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PRICE FORMATION IN ELECTRICITY MARKET DESIGN

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CONLEIGH BYERS
S.M., Massachusetts Institute of Technology
born on 20 April 1993

accepted on the recommendation of

Prof. Gabriela Hug, examiner
Prof. Benjamin F. Hobbs, co-examiner
Prof. William W. Hogan, co-examiner
Prof. Shmuel S. Oren, co-examiner

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ABSTRACT

This work examines how we can derive economic signals from the non-convex optimal value functions of mixed integer programs used to dispatch resources in the power grid. The objectives of market design and price formation are to promote economic efficiency, by providing prices that support social surplus-maximizing operations in the short-run and investment in the long-run. Under certain restrictive conditions, these are prices that reflect short-run marginal costs (including scarcity costs), and provide recovery of fixed costs in the long-run. Two critical features of electricity limit its ability to achieve the theoretical microeconomic ideal of perfect long-run cost recovery via marginal pricing: the physics of the grid and non-convex costs of generators. This thesis uses a series of engineering-economic models of optimal power plant scheduling and investment to explore alternative market designs to maximize the economic surplus of consumers. Chapter 2 provides the mathematical theory to compare central planning and markets. Chapters 3, 6, and 7 examine short-run market design to manage transmission congestion, the impact of near-optimal solutions under elastic demand, and market power in non-convex markets, while Chapters 4 and 5 focus on investment, modeling the long-run investment efficiency implications of alternative short-run designs for deriving prices when operating costs are non-convex and shares of variable renewable energy increase.

A central difference between power markets globally is whether the market is cleared based on an aggregated version of the underlying transmission network and simple bids (zonal market) or the full network model and complex bids (nodal market). Chapter 3 explores the methodological choices behind a new approach called flow-based market coupling (FBMC) that seeks to better represent network congestion in zonal markets. While zonal markets typically force participants to internalize their non-convexities in simple bids, this chapter shows the impact of combining an aggregated transmission network with complex bids in the form of unit commitment (the power plant scheduling problem) constraints. The chapter also explores the impact of the methods to calculate the FBMC base case and the re-dispatch of power plants from the zonal solution to a physically feasible

solution. A substantial welfare gap between the market clearing with an aggregated transmission network and the nodal market ideal remains.

However, even in the theoretical ideal of nodal pricing, marginal pricing as a market-clearing mechanism does not have the desired economic properties of being able to clear the market while providing a dispatch solution from which no agent has an incentive to deviate. This is because there are non-convexities in electricity markets due to operating costs and technical constraints.

System operators are actively debating what pricing model to use, but it is important to remember that prices are not meant to support the current resource mix but rather to provide signals for entry and exit so that the social welfare-maximizing resource mix is achieved in the long-run. Chapter 4 analyzes non-convex pricing models in a long-run analysis, developing a method to find resource mixes adapted to a given market model. Convex hull pricing, a method in which prices are derived from the convex hull of the optimal value function, is found to provide the least compensation in excess of short- and long-run costs to inframarginal electric generating units, leading to resource mixes that maximize consumer surplus. In theory, assuming convexity of cost functions and feasible regions, an energy-only market provides perfect cost recovery in the long-run for generators in the optimal resource mix as well as signals for resources to enter or exit the market as new, lower-cost innovative technologies come online. Concern has risen as to whether energy-only markets with non-convex costs can adequately compensate providers of flexibility, as units may need to cycle on and off more frequently to meet a net load curve with shorter peaks and steeper ramps. Chapter 5 demonstrates that relaxing the assumption of convexity still leads to long-run cost recovery for flexible generators in the presence of high shares of zero-marginal cost variable renewable energy, but that there is a penalty to consumers relative to the convex case in the form of higher profits for producers (higher prices for consumers) in the long-run adapted resource mix. This penalty is proportional to the amount of non-convex resources in the system.

Unit commitment problems are typically too large to be solved to optimality and must be relaxed to find market-clearing prices due to non-convexities. Chapter 6 shows that with flexible demand and pricing models that depend on the primal solution, finding a better near-optimal solution can improve outcomes for consumers. Because non-convexities mean that a uniform price often does not support the socially optimal solution, some units will desire to deviate from the central dispatch decision. Units that perceive the opportunity to make a profit may be incentivized to self-commit (submitting an offer with zero fixed operating costs) or self-schedule their production (submitting an offer with zero total cost). Using reinforcement learning, Chapter 7 assesses incentive compatibility in non-convex markets, showing that market power can be exercised by self-scheduling and self-committing. In a realistic test system, strategic bids under the restricted convex pricing model increased total producer profits substantially, while convex hull pricing preserved the profits made at the competitive market solution and resulted in a lower cost to consumers than alternative models.

As fossil-fuel resources are displaced by low-carbon resources, these findings can guide system operators in understanding how price formation impacts the transition, and to what extent energy markets can signal enough of the right kind of resources to be built for reliability needs. With more systems considering implementing nodal pricing, this work demonstrates the gap between nodal pricing and the theoretical ideal of convex markets and offers paths forward for system and market operators to not only maximize social surplus but also the share of social surplus gained by consumers.

ZUSAMMENFASSUNG

In dieser Arbeit wird untersucht, wie wirtschaftliche Signale aus den nichtkonvexen optimalen Wertfunktionen von gemischt-ganzzahligen Programmen, die für die Allokation von Ressourcen im Stromnetz verwendet werden, abgeleitet werden können. Die Ziele des Marktdesigns und der Preisbildung bestehen darin, die wirtschaftliche Effizienz zu fördern, indem Preise bereitgestellt werden, die kurzfristig die Maximierung der gesamtwirtschaftlichen Wohlfahrt und langfristig die Investitionstätigkeit unterstützen. Unter bestimmten einschränkenden Bedingungen sind dies Preise, die kurzfristig die Grenzkosten (einschließlich Knappheitskosten) widerspiegeln und langfristig die Deckung der Fixkosten gewährleisten. Zwei kritische Merkmale der Elektrizität schränken jedoch ihre Fähigkeit ein, das theoretische mikroökonomische Ideal einer perfekten langfristigen Kostendeckung über Grenzpreise zu erreichen: die physikalischen Eigenschaften des Netzes und die nichtkonvexen Kosten der Erzeuger. Diese Arbeit verwendet eine Reihe von techno-ökonomischen Modellen zur optimalen Kraftwerksplanung und Investitionen um alternative Marktdesigns zur Maximierung der Konsumentenrente zu untersuchen. Kapitel 2 liefert die mathematische Theorie zum Vergleich von zentraler Planung und Märkten. Die Kapitel 3, 6 und 7 untersuchen das Design von Kurzfristmärkten zur Bewältigung von Netzengpässen, die Auswirkungen nahezu optimaler Lösungen bei elastischer Nachfrage und die Marktmacht in nichtkonvexen Märkten. Die Kapitel 4 und 5 konzentrieren sich auf Investitionen und modellieren die langfristigen Auswirkungen auf die Investitionseffizienz verschiedener Designs von Kurzfristmärkten und Preismechanismen - immer unter den Bedingungen nichtkonvexer Kosten und steigendem Anteil erneuerbarer Energien.

Ein zentraler Unterschied zwischen den Strommärkten weltweit besteht darin, ob der Markt auf einer aggregierten Version des zugrundeliegenden Übertragungsnetzes und einfacher Gebote (zonaler Markt) oder des vollständigen Netzmodells und komplexer Gebote (nodaler Markt) basiert. Kapitel 3 untersucht die Methodik hinter einem neuen Ansatz, der als flow-based market coupling (FBMC) bezeichnet wird und darauf abzielt, Netzengpässe auf zonalen Märkten besser darzustellen. Während zonale

Märkte die Teilnehmer typischerweise dazu zwingen, ihre Nichtkonvexitäten in einfachen Geboten zu internalisieren, zeigt dieses Kapitel die Auswirkungen der Kombination eines aggregierten Übertragungsnetzes mit komplexen Geboten in Form von Unit Commitment Restriktionen, die bei der Optimierung der Kraftwerkseinsatzplanung angewendet werden. In diesem Kapitel werden auch die Auswirkungen der Methoden zur Berechnung des FBMC-Basisfalls und der Redispatch von Kraftwerken von der zonalen Lösung zu einer physikalisch machbaren Lösung untersucht. Es bleibt eine erhebliche Wohlfahrtslücke zwischen der Markträumung mit einem aggregierten Übertragungsnetz und dem Ideal eines nodalen Marktes.

Doch selbst im theoretischen Ideal des nodalen Marktes hat die Preisbildung auf Grenzkostenbasis nicht die gewünschten wirtschaftlichen Eigenschaften sowohl den Markt zu räumen als auch eine Allokation bereitzustellen, von der kein Akteur einen Anreiz hat abzuweichen. Der Grund dafür liegt in der Nichtkonvexität der Strommärkte aufgrund von Betriebskosten und technischen Einschränkungen.

Die Netzbetreiber debattieren aktiv über das zu verwendende Preismodell, aber es ist wichtig, sich daran zu erinnern, dass die Preise nicht dazu gedacht sind, den aktuellen Ressourcenmix zu unterstützen, sondern vielmehr Signale für den Ein- und Ausstieg zu geben, so dass langfristig ein Ressourcenmix erreicht wird, der die gesamtwirtschaftliche Wohlfahrt maximiert. Kapitel 4 analysiert nichtkonvexe Preismodelle in einer langfristigen Analyse und entwickelt eine Methode, um Ressourcenmixe zu finden, die an ein gegebenes Marktmodell angepasst sind. Es wird festgestellt, dass Convex Hull Pricing, eine Methode, bei der die Preise aus der konvexen Hülle der optimalen Wertfunktion abgeleitet werden, über die kurz- und langfristigen Kosten hinaus die geringsten Entschädigungen für inframarginale Generatoren bietet, was zu einem Ressourcenmix führt, der die Konsumentenrente maximiert. Unter der Annahme konvexer Kostenfunktionen und eines konvexen zulässiges Bereichs bietet ein reiner Energiemarkt langfristig eine perfekte Kostendeckung für Erzeuger im optimalen Ressourcenmix sowie Signale für den Markteintritt oder -austritt von Ressourcen, wenn neue, kostengünstigere innovative Technologien in Betrieb gehen. Es sind allerdings Bedenken aufgekommen, ob reine Energiemärkte mit nichtkonvexen Kosten die Anbieter von Flexibilität angemessen entschädigen können, da die Einheiten möglicherweise häufiger ein- und ausgeschaltet werden müssen, um eine Residuallastkurve mit kürzeren Spitzen und steileren Rampen zu erfüllen. Kapitel 5 zeigt, dass die Lockerung der Konvexitätsannahme immer noch zu einer langfristigen Kostendeckung für flexible Erzeuger führt, wenn ein hoher Anteil an variablen erneuerbaren Energien mit Null-Grenzkosten besteht, dass aber im Vergleich zum konvexen Fall ein Nachteil für die Verbraucher in Form von höheren Gewinnen für die Erzeuger (höhere Preise für die Verbraucher) im langfristig angepassten Ressourcenmix entsteht. Dieser Nachteil ist proportional zur Menge der nichtkonvexen Ressourcen im System.

Unit-Commitment-Probleme sind in der Regel zu groß, um optimal gelöst werden zu können, und müssen aufgrund von Nichtkonvexitäten relaxiert werden, um markträumende Preise zu finden. Kapitel 6 zeigt, dass bei flexibler Nachfrage und Preismodellen, die von der primalen Lösung abhängen, die Suche nach einer besseren nahezu-optimalen Lösung die Konsumentenrente verbessern kann. Da Nichtkonvexitäten bedeuten, dass ein einheitlicher Preis oft nicht die gesamtwirtschaftlich optimale Lösung unterstützt, werden einige Einheiten von der zentralen Dispatch-Entscheidung abweichen wollen. Einheiten, die die Möglichkeit sehen, einen Gewinn zu erzielen, können einen Anreiz haben, ihre Produktion selbst zu planen (ein Angebot mit null Gesamtkosten abzugeben). Unter Verwendung von Reinforcement Learning wird in Kapitel 7 die Anreizkompatibilität in nichtkonvexen Märkten bewertet und gezeigt, dass Marktmacht durch Selbstplanung ausgeübt werden kann. In einem realistischen Testsystem erhöhten strategische Gebote unter dem eingeschränkten konvexen Preismodell die Gesamtgewinne der Erzeuger beträchtlich, während Convex Hull Pricing die auf dem kompetitiven Markt erzielten Gewinne bewahrte und zu niedrigeren Kosten für die Verbraucher führte als alternative Modelle.

Während fossile Energieträger durch kohlenstoffarme Energieträger ersetzt werden, können diese Ergebnisse den Netzbetreibern helfen zu verstehen, wie sich die Preisbildung auf den Übergang auswirkt und inwieweit die Energiemärkte signalisieren können, dass die richtige Art von Energieträgern für den Versorgungssicherheitsbedarf gebaut werden muss. In Anbetracht der Tatsache, dass immer mehr Systeme die Einführung von nodalen Preisen in Erwägung ziehen, zeigt diese Arbeit die Lücke zwischen nodalen Märkten und dem theoretischen Ideal konvexer Märkte auf und bietet Wege für System- und Marktbetreiber, um nicht nur die Gesamtwohlfahrt zu maximieren, sondern auch die Konsumentenrente.

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CONTENTS

1

INTRODUCTION

1.1 MOTIVATION

With the growth in awareness of the impacts of climate change, the world is moving toward decarbonization, and over 100 nations have pledged to achieve net zero carbon emissions by 2050 [1]. A central part of economy-wide decarbonization is increased electrification, with estimates that electricity could account for nearly 50% of total energy consumption by 2050 and that total electricity generation required will be 2.5 times higher than in 2020 [2]. Over the past few decades, much of the world has moved from a centrally planned electricity system where generation, transmission, and distribution were bundled together to one in which market participants interact in a regulated environment. While initially the motivation may have drawn more from ideology than a careful cost-benefit analysis [3], the goal is to foster innovation and create better incentives that eventually lead to lower costs for consumers, avoiding the pitfalls of regulated monopolies. However, as the transition to a decarbonized electricity sector is upon us, questions arise about what markets can and cannot do well, underscoring a tension between centralized planning and market solutions. The system by which we invest, build, and price electricity has enormous consequences for society, as the energy produced is not only an important input into the economy but impacts the pace and pathway of decarbonization.

A centrally planned system may be a defensible position in the face of climate emergency, but the extreme of this approach is beholden to political whims and would likely stifle innovation and lead to higher costs. On the other hand, a purely market-driven approach not accounting for the externalities of carbon emissions may be too slow for the socially optimal pace of decarbonization. While economics can tell us that a price sent by markets ought to equilibrate around the optimal solution, the political question is "when?". In most systems today we see a mix of government intervention to support decabonization goals while relying on markets for coordination of scheduling and dispatch of generators. However, electricity is not like any other commodity; the electric power grid is the largest machine humanity has ever built, and electricity follows the laws of physics, not economics. A system operator must solve a large optimization problem to balance supply and demand in real time while respecting the operating constraints of the power plants and the transmission network. To schedule and dispatch power plants to clear the electricity market, we must solve a simplified version of this problem for computational reasons, and the simplifications we make and how we derive prices from these simplified models can have significant long-run impacts.

In theory, assuming convexity, an energy-only market provides perfect cost recovery in the long-run for generators in the optimal resource mix as well as signals for resources to enter or exit the market as new, lower-cost innovative technologies come online [4]. However, electricity markets exhibit what is known as the "missing money" problem, a phenomenon in which energy market prices are insufficient for generators to fully recover their capital costs [5]. Out-of-market actions by system operators to avoid grid conditions in which scarcity prices emerge and price caps to mitigate market power mean that prices often do not rise high enough for sellers to recover their investment costs. As a result, capacity mechanisms have proliferated in recent years both in the United States, Europe, and beyond [6], [7]. Yet capacity markets rely on calculations of firm capacity that are challenging to apply to variable renewable and energy storage resources [8] and may be biased toward resources with high marginal costs and low capital costs [9], penalizing resources that governments want to promote for decarbonization goals. Electricity system operators around the world are actively discussing the redesign of resource adequacy mechanisms, i.e., how we ensure that there is enough of the right kind of resources installed on the system to meet load reliably.

The core of any proposed market design must be the energy market spot prices from which all other contracts are derived. To the extent that we wish to keep electricity markets as not only a short-run dispatch signal but an optimal long-run investment signal, it is imperative this signal be as efficient as possible. However, two critical features of electricity limit its ability to achieve the theoretical microeconomic ideal of perfect long-run cost recovery via marginal prices. The first is that electricity follows Kirchhoff's laws, creating economically counter-intuitive flows and requiring a representation of the transmission network. The most physically accurate approach would be to clear markets with the full non-linear AC optimal power flow equations, although this is typically not done due to computational intensity and time required. A central difference between power markets globally is whether the market is cleared based on an aggregated version of the underlying transmission network and simple bids or the linearized DC optimal power flow and complex bids. The second critical feature is that conventional electricity generators have non-convex costs.[1] The scheduling problem, unit commitment, requires binary decision variables of whether generators are turned on or off, and no-load and minimum operating requirements may also introduce non-convexities into the system's optimal value function. Non-convexities can additionally arise from the configuration of combined cycle plants and modeling of pumped hydro storage generators. Non-convexities can lead to situations in which the central dispatch solution from the system operator results in a unit not recovering its short-run fixed costs, not recovering its short-run variable costs, or perceiving an opportunity to make a profit but not having its bid accepted.

These challenges of electricity market design are topics of active discussion. While the United States moved during the 2000s and 2010s from zonal to nodal pricing, Europe still has a uniform price per zone, requiring increasingly higher redispatch costs to obtain a physically feasible solution after the economic market clearing. Debate over whether to move to a nodal network is ongoing [10], with the UK seriously considering making the transition [11]. However, even in the academic ideal of nodal pricing, marginal pricing as a market clearing mechanism does not have the desired economic properties of being able to clear the market while providing a dispatch solution from which no generator has an incentive to deviate. Non-convex costs with a uniform price result in lost opportunity costs and often require make-whole payments for short-run cost recovery. System operators in the United States are actively debating what non-convex pricing method to use [12], [13]. New low-carbon technologies or demand-response schemes that are best modeled with integer variables could also increase non-convexities in the future.

The decision of how to form prices in electricity markets is particularly important during the energy transition in which prices act as signals not only to invest in new resources but also to drive retirement of the conventional fossil-fuel fleet. Exit will be just as important as entry in the energy transition, and we want price signals to provide the lowest-cost resource mix possible while still meeting system reliability needs. We want

1 The focus of this work is to isolate the impact of non-convex operating costs, although non-convex investment costs are also present. See Section 2.5 for an expanded definition and example.

to preserve full-strength spot prices to the extent possible to act as efficient dispatch and investment signals while also hedging consumers appropriately. Non-convexities, system operator risk aversion, price suppression for market power mitigation, and increasing shares of variable renewable energy may lead to lack of cost recovery. We must discern how much of this missing money is due to each cause, especially as we will start to see thermal power plants recovering less and less in the wholesale markets as some are correctly signaled to exit. Understanding the drivers behind price formation can prevent overcompensation to fossil-fuel assets with non-convex costs via market intervention, side payments, and capacity payments, which may otherwise slow the transition. This dissertation examines the question of how close we can get to the theoretical ideal of efficient prices given transmission constraints and non-convexities in the system operator's optimal value function.

1.2 ORGANIZATION AND CONTRIBUTIONS

The goal of this thesis is to investigate how features particular to the electricity network impact price formation in wholesale electricity markets, focusing on the representation of the transmission network and non-convexities. A new method of determining zonal prices with more granular transmission representation still lags nodal prices in market efficiency. However, nodal prices with complex bids must be derived from a relaxation of the unit commitment problem, and it is imperative we understand how impactful the choice of non-convex pricing method is and how it may intersect with changes in the grid to include more variable renewable energy and flexible demand.

1.2.1 *Electricity Network and Market Background*

Chapter 2 provides an introduction to the problem of designing markets for electricity. It compares the simplified and integrated market designs dominant in Europe and the United States, respectively. The optimality conditions for an optimization problem of a central planner maximizing social welfare and an equilibrium problem in which participants try to maximize their individual benefits are derived. These conditions are equivalent with marginal pricing assuming convexity. These conditions are then extended to include linear transmission network constraints and investment decisions. Next, it is shown that this equivalence of the optimization and equilibrium solution is broken with the introduction of non-convexities. The role of non-convexities in the integrated and simplified market models is discussed. This chapter ends with a brief discussion of the challenges on the horizon in managing uncertainty from increasing shares of stochastic renewables and risk-management in the long-run.

1.2.2 *Part I: Aggregation of the Transmission Network*

In the simplified market model, the electricity market is cleared based on an aggregated version of the underlying transmission network and simple bids. In the complex model, the market is cleared based on the DC optimal power flow and complex bids. The simplified form is used in Europe, where zonal prices are derived. Chapter 3 explores the methodological choices behind a new approach called flow-based market coupling that seeks to better represent network congestion in zonal markets. While zonal markets typically force participants to internalize their non-convexities in simple bids, this chapter shows the impact of combining an aggregated transmission network with complex bids in the form of unit commitment constraints. Existing base case approaches to define parameters for the aggregated network perform poorly compared to a base case using the nodal solution across all modeling choices considered. A substantial welfare gap between the simplified market clearing with an aggregated transmission network and the nodal market ideal remains.

1.2.3 *Part II: Non-Convex Pricing in the Long-Run*

However, even in the theoretical ideal of nodal pricing, marginal pricing as a market clearing mechanism does not have the desired economic properties of being able to clear the market while providing a dispatch solution for which no generator has an incentive to deviate. This is because there are non-convexities in electricity markets due to binary startup and shutdown decisions (unit commitment), no-load costs, and minimum operating levels. Generators thus may not always recover their fixed startup costs or variable costs or may even see a foregone profit opportunity, leading to lost opportunity costs and the need for make-whole payments.

System operators are actively debating what pricing model to use, but it is important to remember that prices are not meant to support the current resource mix but rather to provide signals for entry and exit so that the lowest-cost resource mix is achieved in the long-run. Chapter 4 analyzes non-convex pricing models in a long-run analysis, developing a new method to find quasi-break-even solutions in a non-convex setting. Convex hull pricing, a method in which prices are derived from the convex hull of the optimal value function, is found to provide the least over-compensation to inframarginal units, leading to resource mixes that maximize consumer surplus.

