.84	0	0
8	31.78	25.62	0	0
9	35.32	35.32	0	0
10	35.28	35.28	0	0
11	35.28	35.28	0	0
12	35.68	35.68	0	0
13	35.68	35.68	0	0
14	**35.90**	**14.44**	0	1
15	14.40	14.40	0	0
16	35.37	35.37	0	0
17	37.32	35.68	0	1
18	37.62	35.90	0	1
19	37.62	35.41	0	1
20	37.32	35.03	0	1
21	38.49	38.49	0	0
22	38.48	38.46	0	0
23	14.38	14.38	0	0
24	12.62	12.62	0	0

When the EES owner makes the arbitrage decision, this effect should be taken into consideration.

Next, different locations of EES are examined for arbitrage. Moreover, the market welfare allocations are listed for comparison. Table 4.3 shows the results.

As discussed in section 4.2.1, the locational model is run assuming the EES owner is a vertically-integrated utility. Specifically, all 118 buses are examined for their potential load-shifting savings. A couple of potential EES locations are compared. Bus 67 gives the optimal location for load-shifting savings. Bus 24 gives the minimum savings per MW. Bus 8 gives the minimum total savings. Bus 70 gives the maximum total charged MW. Bus 60 is the wind farm location with maximum average wind power. Bus 89 is the bus with maximum load. Buses 28, 79, and 117 are randomly selected bus.

"TP" stands for the total profits obtained from arbitrage. "U" is the total units that EES charged during 24 hours. "P" is the arbitrage profit per unit, i.e., TP/U. "TC" is the total cost, which includes startup cost, no-load cost, and the variable operating cost. "TLP" is the total load payment. "TGR" is the total generation revenue. "TUL" is the total uplifts payment. "TGRent" is the total generation rent.

Table 4.3: Arbitrage Comparison under Different Locations

BUS	67	24	8	70	36
TP ($)	15,103	2,654	2,905	13,767	2,291
U (MW)	900	900	600	900	500
P ($/MW)	16.78	2.95	4.84	15.30	4.58
TC ($)	905,693	921,595	922,318	910,714	923,030
TLP ($)	1,772,730	1,826,860	1,805,190	1,793,690	1,802,920
TGR ($)	1,447,200	1,483,490	1,471,870	1,454,990	1,471,740
TUL ($)	85,784	89,107	88,526	85,994	87,770
TGRent ($)	627,287	650,999	638,078	630,268	636,478
BUS	60	89	28	79	117
TP ($)	716	14,671	3,624	14,170	15,428
U (MW)	500	900	800	900	900
P ($/MW)	1.43	16.30	4.53	15.74	17.14
TC ($)	924,424	907,220	921,351	907,148	908,484
TLP ($)	1,800,510	1,773,980	1,815,350	1,758,360	1,805,860
TGR ($)	1,471,560	1,443,900	1,475,010	1,433,800	1,465,800
TUL ($)	86,805	86,351	89,438	87,096	85,683
TGRent ($)	633,944	623,026	643,097	613,745	642,997

Thirty real-time wind scenarios are generated and all results are shown as the average of all 30 scenarios. In Table 4.3, all results are based on the forecasting-belief policy.

From the results, bus 67 maximizes the social welfare whereas bus 117 gives the maximum arbitrage profits. This confirms that the best EES location for a vertically-integrated utility is different from the best location for a for-profit private investor. Although bus 67 does not give the highest arbitrage profits, the profits at this location are still very high. Bus 60 gives the minimum arbitrage profits since the wind farm is also located at this bus. The marginal cost of the wind power is considered to be zero; thus, it can be expected that the LMPs at this bus are low and flat among all 24 periods. While PHS is suggested to build along with the wind farm to flatten the variance of the wind power, the arbitrage value at a bus with wind farm is not prominent. This result also communicates that a joint investment effort between the two resources is likely preferred over independent investments.

Different load profiles and different efficiencies are also tested to evaluate the arbitrage effects. The results are listed in Table 4.4 and Table 4.5. H, M and L stand for high, medium and low load profiles respectively. From Table 4.4, the arbitrage profits will drop as the load drops. When load is low, the expensive generators may not be turned on and, thus, the variation in LMPs is lower, which reduces arbitrage opportunities. From Table 4.5, the arbitrage profits will drop as the round-trip efficiency goes down.