In theory, assuming convexity of cost functions and feasible regions and that producers can perfectly adapt,[2] an energy-only market provides perfect cost recovery in the long-run for generators in the optimal resource mix. Concern has arisen as to whether energy-only markets with non-convex costs can adequately compensate providers of flexibility as units may need to cycle on and off more frequently to meet a net load curve with shorter peaks and steeper ramps. Chapter 5 demonstrates that relaxing the assumption of convexity still leads to long-run cost recovery for flexible generators in the presence of high shares of zero-marginal cost variable renewable energy, but that there is a penalty to consumers (relative to the convex case) in the form of higher profits for producers in the long-run adapted resource mix. This penalty is proportional to the amount of non-convex resources in the system.

1.2.4 *Part III: Non-Convex Pricing in the Short-Run*

Unit commitment problems are typically too large to be solved to optimality and must be relaxed to find market-clearing prices due to non-convexities. Most non-convex pricing models depend on the primal solution, and thus prices vary based on which near-optimal solution is chosen. Chapter 6 shows that when we remove the conventional assumption of fixed demand, finding a better near-optimal solution improves outcomes for consumers. This result depends on the level of scarcity rent from price-setting elastic demand.

Because non-convexities mean that a uniform price cannot guarantee incentive compatibility, some units will desire to deviate from the central dispatch decision. Units that perceive the opportunity to make a profit may be incentivized to self-commit (submitting an offer with zero fixed operating costs) or self-schedule their production (submitting an offer with

2 Producers that can perfectly adapt in the long-run can build an unlimited quantity of a given technology type at a given cost. See Section 2.4 for further discussion.

zero total cost). Using reinforcement learning, Chapter 7 simulates bidder behavior to show that market power can be exercised by self-scheduling and self-committing. In a realistic test system, adverse bids under the restricted convex pricing model increased total producer profits substantially, while convex hull pricing preserved the profits made at the competitive market solution and resulted in a lower cost to consumers.

1.3 PUBLICATIONS

The work presented in this thesis has been reported in the following publications:

1.3.1 *Journal articles*

Byers, C., Hug, G. (2022). "Long-run optimal pricing in electricity markets with non-convex costs." *European Journal of Operational Research.* doi:10.1016/j.ejor.2022.07.052 [14] [Chapter 4]

Byers, C., Hug, G. (2022). "Economic impacts of near-optimal solutions with non-convex pricing." *Electric Power Systems Research* 211, 108287. doi:10.1016/j.epsr.2022.108287 [15] [Chapter 6]

1.3.2 *Conference proceedings*

Byers, C., Hug, G. (2022). "Economic impacts of near-optimal solutions with non-convex pricing." *22nd Power Systems Computation Conference (PSCC).* doi:10.1016/j.epsr.2022.108287 [15] [Chapter 6]

Byers, C., Hug, G. (2022). "Flexibility compensation with increasing stochastic variable renewable energy in non-convex markets." *17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS).* doi:10.1109/PMAPS53380.2022.9810627 [16] [Chapter 5]

Byers, C., Hug, G. (2020). "Modeling flow-based market coupling: Base case, redispatch, and unit commitment matter." *17th International Conference on the European Energy Market (EEM).* doi:10.1109/EEM49802.2020.9221922 [17] [Chapter 3]

1.3.3 *Working papers*

Byers, C., Eldridge, B. (2022) "Auction designs to increase incentive compatibility and reduce self-scheduling in electricity markets."
arXiv:2212.10234 [18] [Chapter 7]

2

ELECTRICITY NETWORK AND MARKET BACKGROUND

This chapter provides an overview of the background and mathematical preliminaries necessary for the following chapters. For additional discussion of power system economics and regulation, see [19]–[21]. The focus of subsequent chapters is on questions related to the ability of real-world electricity markets to achieve the theoretical properties presented here. Section 2.1 introduces the differences between the simplified and integrated market model. Section 2.2 describes the optimality conditions for an ideal central planner and a perfectly competitive market. Section 2.3 introduces transmission constraints to these two problem formulations, Section 2.4 introduces investment decisions, and Section 2.5 introduces non-convexities. The chapter concludes with a discussion of uncertainty, resource adequacy, and risk management in Section 2.6.

2.1 SIMPLIFIED VS INTEGRATED MARKET MODEL

Electricity takes the path of least resistance based on the laws of physics, not economics. Supply must match demand in real time, and the flow of electricity can be economically counter-intuitive. This is because electricity obeys AC optimal power flow (OPF) constraints based on Kirchhoff's laws [22]. These constraints are highly nonlinear and non-convex [23], and approximations are used in reality to schedule and dispatch generators. Broadly, two approaches have formed: an integrated and a simplified market structure [24].

2.1.1 *Integrated Market Model*

In the integrated market, participants submit complex bids reflecting their operating constraints. Such constraints include ramping rate limits, minimum load requirements, minimum up and down times, no-load costs, startup costs, and non-decreasing variable costs. The system operator solves an optimization problem to minimize costs subject to network constraints represented by a DCOPF with losses, a linear approximation of AC power flow [25]. Market prices are ideally set by the marginal cost to deliver power at each network location, or node, in the network, which incentivizes generators in the most efficient dispatch solution subject to transmission system limits to produce power [26]–[28]. This approach is called nodal pricing. However, the scheduling problem for generators is modeled with binary variables reflecting whether a unit is committed, leading to an optimal value function in this integrated market model that is non-convex, and thus does not always have marginal prices. Where marginal prices are derived from the convex relaxation with binary variables fixed to the optimal values previously found, they may not support a competitive equilibrium in which no participant wishes to deviate from the system operator's dispatch decision [29]. Determining which pricing model to use, especially as the energy transition requires the entry and exit of large numbers of generators, is a subject of ongoing debate [12], [13], [30].

2.1.2 *Simplified Market Model*

In the simplified market, participants internalize their non-convexities into simple bids and an aggregated, approximated transmission network is used [24], [31]. This approach is called zonal pricing. The dispatch solution is often far from physically feasible and units must be redispatched by the system operator. The zonal market clearing and nodal redispatch creates the opportunity for the exercise of market power via strategic bidding, known as inc-dec gaming [32]. While jurisdictions with competitive electricity markets in the United States have moved from zonal markets to nodal markets [3], the market in Europe is still cleared zonally, followed by redispatch. Europe has begun transitioning from available transfer capacity (ATC) to flow-based market coupling (FBMC) in attempt to decrease redispatch requirements [31]. However, [33] demonstrate that both zonal market designs achieve similar overall cost efficiencies and are vastly outperformed by a nodal design. Zonal pricing also obscures important locational investment signals, leading to inefficient investment in the long run [34]. There is also growing concern that incorporating high shares of variable renewable energy is likely to increase redispatch costs and widen the gap between the zonal and nodal designs [24], [35].

2.2 CENTRAL PLANNING VS COMPETITIVE MARKETS

In the electricity scheduling and dispatch problem, we wish to maximize social welfare, or social surplus, subject to the operating constraints of the generators and the power balance equality. The social surplus is the sum of consumer and producer surplus, where consumer surplus is the benefit to demand in excess of costs paid, and producer surplus is the revenue received in excess of costs, i.e., profit. This is equivalent to maximizing the benefit to demand minus the total producer costs.

We can formulate this problem as an optimization problem, in which a central planner seeks to maximize social welfare. Conversely, we can formulate this problem as an equilibrium problem, in which each participant seeks to maximize individual benefit [36], [37]. If the problem is convex, then the optimality conditions of the optimization and equilibrium problem are equivalent, and thus the solutions are identical. The interpretation is that an ideal central planner maximizing social welfare reaches the same decision as a perfectly competitive market with marginal pricing, as depicted in Figure 2.1.

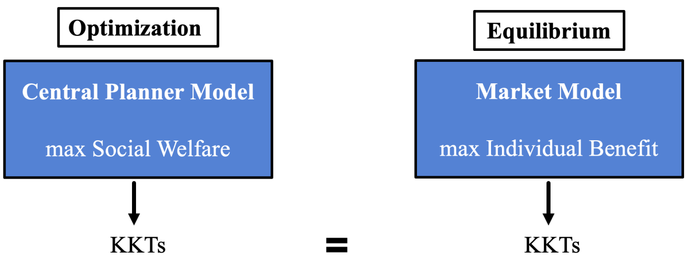


FIGURE 2.1: Equivalence of central planning and market equilibrium

2.2.1 *Optimization*

To illustrate this concept, we formulate a simple market clearing problem for a convex electricity market with partially elastic demand with no network, ramping, or unit commitment constraints. The example is adapted from [36], [37].

Nomenclature

Indices and Sets

$g \in G$	Set of generators
$G^T \subseteq G$	Set of thermal generators
$G^V \subseteq G$	Set of VRE resources
$t \in T$	Set of time periods (hours)
$l \in L$	Set of demand bids

Parameters

C_g	Variable cost (\$/MWh)
P_g^{max}	Maximum operating capacity (MW)
$\mathcal{P}_{tg}$	Maximum output for VRE resource (MW)
B_l	Value of demand bid l (\$/MWh)
D_{tl}	Maximum quantity of demand bid l at time t (MW)

Variables

p_{tg}	Committed generation for generator g at time t (MW)
d_{tl}	Amount of cleared demand bid l at time t (MW)

Primal Formulation

The primal formulation is given as:

$$\max_{p,d} \quad \sum_{t \in T} \sum_{l \in L} B_l d_{tl} - \sum_{t \in T} \sum_{g \in G} C_g p_{tg} \tag{2.1a}$$

$$\text{s.t.} \quad \sum_{l \in L} d_{tl} = \sum_{g \in G} p_{tg} \quad \forall t \in T \tag{2.1b}$$

$$0 \leq d_{tl} \leq D_{tl} \quad \forall t \in T, l \in L \tag{2.1c}$$

$$0 \leq p_{tg} \leq P_g^{max} \quad \forall t \in T, g \in G^T \tag{2.1d}$$

$$0 \leq p_{tg} \leq \mathcal{P}_{tg} \quad \forall t \in T, g \in G^V \tag{2.1e}$$

The objective function (2.1) maximizes social surplus by maximizing benefit to demand and minimizing costs to producers. Constraint (2.1b) enforces power balance at each time step, (2.1c) defines a range for each demand bid, (2.1d) limits the minimum and maximum operating capacity of each thermal generator, and (2.1e) allows for penalty-free curtailment of variable renewable energy (VRE) generators.

KKT Conditions

We have a primal problem of the form:

$$\min_{x} \quad f(x) \tag{2.2a}$$

$$\text{s.t.} \quad h(x) = 0 \quad : \lambda \tag{2.2b}$$

$$g(x) \leq 0 \quad : \mu \tag{2.2c}$$

where the Lagrangian is given as:

$$\mathcal{L}(x, \lambda, \mu) = f(x) + \lambda^\top h(x) + \mu^\top g(x) \tag{2.3}$$

The optimality Karush–Kuhn–Tucker (KKT) conditions require setting the derivative of the Lagrangian with respect to each primal variable to 0 and adding complementarity conditions to the inequalities:

$$\frac{\delta \mathcal{L}(x, \lambda, \mu)}{\delta x} = 0 \tag{2.4}$$

$$h(x) = 0 \tag{2.5}$$

$$0 \leq -g(x) \perp \mu \geq 0 \tag{2.6}$$

$$\lambda \in \text{free} \tag{2.7}$$

For our problem, the Lagrangian is:

$$\begin{aligned}\mathcal{L}(p,d,\lambda,\mu) = &-\sum_{t\in T}\sum_{l\in L} B_l d_{tl} + \sum_{t\in T}\sum_{g\in G} C_g p_{tg} \\ &+ \sum_{t\in T}\lambda_t(\sum_{l\in L} d_{tl} - \sum_{g\in G} p_{tg}) \\ &+ \sum_{t\in T}\sum_{l\in L}\mu_{tl}^{\overline{D}}(d_{tl} - D_{tl}) \\ &+ \sum_{t\in T}\sum_{g\in G^T}\mu_{tg}^{\overline{GT}}(p_{tg} - P_g^{max}) \\ &+ \sum_{t\in T}\sum_{g\in G^V}\mu_{tg}^{\overline{GV}}(p_{tg} - \mathcal{P}_{tg}) \\ &- \sum_{t\in T}\sum_{l\in L}\mu_{tl}^{D} d_{tl} \\ &- \sum_{t\in T}\sum_{g\in G}\mu_{tl}^{G} p_{tg} \end{aligned} \tag{2.8}$$

and thus the optimality KKT conditions are:

$$C_g - \lambda_t + \mu_{tg}^{\overline{GT}} - \mu_{tg}^{G} = 0 \quad \forall t \in T, g \in G^T \tag{2.9}$$

$$C_g - \lambda_t + \mu_{tg}^{\overline{GV}} - \mu_{tg}^{G} = 0 \quad \forall t \in T, g \in G^V \tag{2.10}$$

$$-B_l + \lambda_t + \mu_{tl}^{\overline{D}} - \mu_{tl}^{D} = 0 \quad \forall t \in T, l \in L \tag{2.11}$$

$$\sum_{l\in L} d_{tl} - \sum_{g\in G} p_{tg} = 0 \quad \forall t \in T \tag{2.12}$$

$$0 \leq d_{tl} \perp \mu_{tl}^{D} \geq 0 \quad \forall t \in T, l \in L \tag{2.13}$$

$$0 \leq p_{tg} \perp \mu_{tg}^{G} \geq 0 \quad \forall t \in T, g \in G \tag{2.14}$$

$$0 \leq -d_{tl} + D_{tl} \perp \mu_{tl}^{\overline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.15}$$

$$0 \leq -p_{tg} + P_g^{max} \perp \mu_{tg}^{\overline{GT}} \geq 0 \quad \forall t \in T, g \in G^T \tag{2.16}$$

$$0 \leq -p_{tg} + \mathcal{P}_{tg} \perp \mu_{tg}^{\overline{GV}} \geq 0 \quad \forall t \in T, g \in G^V \tag{2.17}$$

$$\tag{2.18}$$

Dual Formulation

The marginal prices are the dual variables (or Lagrangian multipliers) of the power balance constraints. Here we formulate the dual, removing variables associated with non-negativity constraints by converting equalities to inequalities:

$$\max_{\lambda, \mu_{tl}^{\overline{D}}, \mu^{\overline{GT}} \mu^{\overline{GV}}} \quad \sum_{t \in T} \sum_{l \in L} -\mu_{tl}^{\overline{D}} D_{tl} + \sum_{t \in T} \sum_{g \in G^T} -\mu_{tg}^{\overline{GT}} P_g^{max} + \sum_{t \in T} \sum_{g \in G^V} -\mu_{tg}^{\overline{GV}} \mathcal{P}_{tg} \tag{2.19a}$$

$$\text{s.t.} \qquad -B_l + \lambda_t + \mu_{tl}^{\overline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.19b}$$

$$C_g - \lambda_t + \mu_{tg}^{\overline{GT}} \geq 0 \quad \forall t \in T, g \in G^T \tag{2.19c}$$

$$C_g - \lambda_t + \mu_{tg}^{\overline{GV}} \geq 0 \quad \forall t \in T, g \in G^V \tag{2.19d}$$

$$\mu_{tl}^{\overline{D}}, \mu^{\overline{GT}}, \mu^{\overline{GV}} \geq 0 \tag{2.19e}$$

2.2.2 *Equilibrium*

Now we turn to the question of whether the market participants are satisfied with the solution of the optimization problem. Given the set of prices, do any generators wish to deviate from the dispatch schedule? To answer this question, we can formulate an optimization problem for each market participant [36].

Individual Optimization Problems

The optimization problem faced by each elastic demand offer $l \in L$:

$$\max_{d_l} \quad \sum_{t \in T} (B_l - \lambda_t) d_{tl} \tag{2.20a}$$

$$\text{s.t.} \quad 0 \leq d_{tl} \leq D_{tl} \quad \forall t \in T \quad : \mu^{\underline{D}}, \mu^{\overline{D}} \tag{2.20b}$$

The optimization problem faced by each thermal generator $g \in G^T$ is:

$$\max_{p_g} \quad \sum_{t \in T} (\lambda_t - C_g) p_{tg} \tag{2.21a}$$

$$\text{s.t.} \quad 0 \leq p_{tg} \leq P_g^{max} \quad \forall t \in T \quad : \mu^{\underline{GT}}, \mu^{\overline{GT}} \tag{2.21b}$$

The optimization problem faced by each VRE generator $g \in G^V$ is:

$$\max_{p_g} \quad \sum_{t \in T} (\lambda_t - C_g) p_{tg} \tag{2.22a}$$

$$\text{s.t.} \quad 0 \leq p_{tg} \leq \mathcal{P}_{tg} \quad \forall t \in T \quad : \mu^{\underline{GV}}, \mu^{\overline{GV}} \tag{2.22b}$$

The price λ_t is a parameter in each individual optimization problem. For each participant to contribute to price formation, we must add the optimization problem of the price setter, who wishes to minimize the supply and demand mismatch.

$$\min_{\lambda} \quad \sum_{t \in T} \lambda_t \Big(\sum_{l \in L} d_{tl} - \sum_{g \in G} p_{tg}\Big) \tag{2.23a}$$

KKT Conditions

To solve this equilibrium problem, we replace each individual optimization problem by its KKT optimality conditions.

The sum of the Lagrangians for the elastic demand offers is:

$$\begin{aligned} \mathcal{L}(d, \mu) = &- \sum_{t \in T} \sum_{l \in L} (B_l - \lambda_t) d_{tl} \\ &+ \sum_{t \in T} \sum_{l \in L} \mu_{tl}^{\overline{D}} (d_{tl} - D_{tl}) \\ &- \sum_{t \in T} \sum_{l \in L} \mu_{tl}^{\underline{D}} d_{tl} \end{aligned} \tag{2.24}$$

The KKT conditions are:

$$\frac{\delta\mathcal{L}}{\delta d_{tl}} = -B_l + \lambda_t + \mu_{tl}^{\overline{D}} - \mu_{tl}^{\underline{D}} = 0 \quad \forall t \in T, l \in L \tag{2.25}$$

$$0 \leq d_{tl} \perp \mu_{tl}^{\underline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.26}$$

$$0 \leq -d_{tl} + D_{tl} \perp \mu_{tl}^{\overline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.27}$$

$$\tag{2.28}$$

The sum of the Lagrangians for the thermal generators is:

$$\begin{aligned}\mathcal{L}(p,\mu) = &-\sum_{t\in T}\sum_{g\in G^T}(\lambda_t - C_g)p_{tg} \\ &+\sum_{t\in T}\sum_{g\in G^T}\mu_{tg}^{\overline{GT}}(p_{tg} - P_g^{max}) \\ &-\sum_{t\in T}\sum_{g\in G^T}\mu_{tl}^{\underline{G}}p_{tg}\end{aligned} \tag{2.29}$$

and the KKT conditions are:

$$\frac{\delta\mathcal{L}}{\delta p_{tg}} = C_g - \lambda_t + \mu_{tg}^{\overline{GT}} - \mu_{tg}^{\underline{G}} = 0 \quad \forall t \in T, g \in G^T \tag{2.30}$$

$$0 \leq p_{tg} \perp \mu_{tg}^{\underline{G}} \geq 0 \quad \forall t \in T, g \in G^T \tag{2.31}$$

$$0 \leq -p_{tg} + P_g^{max} \perp \mu_{tg}^{\overline{GT}} \geq 0 \quad \forall t \in T, g \in G^T \tag{2.32}$$

The sum of the Lagrangians for the VRE generators is:

$$\begin{aligned}\mathcal{L}(p,\mu) = &-\sum_{t\in T}\sum_{g\in G^V}(\lambda_t - C_g)p_{tg} \\ &+\sum_{t\in T}\sum_{g\in G^V}\mu_{tg}^{\overline{GV}}(p_{tg} - \mathcal{P}_{tg}) \\ &-\sum_{t\in T}\sum_{g\in G^V}\mu_{tl}^{\underline{G}}p_{tg}\end{aligned} \tag{2.33}$$

and the KKT conditions are:

$$\frac{\delta \mathcal{L}}{\delta p_{tg}} = C_g - \lambda_t + \mu_{tg}^{\overline{GV}} - \mu_{tg}^{\underline{G}} = 0 \quad \forall t \in T, g \in G^V \tag{2.34}$$

$$0 \leq p_{tg} \perp \mu_{tg}^{\underline{G}} \geq 0 \quad \forall t \in T, g \in G^V \tag{2.35}$$

$$0 \leq -p_{tg} + \mathcal{P}_{tg} \perp \mu_{tg}^{\overline{GV}} \geq 0 \quad \forall t \in T, g \in G^V \tag{2.36}$$

$$\tag{2.37}$$

The Lagrangian for the price setter is simply:

$$\mathcal{L}(\lambda) = \sum_{t \in T} \lambda_t (\sum_{l \in L} d_{tl} - \sum_{g \in G} p_{tg}) \tag{2.38}$$

and thus the KKT conditions are satisfied when:

$$\frac{\delta \mathcal{L}}{\delta \lambda_t} = \sum_{l \in L} d_{tl} - \sum_{g \in G} p_{tg} = 0 \quad \forall t \in T \tag{2.39}$$

Collectively, these conditions are:

$$C_g - \lambda_t + \mu_{tg}^{\overline{GT}} - \mu_{tg}^{\underline{G}} = 0 \quad \forall t \in T, g \in G^T \tag{2.40}$$

$$C_g - \lambda_t + \mu_{tg}^{\overline{GV}} - \mu_{tg}^{\underline{G}} = 0 \quad \forall t \in T, g \in G^V \tag{2.41}$$

$$-B_l + \lambda_t + \mu_{tl}^{\overline{D}} - \mu_{tl}^{\underline{D}} = 0 \quad \forall t \in T, l \in L \tag{2.42}$$

$$\sum_{l \in L} d_{tl} - \sum_{g \in G} p_{tg} = 0 \quad \forall t \in T \tag{2.43}$$

$$0 \leq d_{tl} \perp \mu_{tl}^{\underline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.44}$$

$$0 \leq p_{tg} \perp \mu_{tg}^{\underline{G}} \geq 0 \quad \forall t \in T, g \in G \tag{2.45}$$

$$0 \leq -d_{tl} + D_{tl} \perp \mu_{tl}^{\overline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.46}$$

$$0 \leq -p_{tg} + P_g^{max} \perp \mu_{tg}^{\overline{GT}} \geq 0 \quad \forall t \in T, g \in G^T \tag{2.47}$$

$$0 \leq -p_{tg} + \mathcal{P}_{tg} \perp \mu_{tg}^{\overline{GV}} \geq 0 \quad \forall t \in T, g \in G^V \tag{2.48}$$

$$\tag{2.49}$$

The KKT conditions are identical to those found for the original optimization problem, meaning that the optimal solution to the central planner's optimization problem is the same as the equilibrium solution for the competitive market. The marginal prices both clear the market (the power balance constraint is satisfied) and support dispatch, meaning that no producer wishes to deviate from the central operator's dispatch decision. The solution is thus a Nash equilibrium.

2.2.3 *Example Problem Solution*

Here we solve the example problem using data from the Grid Modernization Lab Consortium's Reliability Test System [38]. We aggregate the 3 zones, omit the energy storage unit, and use bid-in demand assuming 70% of demand at each time period is inelastic (with a benefit of \$100/MWh) and 30% of demand is elastic, represented by 20 equally-sized bids descending in price from \$100/MWh to \$5/MWh. We solve the problem for the horizon of January 1.

We solve the primal problem with JuMP in Julia with Gurobi as the solver. $|T|$=24, $|G|$=122, $|G^T|$=73, $|G^V|$=49, and $|L|$=21. The model has an objective value of \$6.96 million. There are $|T| * |L| + |T| * |G| = 3432$ variables and $|T| * |L| + |T| * |G| + |T| = 3456$ constraints. Results are shown in Figure 2.2 and Figure 2.3.

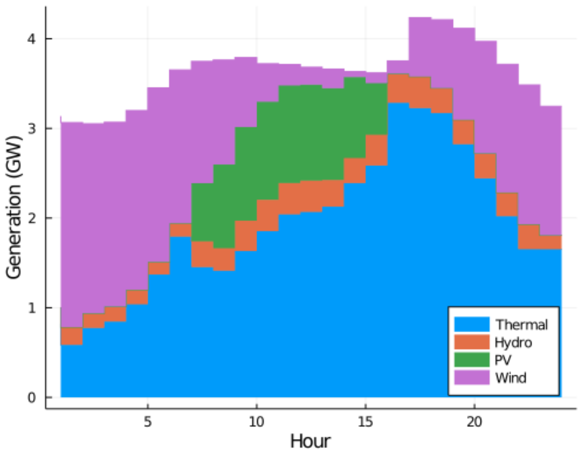


FIGURE 2.2: Optimal values

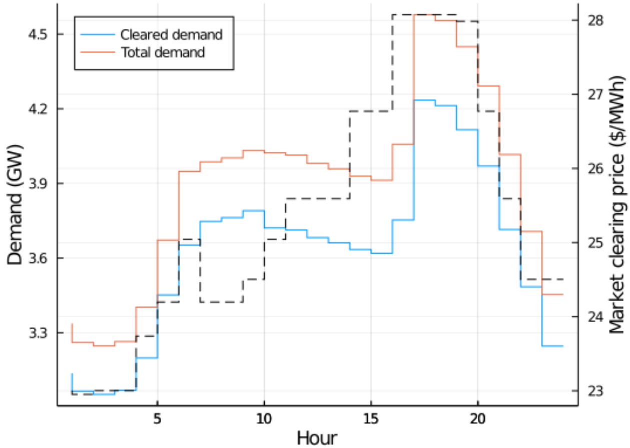


FIGURE 2.3: Market clearing prices

The dual problem has an objective value identical to the primal solution of $6.96 million with 3432 constraints and 3456 variables, the opposite of the primal. Market clearing prices are identical to the primal, as shown in Figure 2.4.

The KKT conditions formulation is solved as a minimization problem with an objective function of 1 with the KKT conditions as the constraints. Complementarity constraints are reformulated using the Big M method, yielding an identical objective function of $6.96 million. The prices found are identical to the methods via the primal and dual formulations, as shown in Figure 2.4.

2.2.4 *Properties of Market-Clearing Mechanisms*

We have seen that marginal pricing in the convex setting has the desirable properties of being able to clear the market and support dispatch. In general, there are four properties that we would like a market-clearing mechanism to have [39]:

- **Market efficiency**: The social surplus is maximized, and participants cannot improve their payoffs by unilaterally deviating from the market outcome. This is the property we are describing when we say that marginal pricing clears the market and supports dispatch.

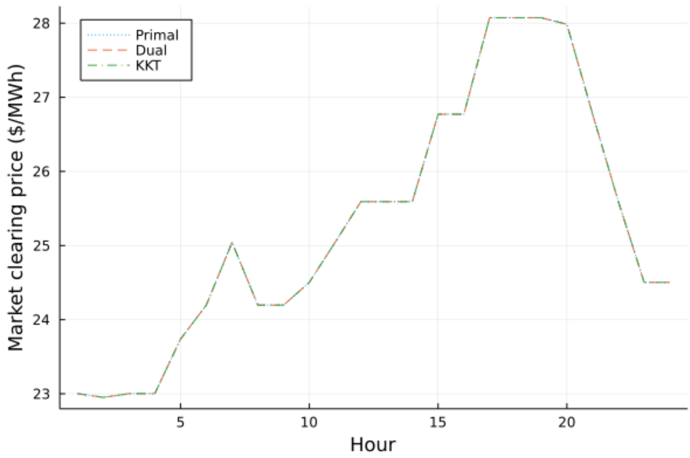


FIGURE 2.4: Market clearing prices found via primal, dual, and KKT formulations

- **Cost recovery**: Participants should recover their operational costs. In the short-run, participants do not necessarily profit sufficiently to recover their fixed capital costs (see further discussion in Section 2.4 about the relationship between marginal pricing and long-run cost recovery).
- **Revenue adequacy**: The market operator does not have a deficit. The amount of revenue recovered from consumers is at least as great as the amount of revenue paid to suppliers.
- **Incentive compatibility**: Participants do best when offering their true preferences or costs. A generator in a market that is incentive-compatible maximizes its own payoff by bidding its true supply costs. No participants have an incentive to exercise market power by bidding strategically.

From the Hurwicz theorem (also known as the "impossibility theorem"), no market-clearing mechanism ensures all four properties at the same time [39]–[41]. Trade-offs must be made based on what properties are considered most desirable. If participants all bid truthfully, marginal pricing in the convex setting achieves market efficiency, cost recovery, and revenue adequacy. However, incentive compatibility cannot be guaranteed in the absence of perfect competition. If incentive compatibility does not hold, then participants may exercise market power, which means that market efficiency is no longer achieved.

Alternative mechanisms include pay-as-bid, in which each participant is compensated based on their supply offer instead of a market-clearing uniform price. However, the incentive in a pay-as-bid auction is for each participant to bid as close to the highest-cleared bid without exceeding it. The resulting equilibrium may distort the merit order, e.g., generators that actually have a lower variable cost may be dispatched after generators that have a higher variable cost [42], [43]. Vickrey–Clarke–Groves (VCG) has the interesting property of ensuring incentive compatibility; truthful bidding is the dominant strategy [44]. However, VCG does not guarantee revenue adequacy, although strategies have been proposed to reduce the market operator's budget deficit [44], [45].

2.2.5 *Regulatory Challenges*

Under convexity and perfect competition that incentivizes truthful bidding, marginal pricing yields a competitive equilibrium. However, the conditions of perfect competition, including perfect information, no externalities, no transaction costs, a large number of buyers and sellers, and no economies of scale [46] are unlikely to be met in reality. Market power mitigation measures are an important component of real-world electricity markets for this reason [47].

While markets are not perfectly competitive in reality, central planners are also imperfect. Central planning has many inefficiencies [48], including a lack of perfect information and slow adaptation to changing conditions. A regulated monopolist must be prevented from exploiting its market power and may have insufficient incentives to innovate [21].

The bet made in restructuring or liberalizing the electricity sector is that new organizational structures will provide long-term benefits to consumers. Competitive wholesale and retail markets could improve efficiency and better adapt to consumer preferences, incentive regulation of the transmission network could improve the efficiency of operations via facilitating competition, and technology-neutral competitive procurement could reduce the role of government and political influence [49], [50]. The argument for electricity markets over central planning is summarized in Figure 2.5.

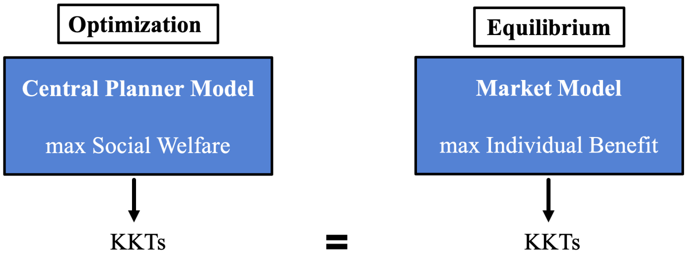


FIGURE 2.5: A market solution proposes that the social surplus achievable in reality with markets is higher than with central planning

2.3 TRANSMISSION CONSTRAINTS

The properties of marginal pricing described above still hold with the inclusion of transmission constraints, so long as the formulation remains convex. In the equilibrium problem representing the competitive market, the transmission owner acts as a spatial arbitrager, buying power at low-price nodes and selling power at high-price nodes [36]. The following example is adapted from [36].

The DCOPF, a linearization of the ACOPF [25], changes the primal formulation of the central operators problem, replacing the power balance equation (2.1b) with the following constraints:

$$\sum_{l \in I_n} d_{tl} + \sum_{m \in \Omega_n} \mathcal{B}_{n,m}(\theta_{tn} - \theta_{tm}) = \sum_{g \in I_n} p_{tg} \quad \forall t \in T, n \in N \tag{2.50}$$

$$-F_{n,m} \leq \mathcal{B}_{n,m}(\theta_{tn} - \theta_{tm}) \leq F_{n,m} \quad \forall t \in T, n \in N, m \in \Omega_n \tag{2.51}$$

$$\theta_{t,ref} = 0 \quad \forall t \in T \tag{2.52}$$

where $l, g \in I_n$ indicates all elastic demands and generators at node n, $m \in \Omega_n$ indicates all nodes m connected to node n, N is the set of all nodes, $\mathcal{B}$ is the branch susceptance matrix, θ is the nodal voltage angles, and F is the branch flow limit.

The portion of the Lagrangian $\mathcal{L}_\Delta$ associated with these constraints is:

$$\begin{aligned}\mathcal{L}_\Delta(p,d,\lambda,\mu,\eta) = &\sum_{t\in T}\sum_{n\in N}\lambda_{tn}(\sum_{l\in I_n} d_{tl} + \sum_{m\in\Omega_n}\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}) - \sum_{g\in I_n} p_{tg})\\ &-\sum_{t\in T}\sum_{n\in N}\sum_{m\in\Omega_n}\mu^{\underline{F}}_{t,n,m}(F_{n,m}+\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}))\\ &+\sum_{t\in T}\sum_{n\in N}\sum_{m\in\Omega_n}\mu^{\overline{F}}_{t,n,m}(\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm})-F_{n,m})\\ &+\sum_{t\in T}\eta_t\theta_{t,ref} \end{aligned} \tag{2.53}$$

The KKT conditions are:

$$\frac{\delta\mathcal{L}}{\delta\theta_{tn}} = \sum_{m\in\Omega_n}\mathcal{B}_{n,m}(\lambda_{tn}-\lambda_{tm}+\mu^{\overline{F}}_{t,n,m}-\mu^{\overline{F}}_{t,m,n}-\mu^{\underline{F}}_{t,n,m}+\mu^{\underline{F}}_{t,m,n})+\eta_t = 0 \quad \forall t\in T, n\in N \tag{2.54}$$

$$\sum_{l\in I_n} d_{tl} + \sum_{m\in\Omega_n}\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}) - \sum_{g\in I_n} p_{tg} = 0 \quad \forall t\in T, n\in N \tag{2.55}$$

$$\theta_{t,ref} = 0 \quad \forall t\in T \tag{2.56}$$

$$0 \le F_{n,m}+\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}) \perp \mu^{\underline{F}}_{t,n,m} \ge 0 \quad \forall t\in T, n\in N, m\in\Omega_n \tag{2.57}$$

$$0 \le F_{n,m}-\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}) \perp \mu^{\overline{F}}_{t,n,m} \ge 0 \quad \forall t\in T, n\in N, m\in\Omega_n \tag{2.58}$$

In the market equilibrium problem, both the demands and the generators now have the parameter λ_{tn}, the price at a given time at the node to which they are connected. The price setter's problem becomes:

$$\min_{\lambda} \quad \sum_{t\in T}\sum_{n\in N}\lambda_{tn}(\sum_{l\in I_n} d_{tl} + \sum_{m\in\Omega_n}\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}) - \sum_{g\in I_n} p_{tg}) \tag{2.59a}$$

The transmission owner's problem is:

$$\max_{\theta} \quad \sum_{n\in N, m\in\Omega_n} \lambda_{tn}(\mathcal{B}_{n,m}(\theta_{tm}-\theta_{tn})) \tag{2.60a}$$

$$\text{s.t.} \quad -F_{n,m} \leq \mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}) \leq F_{n,m} \quad \forall t\in T, n\in N, m\in\Omega_n \quad : \mu^{\underline{F}}, \mu^{\overline{F}} \tag{2.60b}$$

$$\theta_{t,ref} = 0 \quad \forall t \in T \quad : \eta \tag{2.60c}$$

where the objective function is the congestion rent.

The KKT condition associated with the price setter's problem is simply:

$$\frac{\delta\mathcal{L}}{\delta\lambda_{tn}} = \sum_{l\in I_n} d_{tl} + \sum_{m\in\Omega_n} \mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}) - \sum_{g\in I_n} p_{tg} = 0 \quad \forall t\in T, n\in N \tag{2.61}$$

The Lagrangian of the transmission owner's problem is:

$$\begin{aligned}\mathcal{L}(\theta) = &-\sum_{t\in T}\sum_{n\in N}\lambda_{tn}(\mathcal{B}_{n,m}(\theta_{tm}-\theta_{tn}))\\ &-\sum_{t\in T}\sum_{n\in N}\sum_{m\in\Omega_n}\mu^{\underline{F}}_{t,n,m}(F_{n,m}+\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm}))\\ &+\sum_{t\in T}\sum_{n\in N}\sum_{m\in\Omega_n}\mu^{\overline{F}}_{t,n,m}(\mathcal{B}_{n,m}(\theta_{tn}-\theta_{tm})-F_{n,m})\\ &+\sum_{t\in T}\eta_t\theta_{t,ref}\end{aligned} \tag{2.62}$$

The KKT conditions for the transmission owner's problem are:

$$\frac{\delta \mathcal{L}}{\delta \theta_{tn}} = \sum_{m \in \Omega_n} \mathcal{B}_{n,m}(\lambda_{tn} - \lambda_{tm} + \mu^{\overline{F}}_{t,n,m} - \mu^{\overline{F}}_{t,m,n} - \mu^{\underline{F}}_{t,n,m} + \mu^{\underline{F}}_{t,m,n}) + \eta_t = 0 \quad \forall t \in T, n \in N \tag{2.63}$$

$$\theta_{t,ref} = 0 \quad \forall t \in T \tag{2.64}$$

$$0 \leq F_{n,m} + \mathcal{B}_{n,m}(\theta_{tn} - \theta_{tm}) \perp \mu^{\underline{F}}_{t,n,m} \geq 0 \quad \forall t \in T, n \in N, m \in \Omega_n \tag{2.65}$$

$$0 \leq F_{n,m} - \mathcal{B}_{n,m}(\theta_{tn} - \theta_{tm}) \perp \mu^{\overline{F}}_{t,n,m} \geq 0 \quad \forall t \in T, n \in N, m \in \Omega_n \tag{2.66}$$

Combining the KKTs of the price setter and transmission owner, we see we have identical KKTs to the modified central planner's optimization problem. Thus, the inclusion of DCOPF constraints still yield a solution to the optimization problem that is a Nash equilibrium, in which no participants wish to unilaterally deviate. This method of pricing inclusive of transmission constraints is called nodal pricing [28].

2.4 INVESTMENT

In a deterministic setting with convex costs, if producers can perfectly adapt in the long-run, then the producer supply curve becomes perfectly elastic, yielding no producer surplus. Producers can perfectly adapt in the long-run when an unlimited amount of a given technology type can be built at a given cost.[1] All social surplus is then consumer surplus, and producers make no profits but instead perfectly recover their investment and operating costs.

The central planner's capacity expansion problem is a modification of (2.1):

1 In reality, producers are unlikely to be able to perfectly adapt in the long-run as technology types may only be able to be built in certain fixed sizes, costs may change as additional units are built at the same location, and certain locations can only support a limited quantity of units.

$$\max_{x,d,p} \quad \sum_{t\in T}\sum_{l\in L} B_l d_{tl} - \sum_{t\in T}\sum_{g\in G} C_g p_{tg} - \sum_{g\in G} C_g^{inv} x_g \tag{2.67a}$$

$$\text{s.t.} \quad \sum_{l\in L} d_{tl} = \sum_{g\in G} p_{tg} \qquad \forall t \in T \tag{2.67b}$$

$$0 \leq d_{tl} \leq D_{tl} \qquad \forall t \in T, l \in L \tag{2.67c}$$

$$0 \leq p_{tg} \leq P_g^{max} x_g \quad \forall t \in T, g \in G \tag{2.67d}$$

$$x_g \geq 0 \qquad \forall g \in G \tag{2.67e}$$

where x is the build decision and C^{inv} is the investment cost.

The Lagrangian is:

$$\begin{aligned}
\mathcal{L}(p,d,\lambda,\mu) = &- \sum_{t\in T}\sum_{l\in L} B_l d_{tl} + \sum_{t\in T}\sum_{g\in G} C_g p_{tg} + \sum_{g\in G} C_g^{inv} x_g \\
&+ \sum_{t\in T} \lambda_t (\sum_{l\in L} d_{tl} - \sum_{g\in G} p_{tg}) \\
&+ \sum_{t\in T}\sum_{l\in L} \mu_{tl}^{\overline{D}} (d_{tl} - D_{tl}) \\
&+ \sum_{t\in T}\sum_{g\in G} \mu_{tg}^{\overline{G}} (p_{tg} - P_g^{max} x_g) \\
&- \sum_{t\in T}\sum_{l\in L} \mu_{tl}^{\underline{D}} d_{tl} \\
&- \sum_{t\in T}\sum_{g\in G} \mu_{tl}^{\underline{G}} p_{tg} \\
&- \sum_{g\in G} \mu_g^{\underline{X}}
\end{aligned} \tag{2.68}$$

The KKT conditions are:

$$\frac{\delta \mathcal{L}}{\delta d} = -B_l + \lambda_t + \mu_{tl}^{\overline{D}} - \mu_{tl}^{\underline{D}} = 0 \quad \forall t \in T, l \in L \tag{2.69}$$

$$\frac{\delta \mathcal{L}}{\delta p} = C_g - \lambda_t + \mu_{tg}^{\overline{G}} - \mu_{tg}^{\underline{G}} = 0 \quad \forall t \in T, g \in G \tag{2.70}$$

$$\frac{\delta \mathcal{L}}{\delta x} = C_g^{inv} - \sum_{t \in T} \mu_{tg}^{\overline{G}} P_g^{max} - \mu_g^{\underline{X}} = 0 \quad \forall g \in G \tag{2.71}$$

$$\sum_{l \in L} d_{tl} - \sum_{g \in G} p_{tg} = 0 \quad \forall t \in T \tag{2.72}$$

$$0 \le d_{tl} \perp \mu_{tl}^{\underline{D}} \ge 0 \quad \forall t \in T, l \in L \tag{2.73}$$

$$0 \le p_{tg} \perp \mu_{tg}^{\underline{G}} \ge 0 \quad \forall t \in T, g \in G \tag{2.74}$$

$$0 \le x_g \perp \mu_g^{\underline{X}} \ge 0 \quad \forall g \in G \tag{2.75}$$

$$0 \le -d_{tl} + D_{tl} \perp \mu_{tl}^{\overline{D}} \ge 0 \quad \forall t \in T, l \in L \tag{2.76}$$

$$0 \le -p_{tg} + P_g^{max} x_g \perp \mu_{tg}^{\overline{G}} \ge 0 \quad \forall t \in T, g \in G \tag{2.77}$$

$$\tag{2.78}$$

The equilibrium problem for a competitive market consists of the individual optimization functions for each elastic demand, each producer, and the price setter.

The optimization problem for demand $l \in L$ is the same as in Section 2.2.2:

$$\max_{d_l} \quad \sum_{t \in T} (B_l - \lambda_t) d_{tl} \tag{2.79a}$$

$$\text{s.t.} \quad 0 \le d_{tl} \le D_{tl} \quad \forall t \in T \quad : \mu^{\underline{D}}, \mu^{\overline{D}} \tag{2.79b}$$

The optimization problem for each generator $g \in G^T$ is:

$$\max_{p_g} \quad \sum_{t \in T} (\lambda_t - C_g) p_{tg} - C_g^{inv} x_g \tag{2.80a}$$

$$\text{s.t.} \quad 0 \le p_{tg} \le P_g^{max} x_g \quad \forall t \in T : \mu^{\underline{G}}, \mu^{\overline{G}} \tag{2.80b}$$

$$x_g \ge 0 \quad : \mu^{\underline{X}} \tag{2.80c}$$

The optimization problem for the price setter is also the same as in Section 2.2.2:

$$\min_{\lambda} \quad \sum_{t\in T} \lambda_t (\sum_{l\in L} d_{tl} - \sum_{g\in G} p_{tg}) \tag{2.81a}$$

The Lagrangians of the demands and price setters are the same as in Section 2.2.2, yielding identical KKT conditions.