Table 4.4: Arbitrage Comparison under Different Load Profiles

Load	H	M	L
TP ($)	14,643	954	4,813
U (MW)	900	600	1,100
P ($/MW)	16.27	1.59	4.38
TC ($)	915,055	378,663	229,429
TLP ($)	1,745,660	539,814	272,213
TGR ($)	1,401,960	425,155	213,451
TUL ($)	87,211	67,093	61,547
TGRent ($)	574,111	113,585	45,568

Table 4.5: Arbitrage Comparison under Different EES Efficiency

Eff	0.9	0.85	0.8
TP ($)	14,643	12,194	10,103
U (MW)	900	900	900
P ($/MW)	16.27	13.55	11.23
TC ($)	915,055	917,348	919,772
TLP ($)	1,745,660	1,759,020	1,773,870
TGR ($)	1,401,960	1,414,600	1,428,190
TUL ($)	87,211	86,495	85,222
TGRent ($)	574,111	583,747	593,639

Finally, the arbitrage behaviors under different policies are compared. The results are shown in Table 4.6. "P1", "P2" and "P3" stand for the policy 1, 2 and 3 respectively. The high load profile and medium load profile are tested.

Table 4.6: Arbitrage Comparison under Different Policies

	P1_H	P2_H	P3_H	P1_M	P2_M	P3_M
TP ($)	14,643	14,862	14,030	954	1,855	1,942
U (MW)	900	900	962	600	300	623
P ($/MW)	16.27	16.51	14.70	1.59	6.18	3.19
TC ($)	915,055	913,888	913,543	378,663	380,046	377,964
TLP ($)	1,745,660	1,730,110	1,745,570	539,814	513,895	534,313
TGR ($)	1,401,960	1,387,930	1,397,090	425,155	421,727	421,811
TUL ($)	87,211	87,947	89,422	67,093	64,585	68,089
TGRent ($)	574,111	561,984	572,969	113,585	106,266	111,936

From Table 4.6, the robust policy makes more profits than the forecasting-belief policy since it takes different real-time wind power uncertainty into consideration. The robust policy is a conservative policy, i.e., charges less frequently than the other two policies. The dynamic policy minimizes the total cost of the system but not necessarily returns the maximum arbitrage profits. This contradicts what was intuitively expected, that a dynamic policy that frequently updates its scheduling would be preferred. The reasons might be the inaccurate forecasts and the frequent charging and discharging. More tests are desired to confirm this result.

4.5 Conclusions

In this chapter, EES arbitrage in electric energy markets is studied. When EES power capacity is large, the charging or discharging events may change the real-time LMP from the day-ahead predicted value. Since the arbitrager bids in the real-time markets, the potential LMP changes should be taken into consideration. The test case shows that the LMP in real time changes significantly in some periods with charging or discharging. If the EES owner makes arbitrage decision only based on the day-ahead LMP, it might end up losing money. Locations of the EES facility play a very important role in the arbitrage. From test case results, the best location of EES for a private investor is likely to be different from the best location if the EES owner is a vertically-integrated utility. Nevertheless, in many cases the two have similar beneficial impacts on both arbitrage profits and social welfare improvement, i.e., the location that maximizes arbitrage profits usually has a high social welfare and the location that maximizes social welfare usually has relatively high arbitrage profits. When the location of EES is selected at some inappropriate bus, the benefits of arbitrage may be little. Load levels and EES round-trip efficiency would also affect the arbitrage profits. The arbitrage decision will also be affected by the wind power penetration. Better prediction of wind power can help improve the arbitrage profits.

Although EES brings many benefits to the power grid planning and operation, making profits through price arbitrage in real-time market has low return on investment and may be very vulnerable considering the high penetration of renewable energy. It is also vulnerable to the placement of the storage; over the long time horizon to recover the investment cost, the ideal arbitrage location is likely to change. Current market design does not incentivize private investors to build EES. Furthermore, existing market bidding structures are designed for fossil fuel based generators, not other forms of resources. Storage resources naturally offer a different product, a different service to the industry but yet they are forced to conform to the bidding and characteristics of a fossil fuel generator based on how supply resources are modeled with electricity market auctions. It is time for market design reform, a market structure that acknowledges the variation in products offered by different supply resources instead of conforming to one such structure. As long as the market structures conform to only one dominant resource type, the incentives are not what they should be to encourage investment in alternative resources that are critical to the operations of future power systems. While this is a critical topic and one of high interest, at this time this challenge is left to future work.

Chapter 5

CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

The deregulation of the electrical power industry in the U.S. was motivated by the growing dissatisfaction of the regulatory structure governing the vertically-integrated utilities. This dissatisfaction stemmed from apparent operating inefficiencies, a lack of variety in the products and services available, as well as the potential for exercising market power resulting from the absence of transparency of information regarding the system state and prices.

Followed the Federal Energy Policy Act in 1992, the concepts of RTO and ISO were first introduced. RTO/ISOs are nonprofit independent entities and play a similar role to that of air traffic controllers in air transportation industry. RTO/ISOs operate the electric power systems in market structures while ensuring the security and efficiency in power systems. The goal of the creation of market structures is to bring competition in order to maximize social welfare.