The sum of the Lagrangians for the elastic demand offers is:

$$\begin{aligned} \mathcal{L}(d,\mu) = &- \sum_{t\in T}\sum_{l\in L} (B_l - \lambda_t) d_{tl} \\ &+ \sum_{t\in T}\sum_{l\in L} \mu^{\overline{D}}_{tl} (d_{tl} - D_{tl}) \\ &- \sum_{t\in T}\sum_{l\in L} \mu^{\underline{D}}_{tl} d_{tl} \end{aligned} \tag{2.82}$$

with KKT conditions:

$$\frac{\delta\mathcal{L}}{\delta d_{tl}} = -B_l + \lambda_t + \mu^{\overline{D}}_{tl} - \mu^{\underline{D}}_{tl} = 0 \quad \forall t \in T, l \in L \tag{2.83}$$

$$0 \leq d_{tl} \perp \mu^{\underline{D}}_{tl} \geq 0 \quad \forall t \in T, l \in L \tag{2.84}$$

$$0 \leq -d_{tl} + D_{tl} \perp \mu^{\overline{D}}_{tl} \geq 0 \quad \forall t \in T, l \in L \tag{2.85}$$

$$\tag{2.86}$$

The Lagrangian for the price setter is:

$$\mathcal{L}(\lambda) = \sum_{t\in T} \lambda_t (\sum_{l\in L} d_{tl} - \sum_{g\in G} p_{tg}) \tag{2.87}$$

with KKT conditions:

$$\frac{\delta \mathcal{L}}{\delta \lambda_t} = \sum_{l \in L} d_{tl} - \sum_{g \in G} p_{tg} = 0 \quad \forall t \in T \tag{2.88}$$

The Lagrangian of the producers is:

$$\begin{aligned} \mathcal{L}(p, \mu) = & - \sum_{t \in T} \sum_{g \in G^T} (\lambda_t - C_g) p_{tg} + \sum_{g \in G} C_g^{inv} x_g \\ & + \sum_{t \in T} \sum_{g \in G} \mu_{tg}^{\overline{G}} (p_{tg} - P_g^{max} x_g) \\ & - \sum_{t \in T} \sum_{g \in G} \mu_{tl}^{\underline{G}} p_{tg} && (2.89) \\ & - \sum_{g \in G} \mu_g^{\underline{X}} && (2.90) \end{aligned}$$

and the KKT conditions are:

$$\frac{\delta \mathcal{L}}{\delta p_{tg}} = C_g - \lambda_t + \mu_{tg}^{\overline{G}} - \mu_{tg}^{\underline{G}} = 0 \quad \forall t \in T, g \in G \tag{2.91}$$

$$\frac{\delta \mathcal{L}}{\delta x_g} = C_g^{inv} - \sum_{t \in T} \mu_{tg}^{\overline{G}} P_g^{max} - \mu_g^{\underline{X}} = 0 \quad \forall g \in G \tag{2.92}$$

$$0 \leq p_{tg} \perp \mu_{tg}^{\underline{G}} \geq 0 \quad \forall t \in T, g \in G \tag{2.93}$$

$$0 \leq x_g \perp \mu_g^{\underline{X}} \geq 0 \quad \forall g \in G \tag{2.94}$$

$$0 \leq -p_{tg} + P_g^{max} \perp \mu_{tg}^{\overline{G}} \geq 0 \quad \forall t \in T, g \in G \tag{2.95}$$

Collectively, we have the KKT conditions:

$$\frac{\delta \mathcal{L}}{\delta d} = -B_l + \lambda_t + \mu_{tl}^{\overline{D}} - \mu_{tl}^{\underline{D}} = 0 \quad \forall t \in T, l \in L \tag{2.96}$$

$$\frac{\delta \mathcal{L}}{\delta p} = C_g - \lambda_t + \mu_{tg}^{\overline{G}} - \mu_{tg}^{\underline{G}} = 0 \quad \forall t \in T, g \in G \tag{2.97}$$

$$\frac{\delta \mathcal{L}}{\delta x} = C_g^{inv} - \sum_{t \in T} \mu_{tg}^{\overline{G}} P_g^{max} - \mu_g^{\underline{X}} = 0 \quad \forall g \in G \tag{2.98}$$

$$\sum_{l \in L} d_{tl} - \sum_{g \in G} p_{tg} = 0 \quad \forall t \in T \tag{2.99}$$

$$0 \leq d_{tl} \perp \mu_{tl}^{\underline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.100}$$

$$0 \leq p_{tg} \perp \mu_{tg}^{\underline{G}} \geq 0 \quad \forall t \in T, g \in G \tag{2.101}$$

$$0 \leq x_g \perp \mu_g^{\underline{X}} \geq 0 \quad \forall g \in G \tag{2.102}$$

$$0 \leq -d_{tl} + D_{tl} \perp \mu_{tl}^{\overline{D}} \geq 0 \quad \forall t \in T, l \in L \tag{2.103}$$

$$0 \leq -p_{tg} + P_g^{max} x_g \perp \mu_{tg}^{\overline{G}} \geq 0 \quad \forall t \in T, g \in G \tag{2.104}$$

$$\tag{2.105}$$

These conditions are identical to those of the central planner's problem. A private investor thus does not wish to build more or less than the central planner solution or operate its generator differently when compensated with marginal prices λ.

In this formulation, λ is the long-run marginal cost (LRMC). The short-run marginal costs (SRMC) and LRMC are equal when there isn't a binding reliability constraint [4], i.e., in this formulation, the LRMC are higher than the SRMC when a generator is used at its maximum capacity.

In reality of course, producers cannot perfectly adapt in the long-run. Lumpy investment is a concern in electricity markets and is one of the reasons outcomes may deviate from the theoretical ideal. Lumpy investments refer to investments in fixed sizes, e.g., an integer number of units can be built of a given size. Lumpy investments change the nature of the optimal value function in the optimization problem: it is no longer convex, as we must include the constraint that x is integer. This means the central planner's decision and the market outcome are no longer guaranteed to be equivalent. The investment decision with continuous investments of course may not be integer; thus, adding integer constraints may create multiple quasi-break-even solutions [51].

2.5 NON-CONVEXITIES

2.5.1 *Unit Commitment*

The guarantee of equivalence of the socially optimal solution and the market equilibrium solution assumes the optimal value function is convex. However, the scheduling problem in power systems, unit commitment (UC), is non-convex. Non-convex optimization refers to either (or both) non-convex cost functions rendering the minimization objective function non-convex, and non-convex feasible regions arising from binary variables, nonlinear equality constraints or convex (concave) functions that are subject to lower (upper) bounds. Generators may have startup costs and technical requirements, e.g., minimum operating levels, that introduce non-convexities. It is typically impossible to find a uniform price that supports dispatch. Non-convex pricing models are further discussed in Chapter 4, but here we provide some graphical intuition for the problem.

A simple UC problem with variable cost C, startup cost F, production p, and commitment status u linked to startup decision z with inelastic demand is formulated as:

$$\min_{u,p \in \mathcal{P}} \quad \sum_{t\in T}\sum_{g\in G} (C_g p_{tg} + F_g z_{tg}) \tag{2.106a}$$

$$\text{s.t.} \quad \sum_{g\in G} p_{tg} = D \quad \forall t \in T \tag{2.106b}$$

$$u \in \{0,1\} \tag{2.106c}$$

where $\mathcal{P}$ is the set of operating constraints.

First, consider the convex case in Table 2.1.

	C_g (\$/MWh)	F_g (\$)	P_g^{min} (MW)	P_g^{max} (MW)
Unit 1	5	0	0	150
Unit 2	10	0	0	150

TABLE 2.1: Convex Generator Characteristics

Figure 2.6 shows the optimal dispatch of Units 1 and 2 for a single-period problem ($|T| = 1$) over demand levels. Figure 2.6 also plots the optimal objective value for each demand level. Marginal prices λ are found as the slope of the optimal value function. At 150 MW, any price in the range $\lambda = [5, 10]$ clears the market and supports dispatch. The choice of λ in these cases represents a trade-off between producer and consumer surplus.

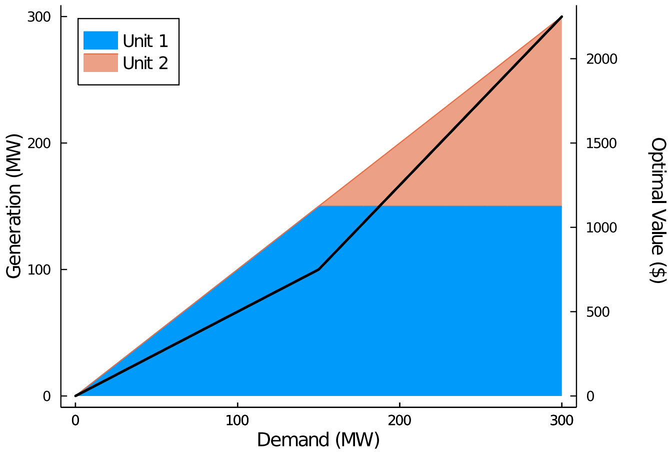


FIGURE 2.6: Convex optimal value function

Consider the following set of generators shown in Table 2.2.[2] Unit 1 has a lower marginal cost but higher startup cost, and Unit 2 has a minimum operating level requirement.

	C_g ($/MWh)	F_g ($)	P_g^{min} (MW)	P_g^{max} (MW)
Unit 1	5	1000	0	150
Unit 2	10	0	100	150

TABLE 2.2: Non-Convex Generator Characteristics

Figure 2.7 shows the optimal dispatch of Units 1 and 2. Unit 1 is dispatched until the minimum operating level of Unit 2, at which point Unit 2 is dispatched. At 150 MW of demand, Unit 2 remains on at its minimum operating level and Unit 1 is dispatched to provide the remaining 50 MW. The optimal objective value for each demand level is also shown in Figure 2.7. The optimal value function of this problem is discontinuous, so λ is

2 Similar illustrative examples are shown in [52].

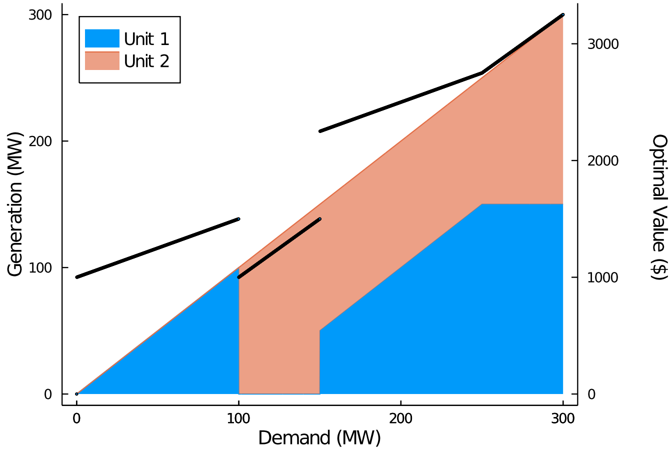


FIGURE 2.7: Non-convex optimal value function

undefined at 100MW and 150MW. Additionally, while $\lambda = 10$ at demand levels (100,150) MW, $\lambda = 5$ at demand levels (150, 250) MW. The price can thus decrease with demand. For the single-period problem, Unit 1 can never recover its startup costs, and Unit 2 cannot recover its variable costs between demand levels of (150, 250) MW.

One option to derive prices in the presence of non-convexities is to relax the problem and restrict the values of the integer variables to the optimal values found in the primal problem [29]. While λ would now always be defined, the incentive compatibility issue remains, as the prices do not support the central dispatch decision, i.e., some generators would wish to deviate. These generators experience lost opportunity costs; given the price λ they would rather produce more or less than the central dispatch decision. This issue has resulted in side payments to generators to partially compensate for lost opportunity costs, typically at least to provide make-whole payments so that units do not operate at a loss.

With marginal prices from the restricted convex relaxation, at the demand level of 200 MW, $\lambda = 5$. The optimal solution is for Unit 2 to produce at its minimum of 100 MW and Unit 1 to produce at 100 MW. Unit 1's profit is ($5-$5)*100MW - $1000 = -$1000. Unit 2's profit is ($5-$10)*100MW = -$500. If Unit 1 and Unit 2 receive make-whole payments, the total cost to consumers is \$5*200MW + \$1500 = \$2500. The total lost opportunity costs are \$1500.

An alternative approach is to calculate a uniform price that minimizes lost opportunity costs. Convex hull pricing, first proposed in [53], [54] and explored further in [55], derives prices from the convex hull of the optimal value function. With a tight UC formulation, approximations to convex hull prices can be found by relaxing integrality [56], [57]. Figure 2.8 shows the optimal value function of the primal problem with relaxed integrality, similar to the dispatchable model in [55]. In these simplified problems, the dispatchable model and convex hull model are often equivalent, although both may have multiple solutions just as in the convex setting at non-differentiable points of the optimal value function.

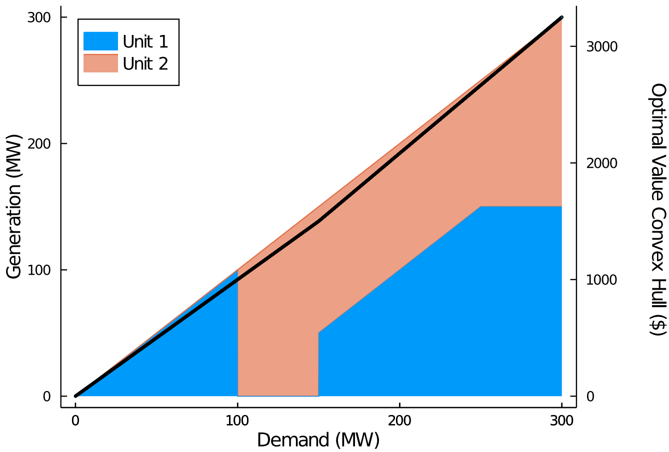


FIGURE 2.8: Approximation of the convex hull of the optimal value function

At 200MW of demand, the slope of the convex hull approximation plotted above yields λ = \$11.67. Unit 1's profit is (\$11.67-\$5)*100MW - \$1000 = $-$\$333. Unit 2's profit is (\$11.67-\$10)*100MW = \$167. Unit 1's lost opportunity cost is \$333, and Unit 2's lost opportunity cost is (\$11.67-\$10)*100MW = \$167 (because it would rather produce at its maximum capacity), yielding total lost opportunity costs of \$500. The make-whole payments required are also lower, \$333 vs \$1500. The total costs to consumers with make-whole payments is \$11.67*200MW +\$333 = \$2667, \$167 higher than in the restricted model.

In this case, there is a range of values, $\lambda = \$[10, 15]$, that would provide equivalent lost opportunity costs, exchanging lost opportunity cost between Unit 1 and Unit 2, and representing a trade-off between producer and consumer surplus. If $\lambda = 10$, Unit 1's profit is -$500 and Unit 2's profit is $0. Unit 1's LOC is $500 and Unit 2's LOC is $0. The total cost to consumers with make-whole payments is $10*200MW + $500 = $2500, the same as in the restricted convex model. If $\lambda = 15$, Unit 1's profit is $0 and Unit 2's profit is $500. Unit 1's LOC is $0 and Unit 2's LOC is $500. The total cost to consumers with make-whole payments is $15*200MW = $3000. Just as in the convex setting, the lowest λ in the range is associated with the highest consumer surplus.

The example above shows a case in which the total cost to consumers from convex hull pricing is as high or higher than the total cost to consumers with the restricted convex model, but side payments required to support dispatch are lower. Convex hull prices can be higher or lower than the prices found in the restricted convex model. Under convex hull pricing, discrete start-up and no-load costs are included in prices seen by all units. However, convex hull pricing treats all production costs as if they were continuous, meaning that prices could also decrease because the relaxation allows the model to find cheaper dispatch solutions. Because of high LOC, the restricted model also provides an incentive in some cases for generators to submit 0-cost offers that could raise the price found in reality (see Chapter 7). Extensive side payments may also be undesirable if the operator does not have perfect information about a generator's true costs and thus the generators are disincentivized to bid truthfully. Revenue for side payments is not directly collected from the market clearing and must be collected separately from market participants. The operator may not be revenue adequate if attempting to compensate LOC.[3]

Importantly, as shown in Section 2.4, a price is not meant to support the current resource mix but rather to be a signal for optimal investment and exit decisions. A market with different prices may settle on different long-run resource mixes, which may diverge from the resource mix an idealized central planner maximizing social welfare would choose. This issue is further discussed in Chapter 4.

3 Under convex hull pricing, if lost opportunity costs were compensated in full, there would be an incentive to submit arbitrarily large bids of zero price that must be accepted entirely if at all [58]. Market regulation may solve this problem in practice.

2.5.2 *Internalizing Non-Convexities*

Simple Bids and Physical Feasibility

Instead of producers submitting complex bids with their costs and operating requirements, an alternative approach is for consumers to internalize their non-convexities into simple price-quantity bids. The simplified and integrated market designs typically differ in the aggregation of the transmission network (zonal and nodal), which can impact cost to consumers when internalizing non-convexities in simple bids. Producers are responsible for submitting bids that are feasible for their units, and the operator runs a pay-as-bid redispatch process to adjust dispatch quantities up or down to create a physically feasible solution for the grid. This is the approach used early on in the United States and still used in Europe. The simplified market design can lead to significant increases in costs to consumers than the integrated market design with complex bids. Using the example given in [24] as inspiration, we consider the possible outcomes of our non-convex problem when a transmission network constraint is active.

Let demand remain at 200 MW. In a simplified market, Unit 2 bids between 100-150 MW at its marginal price of $10. Unit 1 must have some idea of the production quantity it will clear in order to bid a single price that will recover its startup cost. Suppose that from past experience Unit 1 knows it will be dispatched at 80 MW in real time due to a transmission network constraint. Unit 1 must then bid ($5*80 MW + $1000)/80 MW = $17.5. The market operator clears the market at a price of $17.5 with 50 MW of Unit 1 and 150 MW of Unit 2. The redispatch market then pays Unit 1 $17.5*30MW to increase its production and allows Unit 1 to buy back 30 MW at its offer price of $10. The total costs to consumers is $17.5*200 MW + ($17.5-$10)*30 MW = $3725.

In the integrated market with the restricted model, $\lambda = 5$ when Unit 1 produces at 80 MW and Unit 2 at 120 MW. The units require make-whole payments of $1000 and $600. The total cost to consumers is only $5*200 MW + $1600 = $2600.

Simple Bids and Non-Convexity

Beyond the interaction with transmission network constraints, the simplified market design is not exempt from the problem of determining prices in the presence of non-convexities. In the integrated market, the dispatch solution is social-welfare maximizing, but to support this solution compromises must be made in linear pricing; a uniform price is found along with side payments representing LOC or a subset of LOC. In contrast, in the simplified market, a linear price is used but the solution is not social-welfare maximizing [58]. For further discussion and specific formulation of the simplified market model with non-convexities, see [58], [59].

Submitting price-quantity offers that are feasible for a unit requires submitting non-convex orders, or block orders, that must be accepted or rejected in full. This leads to the same challenges posed previously by a non-convex optimal value function. An alternative approach is based on the recognition that market participants are willing to accept having an offer that would be profitable at the market price rejected (paradoxically rejected bids), but will not accept having an offer that is not profitable at the market price accepted [58]. A producer may perceive lost opportunity costs if the offer that appeared to be profitable was rejected, but this is only a theoretical prospect of profit, as the non-convexities mean it may not actually be possible to sell the desired quantity in the market. However, accepting an offer that is unprofitable has a real negative welfare effect. The European solution is to find the subset of block orders (a feasible integral solution) that maximizes social welfare without accepting any block orders that would be out-of-the-money. The solution is thus of course not necessarily social-welfare maximizing and may have high LOC, but it has the benefit of ensuring short-run cost recovery (no make-whole payments). Welfare losses from this method could be substantial, and this may be why the European market limits the amount of non-convex bids [58]. However, convex bids do a poor job representing the underlying non-convex system, which could also result in substantial efficiency losses.

2.6 UNCERTAINTY AND RISK MANAGEMENT

Additional issues that impact pricing in electricity markets but are mostly out-of-scope for this body of work are uncertainty and risk management. Both intersect with issues of pricing with transmission constraints and in the presence of non-convexities.

2.6.1 *Uncertainty*

Electricity markets in the integrated model typically have a day-ahead hourly unit commitment market and a sub-hourly real-time economic dispatch market. Because of uncertainty of future conditions (in addition to computational limitations), electricity markets are cleared with rolling horizons, i.e., prices may be determined for a 24-hour period based on a 36-hour optimization horizon in the day-ahead market or for each 5-minute period of an hour with a multi-hour look-ahead in a real-time market. Unit commitment and transmission switching may decrease the ability of market participants to arbitrage between day-ahead and real-time nodal markets [60]. Lost opportunity costs may exist for rolling-horizon auctions even in convex settings [61]. This challenge may increase with the growing share of variable renewable energy with uncertain forecasts, leading to a number of proposed modifications to multi-interval real-time pricing and ramping products [61]–[67]. An implementation of rolling horizons for convex hull pricing may require fixing past prices as opposed to past outputs [56]. European intraday markets allow for updates to positions as more information is revealed closer to real time, and enhanced intraday price signals have been proposed for the integrated market design in the United States [68].

Increasing shares of stochastic resources have also led to renewed interest in finding efficient prices under uncertainty. While marginal pricing provides cost recovery in a convex, deterministic setting, it only provides cost recovery in expectation in a stochastic setting. In recent years there have been a number of proposals for stochastic market designs [69]–[71] and quasi-stochastic market designs [72], [73]. A chance-constrained stochastic market design to incorporate stochastic renewables is proposed in [71] and [74] introduces a method to recover the expected price for dispatch under the stochastic ideal via a probability-driven operating reserve demand curve. Authors in [73] develop a robust optimization framework of dispatch-aware resource procurement with the aim of diminishing the need for additional flexibility-insuring ancillary services. The intersection of non-convexities and uncertainty is explored in [75].

2.6.2 *Resource Adequacy and Risk Management*

Electricity markets in practice often suffer from a "missing money" problem in which energy market prices are insufficient for generators to fully recover their capital costs. As shown in Section 2.4, in theory, assuming convexity, an energy-only market provides perfect cost recovery in the long-run for generators in the optimal resource mix as well as signals for resources to enter or exit the market as new, lower-cost innovative technologies come online. However, imperfections in the market, uncertainty, out-of-market actions by system operators to avoid grid conditions in which scarcity prices arise, and price caps to mitigate market power mean that prices often do not rise high enough for sellers to recover their investment costs. Combined with largely inelastic demand and the trouble of determining a single value of lost load, this calls into question the ability of energy markets to solve the problem of resource adequacy, i.e., how we ensure that there is enough of the right kind of resources installed on the system to meet load reliably. In response, capacity mechanisms have proliferated in recent years [6], [7].

Capacity mechanisms range from mandatory bilateral contracting to capacity markets, in which the system operator seeks some administratively defined level of firm capacity and reserve margin [76], [77]. The implementation of capacity markets varies considerably by jurisdiction, with different performance incentives, methods for determining qualifying capacity, and demand curve calculations [6]. Capacity markets may be forward markets or may bundle capacity obligations with financial call options to supply energy when the energy price rises above a specified strike price. This approach is the reliability options model proposed first in [78] and later in [79], [80].

Skepticism has increased in recent years surrounding capacity mechanisms as resource adequacy measures, as they can be implemented as an administrative construct vulnerable to rent-seeking. The concept of firm capacity is also less clear for portfolios with large shares of intermittent renewables and energy storage [8], [81]. Recent debates in the United States center around proposed minimum offer price rules that attempt to exclude low-variable cost renewable resources from the market for thermal generator capacity. If the firm capacity value of renewables is appropriately credited, this could lead to over-procurement of capacity at higher costs to consumers and a slower energy transition. However, if the firm capacity value of the portfolio of resources on the system is not correctly calculated, reliability issues may arise.

Increased subsidies for renewable resources change market clearing outcomes to decrease revenues to thermal units in the capacity market, and with the system operator unsure of how closely accredited firm capacity targets align with resource adequacy goals, it becomes easy for thermal units to argue that they are necessary for reliability and being undercompensated. Capacity markets are also biased toward resources with high marginal costs and low capital costs because the revenue removes some of the risk faced by changes in fossil fuel prices [9]. This penalizes resources that governments want to promote for decarbonization goals, which typically have high capital costs and low marginal costs, including variable renewable energy, energy storage, and firm-low carbon resources like nuclear and advanced geothermal.

Alternative approaches to capacity mechanisms emphasize "full-strength" spot prices in the energy markets, allowing volatile prices to provide efficient operational and investment signals. In some markets, including ERCOT in Texas, the energy price also includes an adder via an operating reserve demand curve if total reserves fall below a threshold [82], [83]. High shares of zero-variable cost resources do not change the fundamentals of efficient electricity market design [84]. However, [85] argues there is a reliability externality because blackouts do not preferentially reward retailers who hedged their risk over those who did not. Recent shortages in markets with high price caps in Texas and Australia have demonstrated that consumers are often insufficiently hedged [86]. A number of proposals exist moving forward. One is to have hybrid markets in which there is competition *for* the market in long-run organized markets and competition *in* the market in short-run markets [48]. Arguably, beyond capacity markets, long-run organized markets already exist with national and state-level competitive procurement of wind and solar and procurement by private companies of renewable resources to meet carbon neutrality goals. However, these procurement mechanisms typically do not take into account system needs, and thus are likely to be inefficient investment signals. One form that long-run organized markets could take is a proposal for mandated contracting that preserves the volatility of the spot market. Mandating standardized fixed-price forward contracts would require intermittent resources to hedge their short-term price and production quantity risk with dispatchable generation [87]. Additional proposals include strategic reserves with an insurance mechanism for reliability differentiation [88] and a portfolio of hedge contracts for both market participants and the system operator [89].

Part I

AGGREGATION OF THE TRANSMISSION NETWORK

3

MODELING FLOW-BASED MARKET COUPLING

As Europe moves to expand flow-based market coupling (FBMC) to other regions, revisiting key modeling elements is crucial to interpreting results of different studies. In contrast to nodal pricing, FBMC is a zonal pricing approach that involves approximations of the underlying grid topology. The choice of base case, method of redispatch, whether unit commitment constraints are included, and whether results consider pay-as-bid or market-clearing prices vary widely across published papers. We demonstrate that different methods can have a substantial impact on overall costs. We find that existing base case approaches perform poorly compared to a base case using the nodal solution across all modeling choices considered.

3.1 INTRODUCTION

European electricity markets are cleared with a zonal pricing scheme that, unlike nodal pricing, requires approximating and aggregating various aspects of the underlying physical network. Initially, the Central Western Europe (CWE) electricity markets used the Available Transfer Capacity (ATC) method, in which physical characteristics are strongly simplified, typically consisting of a single aggregated transmission line between zones with no intrazonal lines represented. In recent years, however, CWE day-ahead markets have adopted a flow-based market coupling (FBMC) approach that aims to better represent the underlying physical network to improve dispatch decisions while maintaining pricing at the zonal level. FBMC includes all interzonal lines and select intrazonal lines in the dispatch decisions. Current research examines the expansion of FBMC to other regions [90], [91], different price zone configurations [92], [93], as well as analyzes various FBMC parameters [90], [92], [94], [95].

However, the results of these studies may be impacted by modeling assumptions that are often overlooked. An important example is the FBMC base case parameter selection method. The European Network of Transmission System Operators (ENTSO-E) in 2018 identified calculating base cases as one of the "non-resolvable complexities" of FBMC planning problems [96]. FBMC relies on the calculation of base cases, as the zonal power transfer distribution factors (PTDFs) give the change in flows following a change in injection or withdrawal. However, multiple base cases exist in the feasible region of the nodal network. While ENTSO-E uses historical reference days [97], selection of base case flows when reference days are not available varies. Some approaches use all-zero zonal net positions [93], [94], [98], while others solve an ATC problem [90], [91], [98] or increase limits on intrazonal line capacities until no more intrazonal congestion exists [92]. This work seeks to illustrate how different choices of base case flows affect total market costs, including both the day-ahead (DA) FBMC schedule and redispatch costs.

In modeling zonal markets, several choices in addition to FBMC base case parameter selection vary widely and may significantly impact results. As TSOs rarely specifically outline their redispatch procedure, some approaches in the literature seek to minimize real-time operating costs while preserving DA zonal net positions [99], while others explicitly seek to limit compensation of units redispatched [91], [92] (although many omit redispatch analysis altogether). Additionally, unit commitment (UC) constraints are typically not included. However, UC constraints may lead to such different dispatch decisions that conclusions about a parameter of interest may change. Finally, the magnitude of findings is impacted by whether costs are calculated as pay-as-bid as in [92] or market-clearing prices in the day-ahead market as in [91].

We note that currently FBMC markets do not allow so-called "non-intuitive" prices in which energy flows from a higher price zone to a lower price zone [59]. However, this is economically inefficient and is associated with significant welfare losses [100], and this practice is not included in our market model. We acknowledge movement toward introduction of markets for redispatch, but such a move is far from the economic ideal, as two markets for the same time period over different geographic areas (zonal day-ahead and nodal redispatch) creates perverse incentives for strategic bidding [101]. We thus restrict our comparisons to methods of regulatory redispatch seen in the literature, while acknowledging that actual methods vary by TSO. As in theory nodal pricing provides the social-welfare maximizing outcome, we provide a comparison of changes in the day-ahead, redispatch, and total costs relative to the nodal solution as a baseline across different modeling choices.

3.2 METHODOLOGY

3.2.1 *Nomenclature*

Indices and Sets

i	Index of generators and resources
t	Index of time periods
b	Index of buses (nodes)
a	Index of areas
z	Index of zones
l	Index of lines
T	Set of time periods
B	Set of buses (nodes)
Z	Set of zones
I_b	Set of generators at bus b

I_a	Set of generators in area a
I_z	Set of generators in zone z
B_z	Set of buses in zone z
L	Set of lines
L^Z	Set of lines in zonal formulation
$\mathcal{P}$	Solution space of operating characteristics and reserves constraints
SL	Set of slow units whose commitment decisions cannot be changed in redispatch

Parameters

C_i	Variable cost
C_i^{on}	Startup cost
D_{tb},D_{tz}	Real power demand at bus b or zone z
$PTDF_{lb}^B$	Nodal power transfer distribution factors
$PTDF_{lz}^Z$	Zonal power transfer distribution factors, defined only for lines $l \in L^Z$
F_l	Maximum line rating in MW
$\rho_{tz}^{(ref)}$	Pre-determined zonal net positions from a reference day
$\rho_{tb}^{(e)}$	Expected nodal net positions from base case
$\rho_{tz}^{(e)}$	Expected zonal net positions from base case
ρ_{tz}^{Z*}	FBMC solution zonal net positions
p_{ti}^{Z*}	FBMC solution production schedule
u_{ti}^{Z*}	FBMC solution commitment schedule
C^{dev}	Penalty term for deviations in redispatch from FBMC zonal net positions

Variables

$u_{ti} = 1$	if generator i is on, 0 otherwise
$y_{ti}^{on} = 1$	if generator i is turned on, 0 otherwise
$y_{ti}^{off} = 1$	if generator i is turned off, 0 otherwise
p_i	Committed generation
nse_{tb}	Nodal nonserved energy, $0 \leq nse_{tb} \leq D_{tb}$
ρ_{tb}	Nodal net position

f_{tl}	Line flow
nse_{tb}	Zonal nonserved energy, $0 \leq nse_{tz} \leq D_{tz}$
δ_{tz}	Deviations in redispatch from FBMC zonal net positions
o_{tb}	Production shedding in redispatch
p_{ti}^{UP}, p_{ti}^{UP}	Production above/below scheduled FBMC production

3.2.2 *Computation of Zonal Power Transfer Distribution Factors*

The complete zonal PTDF matrix is found as a weighted sum of the columns of the nodal PTDF matrix. The weights are the Generation Shift Keys (GSKs), each representing a node's contribution to a change in the zonal net position. Methods of calculating GSKs are left up to the TSOs, and here we use the method of the Dutch TSO [97]. FBMC includes all interzonal lines and select intrazonal lines for which any zone-to-zone PTDF (the difference between any two zonal PTDFs for a given line) is over 5% [97]. See [92] for an analysis of the sensitivity of results to this inclusion criterion. Rows corresponding to included lines are preserved in the final zonal PTDF.

3.2.3 *Commonalities in Economic Dispatch Models*

The solution space $\mathcal{P}$ of the set of operating characteristics remains the same for nodal and zonal solutions (see the Appendix for the full formulation) and is defined as:

$$\{p_{ti}, u_{ti}, y_{ti}^{on}, y_{ti}^{off}\} \ \in \mathcal{P} \tag{3.1}$$

The set $\mathcal{P}$ comprises curtailable PV and wind and non-curtailable rooftop PV and run-of-river hydro. Operating constraints for thermal generators include minimum and maximum operating capacities and ramping limits and optional unit commitment, including minimum on and off times. ES operating constraints include power and energy capacity and efficiency.

3.2.4 *Nodal Dispatch*

For the nodal solution, we solve the following problem for each time horizon:

$$\min_{p_i, u_{ti}, y^{on}_{ti}, y^{off}_{ti} \in \mathcal{P}} \quad \sum_t \sum_i C_i p_{ti} + \sum_t \sum_{i \epsilon TH} C^{on}_i y^{on}_{ti} + \sum_t \sum_b C^{nse} nse_{tb} \tag{3.2a}$$

$$\text{s.t.} \quad \sum_{i \in I_b} p_{ti} + \rho_{tb} + nse_{tb} = D_{tb} \quad \forall t, b \quad : \lambda^N \tag{3.2b}$$

$$\sum_b \rho_{tb} = 0 \quad \forall t \tag{3.2c}$$

$$-F_l \leq f_{tl} \leq F_l \quad \forall t, l \in L \tag{3.2d}$$

$$f_{tl} = \sum_b PTDF^B_{lb} \rho_{tb} \quad \forall t, l \in L \tag{3.2e}$$

The additional constraints reflect the nodal power balance (3.2b), the balance of the nodal net positions (3.2c), line flow limits (3.2d), and the computation of the flows using the nodal PTDFs (3.2e). The market clearing prices are λ^N, the dual variables of the nodal power balance constraints, defined for each timestep t and bus b. These prices are also known as nodal prices or locational marginal prices (LMPs). In the UC version, λ^N can be obtained by relaxing the binary constraints and fixing the binary variables to their optimal values, although such a method of course is not guaranteed to compensate for startup costs adequately.

3.2.5 *Base Case Nodal Dispatch*

In our analysis, we compare the results using four different base cases. For the first base case solution, **BC1**, we determine the nodal solution by solving the problem formulated in Section 3.2.4. and obtain the nodal (3.3) and zonal (3.4) net positions:

$$\rho^{(e)}_{tb} = \rho^*_{tb} \tag{3.3}$$

$$\rho^{(e)}_{tz} = \sum_{b \ \epsilon \ B_z} \rho^*_{tb}, \ \forall t, \ z \tag{3.4}$$

For the other base cases, the expected nodal and zonal net positions are found analogously but from variations to the nodal formulation following the description in Table 3.1. **BC2**, with zero zonal net positions, is a common modeling choice. In both of these cases, it is assumed that the nodal solution to the day-ahead problem is known a priori when the base case flows are calculated. However, this is not the case because of the uncertainty in the demand prediction. Therefore, **BC3.1-2** represent variations on the method of **BC1** in which base cases were calculated with the expectation of uniformly higher demand and a poorly forecasted demand, respectively.

Base Case	Additional Constraints	
BC1	— Same as nodal solution	
BC2	$$\sum_{b\ \in B_z} \rho_{tb} = 0, \quad \forall t, z$$ Zonal net positions must be 0	(3.5)
BC3.1	$$\sum_{i \in I_b} p_{ti} + \rho_{tb} + nse_{tb} = 1.2 D_{tb}, \quad \forall t, b$$ Perturbed demand, uniformly 20% higher; replace (3.2b) with (3.6)	(3.6)
BC3.2	$$\sum_{i \in I_b} p_{ti} + \rho_{tb} + nse_{tb} = (1+\epsilon)\, D_{tb}, \quad \forall t, b$$ Perturbed demand randomly between +/- 0-20%; replace with (3.2b) with (3.7)	(3.7)
BC4	$$\sum_{b \in B_z} \rho_{tb} = \rho_{tz}^{(ref)}, \quad \forall t, z$$ Pre-determined zonal net positions	(3.8)

TABLE 3.1: Base Case Definitions

While little detail is provided, CWE in reality uses flows based on historical reference days [97]. BC4 represents an attempt to get around the circular problem in modeling FBMC of desiring zonal flows from the FBMC zonal dispatch on a similar day without having historical data. The approach is adapted from [92], in which intrazonal line capacities are increased until no more intrazonal congestion remains. Here we then additionally take the zonal flows associated to that case and run the base case with fixed zonal net positions to get the final base case nodal net positions. Intertemporal constraints are included, although they are not currently considered in determining the nodal and zonal net positions [97].

3.2.6 *Flow-Based Market Coupling Zonal Dispatch*

For the zonal FBMC solution, we solve the following problem for each time horizon:

$$\min_{\{p_i, u_{ti}, y_{ti}^{on}, y_{ti}^{off}\} \in \mathcal{P}} \quad \sum_t \sum_i C_i p_{ti} + \sum_t \sum_{i \in TH} C_i^{on} y_{ti}^{on} + \sum_t \sum_z C^{nse} nse_{tz} \tag{3.9a}$$

$$\text{s.t.} \quad \sum_{i \in I_z} p_{ti} + \rho_{tz} + nse_{tz} = D_{tz} \quad \forall t, z : \lambda^Z \tag{3.9b}$$

$$\sum_z \rho_{tz} = 0 \quad \forall t \tag{3.9c}$$

$$\Delta F_{lt} = \sum_b PTDF_{lb}^B \rho_{tb}^{(e)} - \sum_z PTDF_{lz}^Z \rho_{tz}^{(e)} \qquad \forall t, l \in L^Z \tag{3.9d}$$

$$- F_l - \Delta F_{lt} \leq f_{tl} \leq F_l - \Delta F_{lt} \quad \forall t, l \in L^Z \tag{3.9e}$$

$$f_{tl} = \sum_z PTDF_{lz}^Z \rho_{tz} \quad \forall t, l \in L^Z \tag{3.9f}$$

These constraints represent the zonal power balance (3.9b), the balance of zonal net positions (3.9c), the introduction of a new term ΔF_{lt} (3.9d), the zonal line flow limits including this new term (3.9e), and the zonal network constraint (3.9f). The market clearing prices are the zonal prices λ^Z, the dual variables of the zonal power balance constraints, defined for each timestep t and zone z. The value ΔF_l (3.9d) is the difference between the expected nodal flow on the line and the expected zonal flow on the line, both determined from the base case. A detailed explanation is found in [102]. In this analysis, for simplicity of comparison, we omit the flow reliability margins and flow adjustment values [97].

3.2.7 *Post-Zonal Nodal Redispatch*

In the redispatch, the underlying full set of nodal network constraints must be satisfied. From the FBMC zonal dispatch, we obtain the scheduled commitment for "slow" units that cannot be changed in redispatch and the FBMC zonal net positions, deviations from which are penalized in redispatch at a cost higher than that of the marginal cost of the most expensive unit. We formulate the following optimization problem for redispatch:

$$\min_{p_i, u_{ti}, y^{on}_{ti}, y^{off}_{ti} \in \mathcal{P}} \quad \sum_t \sum_i C_i p_{ti} + \sum_t \sum_{i \in TH} C^{on}_i y^{on}_{ti} + \sum_t \sum_b C^{nse} nse_{tb} \tag{3.10a}$$

$$+ \sum_t \sum_z C^{dev} \delta_{tz}$$

$$\text{s.t.} \quad \delta_{tz} \geq \left| \rho^{Z*}_{tz} - \sum_{b \epsilon B_z} \rho_{tb} \right| \quad \forall t, z \tag{3.10b}$$

$$\{u_{ti}, y^{on}_{ti}, y^{off}_{ti}\} = \{u^{Z*}_{ti}, y^{on,Z*}_{ti}, y^{off,Z*}_{ti}\} \quad \forall t, i \in SL \tag{3.10c}$$

$$\sum_{i \in I_b} p_{ti} + \rho_{tb} + nse_{tb} - o_{tb} = D_{tb} \quad \forall t, b \tag{3.10d}$$

$$0 \leq o_{tb} \leq \sum_{i \in I_b} p_{ti} \quad \forall t, b \tag{3.10e}$$

$$\sum_b \rho_{tb} = 0 \quad \forall t \tag{3.10f}$$

$$-F_l \leq f_{tl} \leq F_l \quad \forall t, l \in L \tag{3.10g}$$

$$f_{tl} = \sum_b PTDF^B_{lb} \rho_{tb} \quad \forall t, l \in L \tag{3.10h}$$

$$p^{UP}_{ti} - p^{DN}_{ti} = p_{ti} - p^{Z*}_{ti} \quad \forall t, i \tag{3.10i}$$

The redispatch problem is similar to the nodal formulation but penalizes deviations from the zonal net positions found in the FBMC dispatch. The additional or modified constraints define deviations from the FBMC zonal net position (3.10b), keep the unit commitment schedule for "slow" units from the FBMC dispatch (3.10c), allow for production shedding (3.10d) - (3.10e), and distinguish between positive and negative redispatch (3.10i).

We compare two methods of choosing which units to redispatch: (3.10a) minimizes real-time operating costs (redispatch method **R1**) and (3.11) minimizes compensation provided to units for redispatching (**R2**):

$$\sum_t \sum_i \left(C_i p_{ti}^{UP} + \left(\lambda_{tz}^{Z} - C_i \right) p_{ti}^{DN} \right) + \sum_t \sum_{i \in TH} C_i^{on} (y_{ti}^{on} - y_{ti}^{on} u_{ti}^{Z*}) + \sum_t \sum_b C^{nse} nse_{tb} + \sum_t \sum_z C^{dev} \delta_{tz} \quad (3.11)$$

However, in both cases, units are compensated in the same manner and such that a unit is indifferent to being redispatched. The costs of regulatory redispatch are found by compensating units for any additional costs incurred from their FBMC schedule and compensating any perceived losses based on their FBMC schedule. If a unit must increase production or turn on in redispatch when it was scheduled to be off, the system operator will pay the unit at cost (including startup cost if UC constraints). If a unit must decrease production from its FBMC schedule, the unit is compensated based on the product of the decrease in production and the FBMC zonal market clearing price it would have received, minus the operating costs it would have incurred.

3.3 ILLUSTRATIVE CASE STUDY

The case study is based on the RTS-GMLC dataset [38]. This modified version of RTS-96 as used in this case study has 120 lines, 73 buses, and 154 generating units of which 73 are thermal including coal, natural gas, and nuclear. Hydro storage is modeled as a general energy storage unit. Utility-scale PV and wind are curtailable without penalty, while rooftop PV and run-of-river hydro are non-controllable. The nameplate capacity of solar and wind combined is approximately 65% that of thermal generation capacity.

The 3 "areas" in RTS-GMLC are adapted here as distinct price zones. There are 5 interzonal lines and, with the 5% zone-to-zone PTDF criterion, 58 of the 115 intrazonal lines are included in FBMC. The day-ahead energy market is simulated with inelastic demand and solved on a rolling basis hourly for 24 hours with a 6-hour look-ahead. Reserves are omitted. The states of variables are carried over as parameters from the end of one day to the beginning of the next. Slow units in this study are steam, combined-cycle, and nuclear generators.

The simulations are run over 1 month (January) with two versions: one with linear constraints (i.e., without UC constraints) and one with UC constraints. To find the fixed zonal net positions to use each day as inputs to **BC4**, intrazonal line capacities were increased by 80% in a nodal simulation without UC constraints to prevent any intrazonal congestion over the month (but returned to their actual values when finding the **BC4** nodal net positions).

3.3.1 *Impact of Base Case Choice*

Although the total amount of line overloads that would result from the zonal dispatch as a percentage of total system load is in all cases less than 2% as shown in Figure 3.1, different base cases yield significantly different total market costs. Figure 3.2 shows that the total market costs differ by base case, and are of course all strictly higher than the nodal costs. In Figure 3.3, the costs are seen relative to the nodal solution as a baseline. For redispatch method **R1** without UC constraints, the worst-performing base case (**BC2**) results in total costs over 6% greater than the baseline nodal solution, while the best-performing base cases (**BC1** and **BC3.1**) only result in costs less than 2% greater. Notably, the worst-performing base cases are the two more commonly used in modeling FBMC.