A good market design should induce all participants to truthfully reveal their private information, avoid strategic bidding or exercising market power, and be incentive compatible, i.e., participants have no incentive to deviate from market solutions. Pricing schemes are important for the market designs since market participants will make operating and investment decisions based on market prices.

In the first part of this thesis, convex hull pricing scheme in day-ahead energy markets is studied. Current utilized LMP scheme releases good pricing signals for single-period (short-run) dispatch marginal costs. However, the LMPs alone are not incentive compatible since energy markets are nonconvex markets. The non-convexities of energy markets is a result of many reasons. The most important reason is that the commitment status is a binary decision, and the EcoMin of most generators are not zero, i.e., most generators are not perfectly partially dispatchable. Moreover, minimum up/down time requirements restrict generators online/offline when they may not provide economic efficiency for the corresponding period. LMPs capture dispatch costs, but fail to capture commitment costs such as startup cost, fixed cost, and shutdown cost. In fact, the discrete nature of commitment decisions, startup costs, and no-load costs may prevent the existence of a set of incentive compatible market clearing prices in DAM since there is generally no set of market prices that would induce profit maximizing generators and loads to voluntarily follow the pricing scheme. Since the current LMP scheme only captures dispatch marginal costs but does not capture commitment costs, Gribik *et al.* (2007) proposed a convex hull pricing scheme , sometimes referred as the extended locational marginal price. CHP scheme takes the dual of the whole unit commitment model, sets prices as the Lagrangian multipliers of the nodal balance constraints with a goal that the prices release better pricing signal than the standard LMP. Hogan and Ring (2003) proved that CHP scheme minimizes the uplift payments. Moreover, CHP gives a monotonically non-decreasing marginal cost function with respect to the total loads, whereas the current adopted LMP does not.

The existing CHP literature is based on a single-bus system, this thesis extended the CHP model to the system with network constraints, which extended CHPs to locational CHPs. We proposed a overall subgradient algorithm to obtain locational CHPs. We concluded that the properties of CHP under single-bus assumption are still valid under network-constrained market models. Locational CHPs reduce uplift payment. However, after extending the model with network constraints, the dimension of the prices increases significantly, and calculating CHPs becomes extremely difficult due to the curse of dimensionality. Even for our small tested case, the solution algorithm takes long time to converge. The solution time is expected to increase exponentially with the system size. Therefore, few RTO/ISOs have been convinced to switch to CHP even though the issues of the current adopted LMP are well understood.

In the second part of this thesis, the day-ahead energy market non-convexities and uncertainty issues are studied jointed. More and more renewable energy resources (mainly wind and solar farms) are integrated into power grids to provide electric power in order to lower generation costs and reduce environmental pollutions. According renewable portfolio standard policies, the eligible renewable energy resources for most state will be increased significant in the next 20 years (Renewable Portfolio Standard, 2015). However, the intermittent and volatile nature of the renewable resources may impact power system characteristics such as voltages, frequency and generation adequacy, which can potentially increase the vulnerability of power systems. The intermittency refers to the unavailability of renewable for an extended period and the volatility refers to the fluctuations of the renewable within its intermittent characteristics (Wang *et al.*, 2008). While it brings many benefits both economically and environmentally, on the other hand, the high penetration of the renewable also complicates the power system scheduling due to their uncertain nature. The uncertainty in the power systems complicates the power system scheduling process. The uncertainty can cause price inconsistency between DAM and RTM. In other words, the expected RTM price differs from the DAM price. Market manipulation could happen if a participant sees persistent price premia between RTM and DAM, which consequently can cause problems such as revenue inadequacy. Therefore, a deterministic model that is based on summarizing statistics will not result in an efficient pricing scheme under high uncertainty: hence, a stochastic model is desired.

We proposed a stochastic dispatchable model to better represent DAM energy prices. Fixed costs are amortized to generation variable costs and generators' EcoMins are relaxed to zero to allow all units to set marginal prices. Test results show that the uplift payments are reduced under the proposed pricing scheme. In addition, the stochastic pricing framework reduces price inconsistency between DAM and RTM. The proposed stochastic dispatchable pricing scheme releases a better pricing signal.

In the third part of this thesis, the market incentives for energy storage under the current LMP scheme is studied. Electric energy storage (EES) can bring many benefits to power grids and to electric power markets. However, as EES private investors, they make profits mainly by price arbitrage. We studied the impacts of EES arbitrage in electric power energy markets. Prior work frequently assumes that the arbitragers are price-takers, i.e., the participation of EES has little impact on the real-time LMPs and charging or discharging decisions are made based on the predicted LMP. However, the charging or discharging activities for large-scale EES may have huge impacts on real-time LMPs. An optimization model is proposed to maximize the arbitrager's profits with the consideration of the charging and discharging impacts on the LMPs. Three charging policies are discussed to handle the uncertainty that the intermittent wind penetration brings to the power grid.