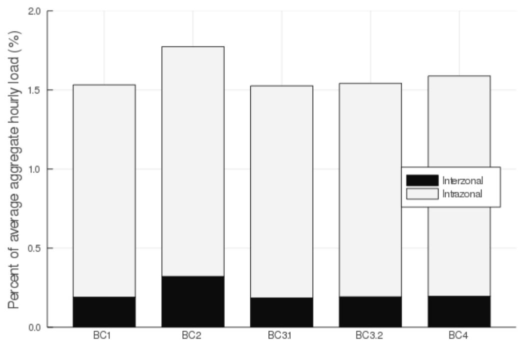


FIGURE 3.1: Average aggregate hourly line overloads as a percentage of average aggregate hourly load with **RC1** and linear constraints.

3.3.2 *Redispatch Approach*

Comparing Figure 3.3 with redispatch method **R1** and Figure 3.4 with redispatch method **R2**, we see that results are substantially affected by the redispatch method. Naturally, explicitly minimizing redispatch costs rather

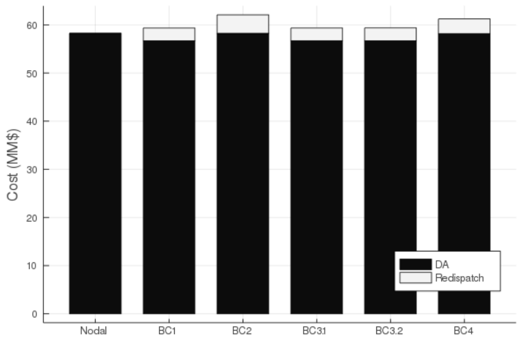


FIGURE 3.2: Market costs under **R1** with market-clearing prices and linear constraints.

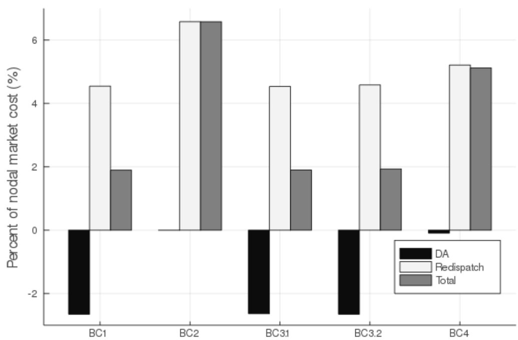


FIGURE 3.3: Market costs under **R1** with market-clearing prices and linear constraints as percentage of nodal market costs.

than real-time operating costs (that are not actually paid) results in lower total costs across all base case scenarios. For the best-performing base cases, **R2** more than halves the increase in total costs compared to the baseline nodal solution. While the preference-order of base cases does not change, the magnitude of differences in performance does. With **R1**, the costs above baseline of **BC2** are approximately 3 times those of **BC1**, while with **R2**, they are over 5 times greater.

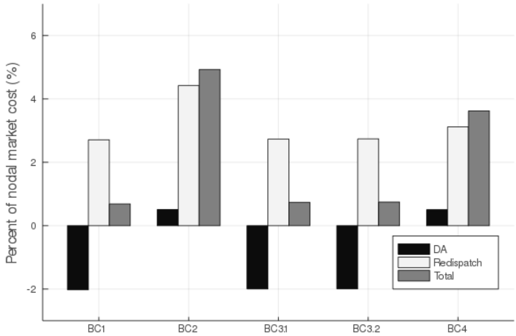


FIGURE 3.4: Market costs under **R2** with market-clearing prices and linear constraints as percentage of nodal market costs.

3.3.3 *Pay-as-Bid vs Market-Clearing Prices*

If the magnitude of results is of importance, as it is in many studies seeking to closely reflect the European grid, then it is important to distinguish between compensation using pay-as-bid and market-clearing prices. The European market is a uniform auction with market-clearing prices and these prices are used to compute the market costs in Figures 3.3 and 3.4. Figure 3.5 gives the same comparison among the base cases but now using pay-as-bid costs. The absolute value of the redispatch costs in Figure 3.3 and Figure 3.5 (note different axes) are the same, yet for **BC2** they represent over 6% of the nodal costs using market-clearing prices but over 15% using pay-as-bid compensation.

3.3.4 *Impact of Unit Commitment Constraints*

When including unit commitment constraints, we see that the overall impact of the redispatch method is much greater with UC constraints than without. The difference in costs between Figure 3.5 and Figure 3.8 is much less than between Figure 3.6 and Figure 3.7 (note the different axes) because paying avoidable startup costs is expensive. With UC constraints, the solution space is decreased, and the additional costs of FBMC over the nodal solution between the best and worst base case choices is approximately 25% across both redispatch scenarios. With UC constraints, we still see that the base cases most commonly used in the literature (**BC2** and **BC4**) under-perform

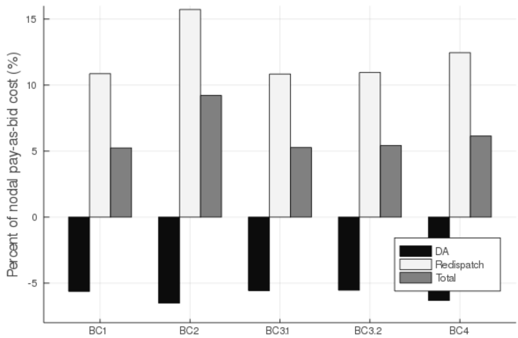


FIGURE 3.5: Total costs under R1 with pay-as-bid and linear constraints as percentage of nodal pay-as-bid costs.

compared to the strategy of **BC1** and its variations with load forecast uncertainty (**BC3.1-2**).

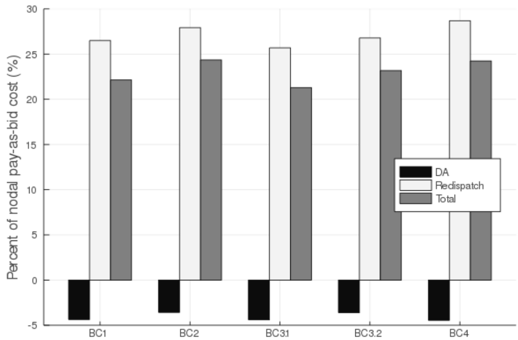


FIGURE 3.6: Total costs under **R1** with pay-as-bid and UC constraints as percentage of nodal pay-as-bid costs.

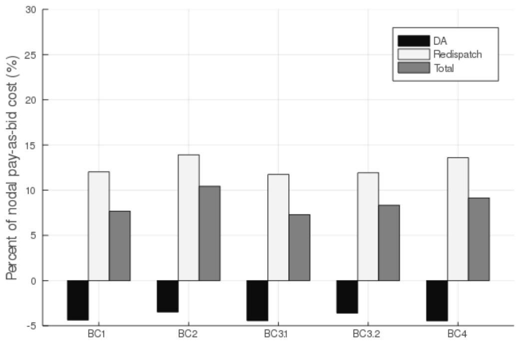


FIGURE 3.7: Total costs under **R2** with pay-as-bid and UC constraints as percentage of nodal pay-as-bid costs.

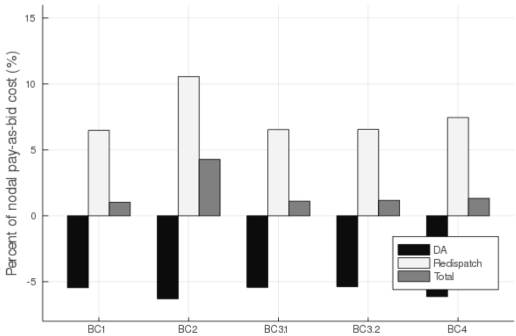


FIGURE 3.8: Total costs under **R2** with pay-as-bid and linear constraints as percentage of nodal pay-as-bid costs.

3.4 CONCLUSION

FBMC is an attempt to improve the efficiency of zonal market dispatch decisions by representing the physical system with greater granularity. However, more research is needed to determine how various modeling choices influence results. When comparing results across studies, it is important to consider what modeling assumptions are made. We find that the method of redispatch, how prices are determined, and inclusion of UC constraints can have a substantial impact on overall costs. In this illustrative case study, different methods of base cases employed in the literature can more than quintuple the additional costs of the zonal market design relative to the baseline nodal design. Both existing modeling approaches – all-zero zonal net positions and a method relieving intrazonal congestion similarly to an ATC solution – perform poorly in this case study compared to base cases following a nodal solution. This result holds whether the nodal solution is significantly perturbed, across both pay-as-bid and market-clearing prices, and with or without UC constraints.

Different FBMC approaches impact not only short-term dispatch decisions but price signals for investment in the long-term. With plans to expand FBMC to other regions in Europe on the horizon, it is imperative to further investigate the effect of base case flow values on market outcomes. The method of redispatch, whether unit commitment constraints are included, and whether costs are presented pay-as-bid or with market clearing prices also impact conclusions. Whether trying to calculate more optimal price zone configurations, analyze the impact of introducing FBMC to new regions, or benchmarking FBMC results to the nodal solution, these modeling choices matter.

APPENDIX

This appendix provides a short description of the unit commitment model used in Chapter 3.

3.4.1 *Nomenclature*

Indices and sets

i	Index of generators
w	Index of wind resources
v	Index of PV resources
f	Index of rooftop PV resources
h	Index of run-of-river hydro resources
s	Index of energy storage units
t	Index of time period
T	Number of time periods

Parameters

C_i	Variable cost
C_i^{on}	Startup cost
P_i^{min}	Minimum operating capacity
P_i^{max}	Maximum operating capacity
M_i^{on}	Minimum on time
M_i^{off}	Minimum off time
R_i	Maximum ramp up and ramp down rate
$P_{t\{w,v,f,h\}}$	Maximum generation for VRE resource
P_s^c	Charging capacity
P_s^d	Discharging capacity
E_s^{max}	Energy capacity
E_s^{init}	Initial stored energy
η_s	Roundtrip efficiency
D_t	Real power demand

S_t	Spinning reserve requirement
C^{nse}	Cost of nonserved energy
C^{nse_res}	Cost of nonserved reserves

Decision variables

u_{ti}	= 1 if generator i is on, 0 otherwise
y_{ti}^{on}	= 1 if generator i is turned on, 0 otherwise
y_{ti}^{off}	= 1 if generator i is turned off, 0 otherwise
$p_{t\{i,w,v,fh\}}$	Committed generation
p_{ts}^{c}	Charging power
p_{ts}^{d}	Discharging power
z_{ts}	= 1 if storage unit s is discharging, 0 if charging
E_{ts}	Energy stored in storage unit s, $0 \leq E_{ts} \leq E_s^{max}$
nse_t	Nonserved energy, $0 \leq nse_t \leq D_t$
nse_t^{res}	Nonserved reserves, $0 \leq nse_t^{res} \leq S_t$

3.4.2 *Formulation*

$$\min \quad \sum_t (C^{nse} nse_t + C^{nse_res} nse_t^{res}) + \sum_t \sum_i (C_i p_{ti} + C_i^{on} y_{ti}^{on}) \tag{3.12a}$$

$$\text{s.t.} \quad \sum_{q \epsilon i,w,v,f,h} p_{tq} + \sum_s \left(p_{ts}^d - p_{ts}^c \right) + nse_t = D_t \quad \forall t \tag{3.12b}$$

$$\sum_i u_{ti} (P_i^{max} - p_{ti}) + nse_t^{res} \geq S_t \quad \forall t \tag{3.12c}$$

$$0 \leq p_{tw},\ p_{tv},\ p_{tf},\ p_{th} \leq P_{tw}, P_{tv},\ P_{tf}, P_{th} \tag{3.12d}$$

$$u_{ti} P_i^{min} \leq p_{ti} \leq u_{ti} P_i^{max} \quad \forall t, i \tag{3.12e}$$

$$-R_i \leq p_{ti} - p_{t-1,i} \leq R_i \quad \forall t \epsilon 2, \ldots, T, i \tag{3.12f}$$

$$y_{ti}^{on} + y_{ti}^{off} \leq 1 \quad \forall t = t, i \tag{3.12g}$$

$$u_{ti} - u_{t-1,i} = y_{ti}^{on} - y_{ti}^{off} \quad \forall t \epsilon 2, \ldots, T, i \tag{3.12h}$$

$$y_{ti}^{on} = u_{ti} \quad \forall t = 1, i \tag{3.12i}$$

$$y_{ti}^{on} + \sum_{\tau = t+1}^{\min(t + M_i^{on} - 1, T)} y_{\tau i}^{off} \leq 1 \quad \forall t \epsilon 1, \ldots, T-1, i \quad : M_i^{on} > 1 \tag{3.12j}$$

$$y_{ti}^{off} + \sum_{\tau = t+1}^{\min(t + M_i^{off} - 1, T)} y_{\tau i}^{on} \leq 1 \quad \forall t \epsilon 1, \ldots, T-1, i \quad : M_i^{off} > 1 \tag{3.12k}$$

$$0 \leq p_{ts}^c \leq P_s^c (1 - z_{ts}) \quad \forall t, s \tag{3.12l}$$

$$0 \leq p_{ts}^d \leq P_s^d z_{ts} \quad \forall t, s \tag{3.12m}$$

$$E_{1s} = E_s^{init} + p_{1s}^c \sqrt{\eta_s} - \frac{p_{1s}^d}{\sqrt{\eta_s}} \quad \forall s \tag{3.12n}$$

$$E_{ts} = E_{t-1,s} + p_{ts}^c \sqrt{\eta_s} - \frac{p_{ts}^d}{\sqrt{\eta_s}} \quad \forall t \epsilon \{2, \ldots, T\}, s \tag{3.12o}$$

$$E_{Ts} = E_s^{init} \quad \forall s \tag{3.12p}$$

Part II

NON-CONVEX PRICING IN THE LONG-RUN

4

LONG-RUN OPTIMAL PRICING WITH NON-CONVEX COSTS

Determining optimal prices in non-convex markets remains an unsolved challenge. Non-convex costs are critical in electricity markets, as startup costs and minimum operating levels yield a non-convex optimal value function over demand levels. While past research largely focuses on the performance of different non-convex pricing frameworks in the short-run or uses convex approximations, we determine long-run adapted resource mixes associated with each pricing framework while preserving the full extent of the non-convex operations. We frame optimal pricing in terms of social surplus achieved and transfer of consumer to producer surplus in adapted long-run market equilibria. We find that convex hull pricing achieves the lowest transfer of consumer to producer surplus. Marginal prices determined by fixing integer variables to their optimal values in the pricing run are also associated with high social surplus and high consumer surplus when the optimality gap in the original mixed integer linear program is very small. Other pricing frameworks tend to over-compensate inframarginal units, leading to resource mixes with lower social surplus and a greater transfer of consumer surplus to producer surplus in the long-run.

4.1 INTRODUCTION

The bet made in electricity market liberalization is that markets can get closer to achieving the theoretical maximum social surplus than vertically integrated utilities. An idealized central planner with perfect information charging at cost maximizes social surplus. In the convex setting, a perfectly competitive market with prices set at marginal costs can achieve this same level of social surplus. However, in reality, neither an imperfect competitive market nor a regulated monopolist may be able to achieve this ideal outcome. In the case of the electricity sector, an additional factor complicates the role of markets: non-convex costs. Characteristics of conventional thermal generation including startup costs and minimum load requirements create a non-convex optimal value function for which the applicability of marginal pricing is not inherently clear. Additionally, non-convexities can also arise due to the configuration of combined cycle plants and modeling of pumped hydro storage generators (see, e.g., [103]), and may increase as new technologies are adopted that require their own modeling approach.

The issue of optimal pricing in markets with non-convex costs remains unresolved. Scarf [104] connected microeconomic theory with mathematical programming, noting that the optimal solution of a linear program (LP) with convexity assumptions in a market equilibrium yields dual variables as prices that are sufficient entry signals for new participants. However, such a price may not exist in the presence of non-convexities. Liberopoulos & Andrianesis [105] review a number of proposed pricing frameworks. Many of these approaches take for granted a primal-feasible solution for which some ex-post prices must be determined, which is the situation faced by many electricity market operators. In centrally committed markets, operators inherited the same problem faced by the former vertically integrated utilities: finding the optimal centralized security-constrained unit commitment and dispatch. Market participants submit their technical constraints and costs and the operator typically formulates the problem as a mixed integer program (MIP) or mixed integer linear program (MILP). An early proposal by O'Neill, Sotkiewicz, Hobbs, Rothkopf, & Stewart [29], referred to as integer programming (IP) pricing, fixes the integer variables to their optimal values in the pricing run, yielding prices for marginal production as well as for commitment. Ring [53], Hogan & Ring [54], and Gribik, Hogan, & Pope [55] propose defining prices via the convex hull of the optimal value function. Methods vary in their treatment of short-run revenue adequacy, with some relying on side payments or adders to a commodity price, and to what extent participants are incentivized to follow the centralized dispatch decision. A recent overview by [13] describes variants of pricing frameworks used in practice in electricity markets in the United States, which differ substantially by jurisdiction.

When evaluating these pricing frameworks, our goal is — as in the convex case — to find a price that maximizes social surplus in the long-run. From basic microeconomic theory, we know that the quantity of demand cleared at the intersection of supply and demand maximizes social surplus in the short-run. If producers are able to perfectly adapt in the long-run (the supply curve becomes perfectly elastic), all the social surplus becomes consumer surplus. This long-run competitive market equilibrium is equivalent to an idealized central planner (CP) compensating producers at-cost. This requires that units that should not be in the long-run equilibrium are allowed to operate at a loss, receiving the appropriate signal to exit the market. We have three distinct but interrelated factors that complicate this picture: the non-convex nature of the optimal value function, the sufficiency of scarcity rents (how often and by how much prices are higher than the cost of the highest marginal-cost producer), and lumpy investments (producers may not be able to perfectly adapt in the long-run). Price and offer caps are the most obvious driver of insufficient scarcity rents, but operational issues or system operator actions, e.g. out-of-market actions to address a reliability concern, may also suppress prices. When comparing achievable consumer surplus in the long-run among pricing frameworks, we must separate the issue of non-convex operational costs from the issues of sufficient scarcity rents and lumpy investments. While often conflated, we frame the "missing money problem" due to insufficient scarcity rent as a separate issue (that may have related solutions) to the challenges inherent in pricing in the presence of non-convexities, as the missing money problem may still exist in the convex case.

In this work, we compare market outcomes as applied to the long-run, social surplus-maximizing CP resource mix and a competitive market equilibrium resource mix adapted to a given pricing framework. This allows us to explicitly consider in what ways we would expect resource mixes adapted to a given pricing framework to diverge from the CP optimum, and what consumer surplus losses may result. We consider IP pricing, marginal pricing with the unit commitment configuration fixed, convex hull pricing, average incremental cost pricing, and several methods employed in practice, including partial dispatchable pricing, relaxed minimum operating levels, and a revenue adequate price adder. We compare pricing frameworks by consumer surplus achieved at the long-run adapted mix in addition to remaining producer surplus, performance across near-optimal solutions, lost opportunity costs, and extent of side payments. We also explore how different pricing frameworks may affect market outcomes as the presence of variable renewable energy (VRE) increases.

While this paper considers pricing in a deterministic setting, we note that pricing in the presence of uncertainty and risk should also be a consideration in reality [75]. We deal principally with idealized energy-only markets without price caps in this paper, as the main interest is in the challenges that non-convexities bring to the energy market. In the convex case with sufficient scarcity rents, an energy-only market is sufficient for investment cost recovery. In reality, uncertainty, market power, inelastic demand, or other concerns may warrant additional market mechanisms. We assume truthful bidding when evaluating pricing frameworks but consider how high lost opportunity costs or high side payments may incentivize untruthful bidding behavior. We analyze a centrally committed system with the aim of finding a pricing framework that best supports the social surplus-maximizing CP solution.

4.2 PRICE SIGNALS

In the short-run, we seek a price and quantity that together clear the market and support dispatch. The market is cleared if the central dispatch decision for production p^* at each unit $g \in G$ satisfies cleared demand bids d^* at each bid $l \in L$ (where $d^*_{tl} \leq D_{tl}$, the maximum quantity of demand bid l at time t) at each time interval, i.e.,

$$\sum_{g \in G} p^*_{tg} = \sum_{l \in L} d^*_{tl} \quad \forall t \in T \tag{4.1}$$

We would also like to find a price λ^* that supports dispatch p^*, meaning that that the centralized dispatch decision solves a function that maximizes each generator's profits given λ^*:

$$\max_{p} \quad \Pi_g(\lambda^*, p) \quad \forall g \in G \tag{4.2}$$

Assuming convexity, for an electricity market there is a clear choice λ^* that satisfies both of these conditions: the shadow price of the power balance constraints. In Figure 4.1(a), we see the convex optimal value function resulting from a simple, single-period economic dispatch of two generators with characteristics given in Table 4.1. We see that the less expensive generator produces until its maximum, yielding a slope λ of the optimal value function corresponding to its marginal price, \$5/MWh. The second generator comes online when demand is greater than 150MW, which increases λ to its marginal cost, \$10/MWh. There is a non-differentiable point, but we can choose any λ in this subdifferential (\$[5, 10]/MWh) and still clear the market and support dispatch.

In the long-run, we want a price signal that promotes an optimal resource mix that satisfies system constraints at least cost. In the convex case, no unit would make profits or losses at this equilibrium and no new entrant would make a profit. In order for the highest marginal-cost generator to recover its investment costs, the system-wide marginal price must at some times be greater than the short-run marginal cost of the most expensive generator. Generators must then receive some amount of scarcity rent. Ideally, these scarcity prices would be set by demand's willingness-to-pay. In practice, however, demand is still administratively treated as mostly inelastic in electricity markets. If demand is treated as inelastic, scarcity pricing must be determined as the administratively-defined cost of non-served energy, or value of lost load. Due to market power concerns, prices are often capped below the system's value of lost load. This insufficient scarcity rent is the driver of the often-discussed missing money problem.

4.2.1 *Pricing in the Presence of Non-convexities*

In reality, electricity systems have non-convex cost components. Unit commitment (UC) refers to the need to determine whether a unit will be on or off, using binary variables. Units may have startup and shutdown costs, minimum generation requirements, and minimum up and down times. The first issue is that this makes the marginal price difficult to determine, as the optimal value function may be non-convex or discontinuous. Marginal pricing will also not always support dispatch; the optimal solution may require units to produce when, faced with only the marginal price, they would prefer not to follow the centralized dispatch.

In Figure 4.1(b), we see an example of a simple two-unit, single-period model with a non-convex optimal value function.[1] Unit 1 has a lower

1 We thank Juan Pablo Luna and Claudia Sagastizábal for discussions that provided valuable insight in visualizing the non-convex optimal value function. We use a similar illustrative example to that shown in [52].

marginal cost, but has a startup cost that makes it not economical to produce until a certain level of demand. Once this minimum demand is reached, the marginal cost changes from Unit 2's marginal cost of $10/MWh to Unit 1's marginal cost of $5/MWh. At this level of demand, price decreases with increasing demand. In Figure 4.1(c), we see an example of a discontinuous optimal value function. In this case, Unit 2 has a minimum generation requirement but no startup cost, which causes two jumps in the optimal value function as demand increases. At these discontinuities, λ is not defined. In Figure 4.1(d), we see an example in which the marginal price not only doesn't recover short-run fixed costs, but also does not recover short-run variable costs. In this example, Unit 2 has a higher variable cost, a startup cost, and a minimum generation requirement. At a demand level of 175MW, the marginal price is $5/MWh, and Unit 2's total compensation is $250, while its short-run variable cost is $500 and its short-run fixed cost is also $500. The price of $5/MWh and quantity of 50MW of production from the least-cost dispatch solution does not solve Unit 2's preferred profit function, as it would prefer to not produce rather than operate at a loss.

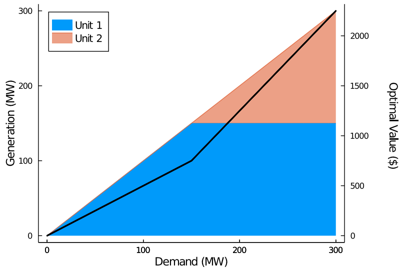
A similar instance in which short-run costs are not recovered arises with block-loaded "fast-start" units. If a unit is online at its maximum operating level (e.g., a block-loaded generator), it cannot set the marginal price. The marginal price may be set by a lower variable cost unit that still has the ability to increase production, causing the block-loaded unit to operate at a loss. In the United States, this particular situation lends its name to a commonly used term for non-convex pricing, "fast-start pricing" [13]. While the issue of high variable cost block-loaded units is significant, it is not the only non-convex feature in electricity markets to be addressed. Just as units may prefer to not produce when faced with a given price λ, some units may prefer to produce when they are not included in the central dispatch solution or to produce more than they are scheduled. In Figure 4.1(d), Unit 2 would be indifferent to producing nothing with no compensation or producing at the central dispatch if given a payment for its short-run losses. However, if a unit saw a price that exceeded its short-run costs and was not dispatched at its maximum operating level, it would perceive a lost opportunity cost. A price λ meeting this condition would thus not support dispatch, as some units may wish to produce more than scheduled.

Scenario		$/MWh	Startup ($)	P^{min} (MW)	P^{max} (MW)
Convex	Unit 1	5	0	0	150
	Unit 2	10	0	0	150
Non-convex	Unit 1	5	500	0	150
	Unit 2	10	0	0	150
Discontinuous	Unit 1	5	1000	0	150
	Unit 2	10	0	100	150
Short-Run Cost	Unit 1	5	0	0	150
	Unit 2	10	500	50	150
Generic UC	Unit 1	5	10000	100	150
	Unit 2	10	500	50	150

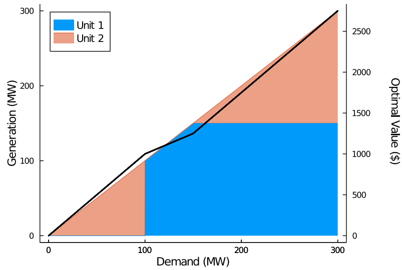
TABLE 4.1: Unit Characteristics

4.2.2 *Central Planner and Competitive Market Solutions*

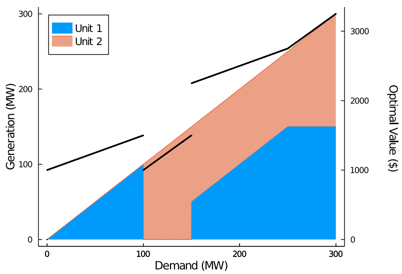
In the long-run, the reason we wish to choose good price signals is to incentivize the entry and exit of market participants until we achieve the optimum resource mix that maximizes social surplus. Social surplus is the sum of consumer surplus and producer surplus. Consumer surplus is the difference between the benefit to consumers (how much they cumulatively value the quantity of demand cleared) and what they pay. The producer surplus is analogous; it is the profit (the difference between the revenue received from the market and their costs). If producers are able to perfectly adapt in the long-run (an elastic supply curve), then the long-run competitive market equilibrium's social surplus will be entirely consumer surplus. The social surplus-maximizing resource mix can be found via a capacity expansion problem that maximizes the benefit to consumers of satisfying demand while minimizing costs to producers. This represents the mix that would be chosen by an idealized central planner with perfect information. We will call this social-surplus maximizing resource mix the CP solution. However, due to imperfect information and incentive mismatches, most jurisdictions have moved away from the regulated monopolist model (vertically integrated utilities) with the expectation that a competitive market could come closer to this ideal CP solution. Thus, price signals can be judged in part by how well the market equilibrium resource mix adapted to a given pricing framework approximates the CP solution (and correspondingly how much consumer vs producer surplus is achieved).



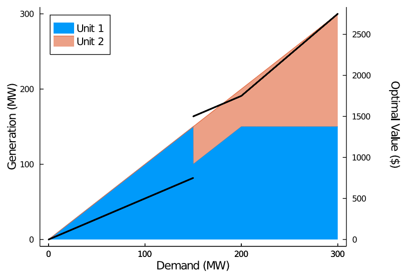
(a) Convex



(b) Non-convex



(c) Discontinuous



(d) Short-Run Cost

FIGURE 4.1: The optimal value function of a two-generator, single-period dispatch across different unit characteristics scenarios.

Convex case

Assuming convexity, we can apply classical marginal pricing theory to electricity markets. If we have a CP that seeks to maximize social surplus, we can show in the convex case that this optimal resource mix corresponds to the long-run competitive market equilibrium with system-wide marginal pricing in which each participant seeks to maximize individual benefit. We refer to [4] for proof of equivalent optimality conditions in the context of electricity markets. This assumes that capacity can be perfectly adapted and no economies of scale exist. Long-run cost recovery can be achieved with short-run marginal costs when accounting for an adjustment for technologies that are used at their maximum capacities. All market participants will achieve exactly zero-profits when the market is in equilibrium, indicating that no additional unit could enter and be profitable, and no unit currently in the market would wish to exit.

The CP problem is

$$\begin{array}{ccc} \underset{\{x,u,p,d\} \in \mathcal{P}}{\max} & \sum_{t\in T}\sum_{l\in L} B_l d_{tl} - \sum_{g\in G} C_g^{inv} x_g - \sum_{t\in T}\sum_{g\in G} (C_g p_{tg} + F_g z_{tg}) \\ \text{s.t.} & \sum_{g\in G} p_{tg} = \sum_{l\in L} d_{tl} \quad \forall t \in T \end{array} \tag{4.3}$$

where x is the build decision, u is the unit commitment status linked to startup decision z, $\mathcal{P}$ is the set of operating constraints linked to x, B is the benefit of a cleared demand bid, C^{inv} is investment cost, C is variable cost, and F is startup cost.[2] Note that inelastic demand with an administratively set value of lost load (VoLL) is a special case of this formulation in which $L = \{1\}$, $B_1 = VoLL$, and $d_{t1} \leq D_t$, where D is the total system demand. If $d^*_{t1} \leq D_t$, then there is $D_t - d^*_{t1}$ non-served energy at time t. For the following examples, we take this single-bid demand approach with a benefit B (or value of lost load) of \$1000/MWh. Let the investment cost C_g^{inv} for Units 1 and 2 (both 150MW) be {200, 196.8}k\$.

In the convex formulation, x can take fractional values $x \geq 0$ and $u \in [0,1]$ (or can be omitted). If we take operational characteristics as in the Convex scenario in Table 4.1 and take the demand profile in Table 4.3, the solution to the CP problem yields dual variables of the power balance constraints that are the long-run marginal costs (LRMC) given in Table 4.3. If we apply these LRMC as prices at the CP solution with fractional units given in Table 4.2, we achieve exactly 0% profit for both units.[3] If we hold the build decisions fixed, we get the short-run marginal costs (SRMC) shown in Table 4.3. LRMC also reflect the marginal cost of building more of each technology used at its full capacity. With a sufficiently long time horizon, this difference between the LRMC and SRMC that appears once in the horizon per technology type becomes trivial, but it is important to correct for in this 6-period example by replacing the SRMC with the marginal cost of building more of the exhausted technology in one time period. Note that there is 20MW of non-served energy in the last time period, and this raises the price to B, providing sufficient scarcity rent for perfect long-run cost recovery.

2 A detailed formulation of the set of operating constraints in the case of non-convex costs is given in Section 4.3.1.

3 Note that there can be multiple optimal dual solutions, as shown graphically at the non-differentiable point in Figure 4.1(a).

Build	Operations	Demand	Number		Profit	
		Scalar	Unit 1	Unit 2	Unit 1	Unit 2
Fractional	Convex	1	1.33	3.2	0%	0%
Integer	Convex	10	14	32	0%	0%
Fractional	UC	1	.67	3.87	0%	0%

TABLE 4.2: Convex and Non-Convex Scenarios Optimal Solutions

Scenario	Pricing	Demand (MW)	100	200	650	660	680	700	NSE@D=700
Fractional, Convex	LRMC	Price ($/MWh)	5	6.33	10	10	332	1000	20MW
	SRMC		5	5	10	10	10	1000	
Integer, Convex	FCP		5	5	10	10	10	1000	100MW
Fractional, UC	FCP		5	10	10	10	1000	1000	20MW
	FCP_{ADJ}		6.33	10	10	10	332	1000	

TABLE 4.3: Convex and Non-Convex Scenarios Prices

Non-convex case

Two sources of non-convexity arise when considering a more realistic case. The first is that units cannot necessarily be built to be perfectly adapted in capacity; units often are built in certain sizes, i.e., an integer number of units of a given size can be built, creating lumpy investments. This restriction shows up as binary build decision variables per unit in a capacity expansion model. In the market model, this means that we lose the guarantee of all zero-profits in equilibrium. However, we expect that the effect of lumpy investments decreases as the size of each unit becomes small relative to the size of the system, and an assumption of convexity may still be reasonable for sufficiently large systems. If we take the same convex operations case as before but require build decisions be binary, $x \in \{0, 1\}$, and scale up the demand profile by a factor of 10, we build 14 of the first unit type (instead of the fractional 1.33) and 32 of the second type (instead of the fractional 3.2). We cannot obtain dual variables directly from this non-convex problem, but if we fix the binary variables to their optimal values (a method we refer to as fixed configuration pricing (FCP), explained in detail in Section 4.2.3), we can obtain short-run prices. These prices are analogous to the SRMC found in the fractional-build case, and when adjusted for exhausted technologies, yield exactly 0% profits. Note that the optimal production schedule differs between the fractional and binary build cases; when scaled down, the binary build case has half the non-served energy at the system peak as the fractional build case because it builds more of Unit 1.

In contrast, the non-convexity resulting from non-convex cost components in operations does not become more convex-seeming at a larger scale. Even a small number of non-convex costs can impact cost recovery of all units. However, units with non-convex cost components are still able to adapt to some degree in the long-run. Next we show an example with fractional build decisions and non-convex operations with characteristics given in the Generic UC scenario in Table 4.1. In addition to investment costs, the minimum and maximum operating capacities as well as startup costs and investment costs all scale with x. The rounded optimal number of units is 0.67 for the first type and 3.87 for the second type, as seen in Table 4.2. This contrasts significantly with the optimal numbers of units in the convex operations case. If we fix the binary operations variables, we get the prices shown in Table 4.3. Note that at an output of 680MW both units are operating at their maximum levels, and the dual variable associated with the power balance constraint is $[10, 1,000]/MWh. Recall that there can be multiple market-clearing prices, and total surplus doesn't change based on which price we choose, but the ratio of consumer to producer surplus does. If we are interested in having more consumer surplus, then we choose the lower price in the range (resulting in no producer surplus in the convex case). The solver in this case returned 1,000, but it could also have returned 10. If we adjust for this as well as for exhausted technologies, we have the adjusted prices FCP_{ADJ}. With this price stream, we are able to achieve perfect long-run cost recovery. Note that the UC scenario constructed here includes only one startup for each unit and no binding ramping constraints or minimum up and down times. In a more realistic setting, we would not expect this perfect cost-recovery to be achieveable with non-convex cost components.

4.2.3 *Pricing Frameworks*

Multiple methods exist to handle the issues arising when defining prices in the presence of non-convexities, each with different trade-offs and guarantees. Total revenue is determined as the sum of the commodity price (the price per unit of electricity found via a relaxation of the MIP), the price to commit a unit (if applicable), any price adders given per unit of electricity on top of the commodity price, and any side payments directly to specific generating units. We will avoid the use of the ambiguous term "uplift payments" in favor of this categorization into commodity prices λ, commitment prices μ, price adders ϵ, and side payments s.[4] Most methods we describe seek to find a commodity price stream. Side payments for any of these methods could compensate short-run losses (make-whole payments) or partial or full lost opportunity costs. Table 4.4 summarizes the potential for short-run losses and lost opportunity costs for each pricing framework.

Short-run profit Π is a function of these components. We define initial short-run profit Π^0 as the profit before any side payments occur and short-run costs Ξ as follows:

$$\Pi_g^0 = \sum_{t \in T} ((\lambda_t + \epsilon_t - C_g) p_{tg} - F_g z_{tg} + \mu_{tg} u_{tg}) \tag{4.4}$$

$$\Xi_g = \sum_{t \in T} (C_g p_{tg} + F_g z_{tg} - \min(0, \mu_{tg} u_{tg})) \tag{4.5}$$

$$\Pi_g = \Pi_g^0 + \sum_{t \in T} s_{tg} \tag{4.6}$$

Note that one method prices commitment with μ, which may be positive or negative. When calculating short-run costs in (4.5), we do not want to include payments received by the system operator for commitment, only costs paid to the system operator for commitment.

To support dispatch, the total compensation must be such that no perceived losses exist, given that compensation package. Perceived losses are lost opportunity costs (LOC), the difference between what a unit could make given a price if able to schedule its own dispatch (its preferred profit) and what it would make with the same price following the centralized dispatch decision, plus any additional compensation received as side payments. Note this definition assumes units know future prices at the time of the commitment decision. We define initial lost opportunity costs LOC^0 without side payments and final LOC as

$$LOC_g^0 = \max_{u_g, p_g} \quad \Pi_g^0(\lambda^*, u_g, p_g) - \Pi_g^0(\lambda^*, u_g^*, p_g^*) \tag{4.7}$$

$$LOC_g = LOC_g^0 + \sum_{t \in T} s_{tg} \tag{4.8}$$

4 Pricing commitment results in individual payments (or costs) to particular units, but we categorize it separately from side payments for clarity.

A subset of LOC is short-run revenue shortfall to cover operating costs at the centralized dispatch decision and price. This occurs when the unit would prefer to not operate because profit would be negative if the unit operated as instructed at the going price. We define a make-whole payment (MWP) as the amount needed to cover any short-run operating losses:

$$MWP_g = -\min(0, \Pi_g^0(\lambda^*, u^*, p^*)) \tag{4.9}$$

MWP are a common form of side payment, as many jurisdictions have requirements that market participants cannot be forced to operate at a short-run loss. It may be required that a unit is made whole, e.g., daily. Paying LOC in full, however, may be a far more costly or even impossible endeavor, as in some pricing frameworks they are potentially unbounded. Nevertheless, understanding the extent of remaining LOC is important for considering incentives to follow the central dispatch decision. If a unit sees high LOC and is able to self-schedule, i.e., indicate to the operator that it wishes to produce a certain amount or modify its submitted bid to the same result, the least-cost dispatch solution may not be supported. High side payments in general, including MWP, may also not support the least-cost central dispatch solution. Units may be incentivized to bid untruthfully when knowing that their stated costs are guaranteed to be reimbursed, a situation similar to the incentive structure in a pay-as-bid auction. However, market power mitigation measures and deviation penalties may make these concerns less important in practice.

Fixed configuration

The original MILP formulation of a UC economic dispatch is as follows:

$$\max_{\{u,p,d\} \in \mathcal{P}} \quad \sum_{t \in T} \sum_{l \in L} B_l d_{tl} - \sum_{t \in T} \sum_{g \in G} (C_g p_{tg} + F_g z_{tg}) \tag{4.10a}$$

$$\text{s.t.} \quad \sum_{g \in G} p_{tg} = \sum_{l \in L} d_{tl} \quad \forall t \in T \tag{4.10b}$$

$$u \in \{0, 1\} \tag{4.10c}$$

One way to find marginal prices, given that the solution to the MILP is known, is to remove (4.10c), relax the integrality constraints, and fix the integer variables to their optimal values:

$$u \in [0, 1] \tag{4.11}$$

$$u = u^* \tag{4.12}$$

This yields a set of prices that we will call fixed configuration pricing (**FCP**), with the price λ as the shadow price of the power balance constraints (4.10b) of the relaxed problem. These marginal prices are those found graphically in Figure 4.1 when defined and are often treated as the non-convex analogue to locational marginal pricing (LMP). At points of discontinuity in the MILP optimal value function in which the system's fixed configuration is operating at full output, the FCP marginal price is any value between the highest variable-cost and the cost of non-served energy. Multiple prices are possible whenever there is more than one element in the subdifferential, and the exact price returned will depend on the solver used. Recall that in the convex case, the dual variables of the power balance constraints are marginal prices that clear the market and support dispatch. FCP will not always fulfill these criteria, as discussed in Section 4.2.1. We have also shown that price does not uniformly increase with demand, which could pose challenges for demand-response program incentives. MWP could ensure no short-run losses, but LOC may still exist.

Integer programming

If we relax the binary variables and fix the commitment variables explicitly, we can obtain the dual variables μ associated with the explicit fixed commitment constraint, a method proposed by O'Neill et al. [29] and known as integer programming (**IP**) pricing. We interpret μ as the "price of a commitment ticket." The set of prices λ and μ support dispatch (meaning no perceived losses exist) in the absence of scarcity, i.e., provided all demand bids are cleared in full. Units may see a negative or positive price μ associated with commitment that is realized as a side payment to or from that unit if committed ($s_g = \mu_g u_g$). The formulation is the same as in FCP, but the dual variables of the explicit fixed commitment constraints are also obtained:

$$u = u^* \quad : \mu \tag{4.13}$$

When calculating profits and LOC with this method, we define side payments to be null and include the commitment prices μ, payments realized only when commitment $u_{tg} = 1$, in the profit function. Multiple sets of prices are also possible; we can obtain different values of μ for arbitrarily different but equivalent UC constraint formulations. This may lead to different distributions of surplus among generators. Another drawback of this method is that it can cancel out profits of efficient units where values of μ are negative, requiring a payment to the operator to be committed (in this case, the term $\min(0, \mu_{tg} u_{tg})$ in (4.5) is negative. A proposed variant is to only allow positive values of μ. However, with this variant, we lose the guarantee of no LOC in the absence of scarcity. As in FCP, λ may not increase with demand, and multiple prices λ exist when there are multiple possible multipliers. Both marginal prices λ and side payments $\mu^\top u$, can be volatile with this method.

Convex hull

Gribik et al. [55] propose using the convex hull of the optimal value function to find prices in the presence of non-convexities with the goal of minimizing perceived losses. The side payments required to support dispatch associated with the convex hull prices are the smallest possible side payments to support dispatch associated with any uniform price in a deterministic setting. Note, however, that the side payments used in practice need not actually be the LOC, and MWP may still exist. Convex hull pricing (**CHP**) requires that we perform a Lagrangian relaxation of the original MILP, dualizing the power balance constraints. The duality gap is the LOC and any revenue shortfall between what is charged to demand and what is paid to suppliers. Multiple prices may exist, but price is guaranteed to increase with demand. A downside to this method is that it is much more computationally intensive, since it requires solving a subproblem for each generator for each possible value of λ and then optimizing over a nonsmooth convex function. Schiro, Zheng, Zhao, & Litvinov [56] discuss some economically counter-intuitive properties that result from CHP as well as the challenge of using the method with rolling time horizons. Pablo Luna, Sagastizábal, & Silva [52] argue that decomposition methods may be useful due to the problem's separable structure, and Andrianesis, Bertsimas, Caramanis, & Hogan [106] propose a new computationally tractable method using Dantzig-Wolfe decomposition to find exact convex hull prices.