Although EES brings many benefits to the power grid planning and operation, making profits through price arbitrage in real-time market has low return on investment and may be very vulnerable considering the high penetration of renewable energy. It is also vulnerable to the placement of the storage; over the long time horizon to recover the investment cost, the ideal arbitrage location is likely to change. Current market design does not incentivize private investors to build EES. Furthermore, existing market bidding structures are designed for fossil fuel based generators, not other forms of resources. Storage resources naturally offer a different product, a different service to the industry but yet they are forced to conform to the bidding and characteristics of a fossil fuel generator based on how supply resources are modeled with electricity market auctions. It is time for market design reform, a market structure that acknowledges the variation in products offered by different supply resources instead of conforming to one such structure. As long as the market structures conform to only one dominant resource type, the incentives are not what they should be to encourage investment in alternative resources that are critical to the operations of future power systems.

5.2 Future Work

The overall market design is a very complex problem. Pricing schemes play a very important role in the market design. In this thesis, some issues in the current market design have been identified and several pricing schemes are proposed to release better pricing signals in order to guide market participant to follow market solutions.

In this thesis, the analysis is based on energy-only markets. While most RTO/ISOs have energy and reserve co-optimization in their market models, future research should focus on the pricing issues between multiple markets, such as reserve market (ancillary services), financial transmission rights (FTR) market, and capacity markets. The change of current energy market pricing mechanisms will affect the design of other markets. The potential research topics include: how to price reserves? Is revenue adequacy guaranteed in FTR market?

This thesis mainly discussed the pricing schemes in DAM. Future research can focus on the pricing schemes in RTM. There are generally two main steams for pricing in RTM: ex ante and ex post pricing mechanisms. The former one price the real-time energy using the forecasted system condition (near real-time estimates). However, since the market models are approximate models to represent the real power system, the real dispatch of generators may be different from the RTM ex ante solutions. Dispatch-based pricing scheme is proposed to better represent the cost of generators. The ex post pricing computes prices based on the actual responses of resources (actual marginal resource clearing the market in real time). Compared to the ex ante pricing, the ex post pricing creates incentives for bidders to act consistently with their bids (Zheng and Litvinov, 2011).

For the stochastic pricing framework, the plausible scenario selections is important for the pricing scheme. How to select the plausible scenarios and the sensitivity of the prices with different scenario selection is left for future study.

For the proposed dispachable model in this thesis, simple fixed cost allocation rules are adopted to approximate the convex hull of the total cost functions. We made some simplification assumptions to carry out the analysis. Future research can focus on more realistic piece-wise bids for each generator.

Finally, from a high level of market design, a design is desired to accommodate different energy markets for different type of resources, i.e., renewable resources should be treated differently than the conventional units. More incentives should be given to the resources that would benefit power systems and markets.

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APPENDIX A

NOMENCLATURE

Sets and Indices:

$g \in G$	generators
$g \in G(n)$	generators at bus n
$l \in L$	transmission lines
$l \in \delta^{-}(n)$	transmission lines from bus n
$l \in \delta^{+}(n)$	transmission lines to bus n
$n \in N$	buses
$t \in T$	time periods
$s \in S$	scenarios

Parameters:

B_l	transmission line susceptance
C_g	linearized dispatch cost
C_g^{NL}/C_g^{SU}	no-load/startup cost
D_{nt}	predicted loads
DT_g/UT_g	minimum down/up time
F_l	transmission line rating
P_g^{max}/P_g^{min}	generator EcoMax/EcoMin
$R_g^{hr}/R_g^{SD}/R_g^{SU}$	hourly/shutdown/startup/ ramping capability
W_j	available wind capacity
π^s	scenario probability
ψ_{ln}	PTDF

Unit Commitment Variables

u_{gt}	commitment status
v_{gt}	startup status
w_{gt}	shutdown status

Dispatch Variables

e_{nt}	energy storage level
f_{lt}	transmission line flow
i_{nt}	bus injection
o_{nt}^{+}/o_{nt}^{-}	storage unit charge/discharge quantity
p_{gt}	generation
r_{gt}	reserves
w_{jt}	dispatched wind power
θ_{nt}	bus angle

Dual Variables

λ_n	dual variables of node-balance constraint
μ_l^{+}/μ_l^{-}	dual variables of transmission bounds
ω_j	dual variables of wind power bounds
ϕ_g^{+}/ϕ_g^{-}	dual variables of generation bounds
ρ_g^{+}/ρ_g^{-}	dual variables of ramping rate constraint
τ	dual variables of total injection constraint