Historically the computational difficulty of CHP has motivated an interest in approximations. Schiro et al. [56] and Hua & Baldick [57] describe relaxed primal formulations of CHP that are equivalent under certain assumptions. Relaxing the binary variables of a sufficiently tight UC formulation proposed by [57] yields reasonable approximations of CHP, and can be exact when there are no binding ramping constraints. Chao [107] note that relaxing the binary variables can produce close approximations to and sometimes exact CHP. This method is similar to the method called "dispatchable" pricing in [55]. We will refer to this as approximate convex hull pricing (**aCHP**). It is equivalent to the original MILP but with relaxed integral variables:

$$u \in [0,1] \tag{4.14}$$

Note that there may exist a set of multiple optimal CHP and aCHP solutions. Depending on how each is solved, CHP and aCHP may yield different answers but draw from the same underlying set of multiple solutions. In practice, aCHP is often implemented only for online units or for some subset of online units so that units not in this set are unable to set the price, as in MISO [13]. With this modification, we lose the guarantee of lowest possible opportunity costs. We refer to this variant as partial (approximate) convex hull pricing (**pCHP**) and implement it here with all online units:

$$u \in [0,1] \tag{4.15}$$

$$u_g = u_g^* \quad \forall g \in G : u_g^* = 0 \tag{4.16}$$

Relaxed minimum operation

Another method commonly used in practice is to relax the minimum operating level of online units (or some subset of online units). We will refer to this method as $\mathbf{RP_{min}}$. This method is currently in use in NYISO and several other regions [13]. The formulation is the same as FCP but with a modified set of operating constraints $\mathcal{P}'$ in which $0 \leq p_g \leq P_g^{max} u_g \ \ \forall g \in G : u_g^* = 1$:

$$u \in [0,1] \tag{4.17}$$

$$u = u^* \tag{4.18}$$

Average incremental costs

A method that guarantees short-run revenue adequacy with no side payments (no MWP required) for all units over their commitment interval is average incremental costs (**AIC**). The startup cost for online generators is amortized over its actual production and binary variables are relaxed. Offline units have their commitment status explicitly fixed to 0. The startup costs are updated as $F_g' = F_g P_g^{MAX} / p_g^* \ \ \forall g \in G : u_g^* = 1$.

$$u \in [0,1] \tag{4.19}$$

$$u_g = u_g^* \quad \forall g \in G : u_g^* = 0 \tag{4.20}$$

When demand is inelastic, this is equivalent to the method proposed by Van Vyve [58]. Perceived losses may exist, so AIC prices do not always support dispatch. Price will not always increase with demand, but arguably this reflects a "quantity discount" in which it is less expensive per MWh to operate a plant with a startup cost at a higher operating level.

Price adders

A method to guarantee short-run cost recovery of all units is to introduce a revenue adequate price adder (**RA**). In this method, a price adder ϵ is added on to the commodity price λ^*. We may require that revenue adequacy is guaranteed for each unit over a given horizon, e.g., one day. This method requires no MWP but the higher marginal price affects all online units, and substantial LOC may exist. Pablo Luna et al. [52] propose a method that guarantees short-run revenue adequacy via a price adder ϵ and side payments s called limited compensation (**LC**). Total side payments to compensate short-run losses are limited by a factor α representing a percentage of total commodity market costs. This transfers some of the MWP to a price adder on the commodity price, when binding. Here we use an α of 5% and find the base price λ^* via FCP. Formulations to find these two price adders are given in the Appendix.

	Short-run losses	**Lost opportunity costs**	**Type**
FCP	Possible	Possible	Commodity price
IP	None	None unless price set by demand	Commodity, commitment price
aCHP	Possible	Minimal	Commodity price
pCHP	Possible	Possible	Commodity price
RP_{min}	Possible	Possible	Commodity price
AIC	None over unit's operation horizon	Possible	Commodity price
RA	None	Possible	Adder to commodity price
LC	Possible, low with low α	Possible	Adder to commodity price

Table 4.4: Pricing Framework Comparison

4.3 METHODOLOGY

Recall that social surplus depends only on the quantity of demand cleared, with different prices representing transfers between consumer and producer surplus. However, producers will not stay in the market in the long-run if they are operating at a loss, and new producers will join the market in the long-run if they could make a profit. Both positive and negative profits could result in a move away from the CP solution to an alternate resource mix that may clear a different level of demand and thus yield a lesser social surplus. If we have positive profits for producers when applying a pricing framework to the CP solution, this means a transfer from consumer to producer surplus, resulting in higher average costs for consumers. If profits are sufficiently high, this likely indicates new participants could enter the market and make a profit, leading the optimal resource mix away from the CP solution. Similarly, if we have negative profits for producers when applying a pricing framework to the CP solution, we also expect movement away from the CP solution. This is why it is important to find a capacity mix that is adapted to a given pricing framework in the long-run. Once we find these different long-run capacity mixes, we can calculate consumer and producer surplus for each.

However, finding the CP solution is a challenge for a large-scale system. If we limit our analysis to only a deterministic problem, ideally we would solve a generation capacity expansion model for a horizon sufficient to fully reflect the demand and VRE generation profiles and the amount of time intervals with scarcity of capacity, e.g., one year. However, a formulation with investment decisions at the plant level and UC constraints for a year quickly becomes computationally prohibitive as the number of generators required increases. On the other hand, a larger scale system is helpful in reducing the impact of lumpy investments on profits, as each generator becomes a smaller fraction of the overall load served. de Sisternes, Webster, & Pérez-Arriaga [108] use an extensive form MILP when investigating four different bidding rules with inelastic demand with a cost of non-served energy of only $500/MWh as a proxy for the cost of back-up generators participating in demand-response programs. While the choice of sample weeks may impact the chosen capacity mix, we are less concerned in this illustrative example in accurately representing any given year. However, we are concerned with the effect that scaling the duration of non-served energy found over smaller time horizons to larger ones can have on profits. Herrero, Rodilla, & Batlle [51] compare two pricing frameworks for a year at hourly resolution with a clustered UC formulation, which may significantly alter the representation of non-convexities compared to the full UC formulation. This approach was chosen because of the non-served energy scaling issues, but the use of partially elastic demand would resolve this problem, as scarcity prices are set more frequently but at lower values. Mays, Morton, & O'Neill [109] use sample weeks and a decomposition algorithm that allows for partial relaxation of UC constraints when searching the solution space for the optimal capacity mix. In the interests of fully capturing the non-convexities, we choose to preserve the full UC formulation. We use an extensive form MILP with price-responsive demand on a large-scale system with representative weeks. We can then determine how well a given pricing framework supports the CP solution and what incentives exist to deviate from this solution in the short-run and long-run.

Next, we are interested in finding a capacity mix that is a long-run market equilibrium adapted to a given pricing framework to evaluate market outcomes for each pricing framework. We seek a quasi-break-even solution in which all units in the market are operating without losses and no new entrant could make a profit. Note that because of lumpy investments, there may be multiple such solutions instead of only one. Herrero et al. [51] use a simplified UC formulation to perform an exhaustive search across many candidate solutions for the capacity mix that maximizes social surplus subject to no generators operating at a loss. Hytowitz et al. [110] require the adapted mix to have a particular reliability target but do not otherwise provide details. Using an allowed profit bound of +/-10%, de Sisternes et al. [108] find the CP solution is supported by all considered pricing frameworks except one in which non-convex costs are internalized as simple bids. For this case they add or remove nuclear units until none are operating outside the profit bounds, followed by CCGT and then OCGT. Mays et al. [109] estimate profit functions via regression coefficients found from profits under a number of near-optimal solutions to a partially relaxed capacity expansion problem. They then find a capacity mix within the convex hull of these near-optimal CP solutions in which profits are close to zero for all technology types. Since we wish to reflect the non-convex features of the market as faithfully as possible, we employ an algorithm that begins at the CP solution and reflects the long-run movement to a market equilibrium away from the CP solution where sufficient incentives exist, at each stage solving a full UC formulation for the new candidate capacity mix and re-calculating prices and profits. We present results for a profit bound of 0% and for +/-5%, reflecting some leniency for lumpy investments. For equilibria with negative profits within this bound, the producer losses are added to the consumer surplus with the interpretation that the consumers pay these small losses at-cost.

Another issue that must be addressed is that large-scale UC dispatch problems are usually only solved to within a certain MIP gap. Eldridge, O'Neill, & Hobbs [111] illustrate how different near-optimal solutions can yield a more diverse array of generator profits depending on the pricing framework. They find that the methods we call FCP and pCHP, which have in common explicit fixed commitment constraints for all or a subset of units, can have large and unbounded payment redistributions among alternate solutions. In contrast, aCHP, which does not fix any unit's commitment in the pricing run, has smaller, bounded redistributions that can become smaller by tightening the UC's convex relaxation. Acknowledging that profits may differ for some pricing frameworks, Mays et al. [109] calculate profits as the average over a number of near-optimal solutions. The short-run centralized dispatch decision used in our analysis of pricing frameworks is determined ex-post, with a fixed capacity expansion decision. When solving the short-run UC dispatch at the CP resource mix, we use Gurobi's solution pool option to find a set of 20 near-optimal solutions with a target MIP gap of 0.02% and attempt to maximize diversity. We present the ranges of profits found. While Sioshansi, O'Neill, & Oren [112] show that changes in intra-producer surplus transfers do not decrease strictly monotonically with the optimality gap, we find that *total* producer surplus does generally decrease with the quality of the solution. Because we tend to find the same relative distribution of producer surplus among technology types for each solution but different overall levels of producer surplus by quality of optimal solution, we do not take the average profits. Instead, we present results for the adapted capacity mixes found via a more modest MIP gap of 0.001% and a targeted MIP gap of 0% with a time limit of 5 minutes per optimal dispatch, in which the resulting MIP gaps were under 0.00005%. This permits a comparison of how impactful the optimality of the primal solution is in the long-run. We assume perfect foresight so that uncertainty and rolling horizons do not additionally distort profits beyond the impact of non-convexities.

4.3.1 *Model Formulations*

Here we define the formulation for the extensive form MILP capacity expansion model and short-run centralized UC economic dispatch.

Nomenclature

Indices and Sets

$g \in G$	Set of generators

$G^T \subseteq G$	Set of thermal generators
$G^N \subseteq G^T$	Set of nuclear generators
$G^V \subseteq G$	Set of VRE resources
$t \in T$	Set of time periods (hours)
$l \in L$	Set of demand bids

Parameters

C_g	Variable cost (\$/MWh)
F_g	Startup cost (\$)
C_g^{inv}	Annualized investment cost of generator g (\$/yr)
P_g^{min}	Minimum operating capacity (MW)
P_g^{max}	Maximum operating capacity (MW)
M_g^{on}	Minimum on time (h)
M_g^{off}	Minimum off time (h)
R_g	Maximum ramp up/down rate (MW/h)
$\mathcal{P}_{tg}$	Maximum output for VRE resource (MW)
B_l	Value of demand bid l (\$/MWh)
D_{tl}	Maximum quantity of demand bid l at time t (MW)

Variables

p_{tg}	Committed generation for generator g at time t (MW)
u_{tg}	(Binary) commitment status for generator g at time t
z_{tg}	(Binary) startup decision for generator g at time t
y_{tg}	(Binary) shutdown decision for generator g at time t
d_{tl}	Amount of cleared demand bid l at time t (MW)
x_g	Binary build decision for each generator $g \in G^T$

Capacity expansion model

The capacity expansion model is formulated as follows:

$$\max_{(x,p,u,z,y,d)} \quad \Theta \sum_{t\in T}\sum_{l\in L} B_l d_{tl} - \sum_{g\in G} C_g^{inv} x_g - \Theta \left[\sum_{t\in T}\sum_{g\in G} (C_g p_{tg} + F_g z_{tg}) \right] \tag{4.21a}$$

$$\text{s.t.} \quad \sum_{g\in G} p_{tg} = \sum_{l\in L} d_{tl} \qquad \forall t \in T \tag{4.21b}$$

$$0 \le d_{tl} \le D_{tl} \qquad \forall t \in T, l \in L \tag{4.21c}$$

$$p_{tg} \le P_g^{max} x_g \qquad \forall t \in T, g \in G^T \tag{4.21d}$$

$$z_{tg} + y_{tg} \le 1 \qquad \forall t \in T, g \in G^T \tag{4.21e}$$

$$u_{tg} - u_{t-1,g} = z_{tg} - y_{tg} \qquad \forall t \in 2...T, g \in G^T \tag{4.21f}$$

$$z_{tg} = u_{tg} \qquad \forall t = 1, g \in G^T : g \notin G^N \tag{4.21g}$$

$$z_{tg} = 0 \qquad \forall t = 1, g \in G^N \tag{4.21h}$$

$$y_{tg} = 0 \qquad \forall t = 1, g \in G^T \tag{4.21i}$$

$$z_{tg} + \sum_{t'=t+1}^{\min(t+M_g^{on}-1,T)} y_{t'g} \le 1 \qquad \forall t \in 1...T-1, g \in G^T : M_g^{on} > 1 \tag{4.21j}$$

$$y_{tg} + \sum_{t'=t+1}^{\min(t+M_g^{off}-1,T)} z_{t'g} \le 1 \qquad \forall t \in 1...T-1, g \in G^T : M_g^{off} > 1 \tag{4.21k}$$

$$P_g^{min} u_{tg} \le p_{tg} \le P_g^{max} u_{tg} \qquad \forall t \in T, g \in G^T \tag{4.21l}$$

$$-R_g \le p_{tg} - p_{t-1,g} \le R_g \qquad \forall t \in T, g \in G^T \tag{4.21m}$$

$$0 \le p_{tg} \le \mathcal{P}_{tg} \qquad \forall t \in T, g \in G^V \tag{4.21n}$$

$$p_{tg} \ge 0 \qquad \forall t \in T, g \in G \tag{4.21o}$$

$$u_{tg}, z_{tg}, y_{tg} \in \{0,1\} \qquad \forall t \in T, g \in G^T \tag{4.21p}$$

$$x_g \in \{0,1\} \qquad \forall g \in G^T \tag{4.21q}$$

The factor Θ scales up short-run costs to an annualized level in objective function (4.21a) that maximizes benefits and minimizes costs with price-responsive demand. Constraint (4.21b) ensures power balance with cleared demand bids. Constraint (4.21d) links production to build decisions for thermal units. Constraints (4.21e)-(4.21k) ensure consistent relationships between startup and shutdown decisions limited by minimum on and off times. Nuclear is allowed to begin the simulation turned on without paying a startup cost in the first time period (with its startup cost included in C^{inv}, reflecting an expectation of one startup cost for nuclear in a year). This addresses inappropriate scaling of nuclear startup costs over simulation periods shorter than one year. Capacity constraints for committed thermal units are given in (4.21l). We provide ramping constraints in (4.21m), but they are not binding at an hourly resolution in the case study data. Curtailable VRE generation is defined in (4.21n). VRE capacity is exogenous to the thermal capacity expansion decision.

Short-run centralized dispatch with unit commitment

Once a capacity mix is fixed, the short-run UC dispatch is solved. This formulation replaces the objective function (4.21a) with (4.22):

$$\max_{(p,u,z,y,d)} \quad \sum_{t\in T}\sum_{l\in L} B_l d_{tl} - \sum_{t\in T}\sum_{g\in G} \left(C_g p_{tg} + F_g z_{tg}\right) \tag{4.22}$$

The subset of units G is redefined as only units that were built in the capacity expansion model, $g \in G : x_g = 1$. Constraints (4.21d) and (4.21q) are omitted. We define long-run profits as a percentage of total costs:

$$\pi_g = \frac{\Theta\Pi_g - C_g^{inv}}{\Theta\Xi_g + C_g^{inv}} \tag{4.23}$$

4.3.2 *Market Equilibrium Adapted to Pricing Framework*

We next define a method to illustrate movement away from the CP solution due to profit incentives with a given pricing framework. We seek a market equilibrium resource mix adapted to a given pricing framework in which no participant is operating at a loss and no new entrant would make a profit under the given pricing framework. While we refer to this resource mix as an equilibrium, we note it is really a quasi-break-even solution, as a true equilibrium may not exist for non-convex markets. Algorithm 1 describes a guided search through capacity mixes, aiming to treat the building of each resource type with equal preference. Note that multiple market equilibria may exist under this definition with lumpy investments, and the order in which we consider which technology types to build may result in a different equilibrium. The algorithm loops through the set of all units, both currently built and unbuilt candidates, alternating the technology type under review iteratively. If a built unit is not profitable, it is removed, and the dispatch is re-solved, generating a new set of profits. If a unit has not been built, it is included in a test dispatch that generates a new set of profits; if the candidate unit is profitable, and it has not made another unit of its type unprofitable, it is built, and current profits are updated. The test dispatch ensures the algorithm terminates. The vector of build decisions x is updated by adding or removing units. The vector x^* has $x_g = 1$ if a unit was built in the capacity expansion model and $x_g = 0$ for all candidate units that have not (yet) been built. G is ordered such that unbuilt units alternate iteratively through technology types. Since we are modeling a system that, while large, we suppose has lumpier investments than a real-world system, we formulate profitability optionally in terms of a bound; we may define losses as profits less than, e.g., -5%. This algorithm is run once with a MIP gap of 0.001% for each UC dispatch and again with a target MIP gap of 0% with a time limit for each UC dispatch.

Algorithm 1: Capacity mix adapted to pricing framework

```
x = x* for i = 0;
I_g ← vector of 0's with 1 in the g-th position;
π_g ← long-run profits for unit g under given pricing framework;
G ← technology type alternates iteratively for unbuilt units in initial x;
i ← initialized to 0;
while | π_g(x) | > bound for any g do
    check ← true for each type ;
    j ← current iteration status i;
    for g ∈ G do
        k ← type of g;
        if x_g = 0 & check(k) then
            Calculate π_g(x + I_g) ;
            Calculate π_g'(x + I_g) ∀g' ∈ k;
            if π_g(x + I_g) > 0 & π_g'(x + I_g) > −bound ∀g' ∈ k then
                x = x + I_g;
                i = i + 1;
            else
                check(k) = false;
            end
        else // x_g = 1
            if π_g(x) < −bound then
                x = x − I_g;
                i = i + 1;
            end
        end
    end
    if j = i then // No units added or removed
        break;
    end
end
```

4.4 RESULTS

4.4.1 *Data*

Scenarios are constructed using correlated demand, wind generation, and solar generation profiles from the Reliability Test System of the Grid Modernization Lab Consortium [38]. In the base case, we scale demand and VRE profiles by a factor of 10, yielding a system with peak load of approximately 47.5GW over the 4 sample weeks selected. Non-coincident peak wind is over 50% of peak load, and non-coincident peak solar is over 25%.

This base case scenario corresponds to VRE scenario S100, with alternative scenarios S75, S50, and S25 representing VRE profiles scaled to 75%, 50%, and 25% of the base case, respectively. We start from a greenfield situation for thermal generator capacity expansion. We use candidate generators of three technology types: nuclear, CCGT, and OCGT, representing base, intermediate, and peaking units. Technical and cost parameters are given in Table 4.5. Parameters are adapted from data used in [108]. We use bid-in demand assuming 90% of demand at each time period is inelastic (with a benefit of $10,000/MWh) and 10% of demand is elastic, represented by 200 equally-sized bids descending in price from $10,000/MWh to $50/MWh, analogously to [109]. Using the base case with completely convex operations (no UC) but binary build decisions, we are able to achieve average profits for nuclear, CCGT, and OCGT of -1%, -2%, and -5% respectively, with no unit operating at a profit of less than -5%. This provides some reassurance that the size of the problem is sufficient to reduce the impacts of lumpy investments and some justification for exploring a +/-5% profit bound.

Tech	Min Output (MW)	Max Output (MW)	Ramp Up/Down (MW/hr)	Up/Down time (hr)	Investment (M$/GW-yr)	Startup (M$)	Variable ($/MWh)
Nuclear	900	1000	190	36	489	1	6.5
CCGT	150	400	320	3	129	0.06	58.5
OCGT	50	200	360	0	106	0.01	99.4

Table 4.5: Technical and Cost Parameters for Thermal Generators

4.4.2 *Central Planner Solution*

We investigate how producer surplus changes with the optimality gap, finding over 40 near-optimal solutions within 0.1% of the best solution found. Figure 4.2 shows the total producer surplus across all units at each near-optimal solution with the CP resource mix for FCP and aCHP with and without daily MWP. Note that achieved relative MIP gaps are quite small because we explicitly include benefit of cleared demand in the objective value. We find that producer surplus tends to decrease with the optimality gap for FCP, but not monotonically. With flexible demand, suboptimal dispatch decisions often lead to less cleared demand, which results in higher prices, and thus greater producer surplus. In contrast, aCHP, which does not depend on the primal solution, has profits that do not vary across near-optimal solutions.

Figure 4.3 shows the average cost to consumer under different pricing frameworks in the base case at the central planner solution with the default MIP gap target of 0.001%. While this resource mix is not yet adapted to any given pricing framework, we see clear differences in the total cost to consumers and the types of costs associated with each method. aCHP is by far the lowest cost, while RP_{min} is the highest. RA includes a price adder, while IP includes a commitment price, but requires no further side payments to be made whole on a daily basis. The difference between FCP, LC, and RA (since LC and RA use FCP's commodity price as the base price) is only in how no daily losses are achieved. FCP requires a MWP, while RA avoids the use of any side payments with a price adder, resulting in higher overall costs. LC limits the amount of side payments, and transfers some of these to a price adder. Overall, however, short-run losses on a daily basis are very small, i.e., little MWP are required. In fact, a key observation in this case study is that with well-adapted systems facing a partially elastic demand curve, all units recover their short-run operating costs over the simulation horizon. Most also recover their short-run costs on a daily basis, helped by the frequency with which price is set by demand, resulting in higher profits. With the exception of RA, we find the inclusion of daily MWP to be negligible for results, resulting in minimal impact on profits and no changes in the adapted resource mix. Since the only way in which RA and LC differ from the method used to calculate its underlying base price is if MWP exist, we do not report results for these methods. The differences in average cost to consumer are driven by different long-run profits at the CP solution, as seen in Figure 4.4(a). The smallest producer profits are seen with FCP and aCHP, and the largest with RP_{min} and AIC.

4.4.3 *Market Equilibrium Adapted to Pricing Framework*

With some individual units with losses outside the profit bound (recall that Figure 4.4(a) shows average profits by technology) and some technology types making considerable profits, we expect movement away from the CP solution when finding a capacity mix adapted to each pricing framework. A full table of results is available in the Appendix. Figure 4.4(b) shows the change in the number of units between the CP and adapted mixes, and Figure 4.4(c) shows the new long-run profits at the adapted mixes specific to each pricing framework. No units are operating at a loss, and no new units could enter and make a profit, even though the existing producers are in some cases making a substantial profit. High profits at the adapted

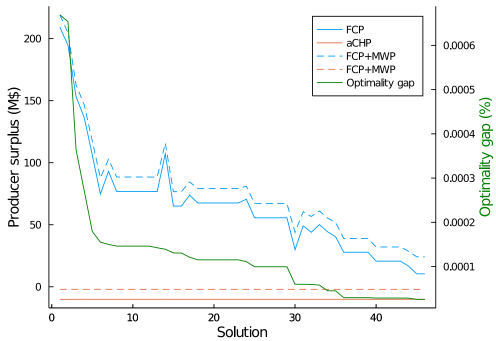


FIGURE 4.2: Total producer surplus and optimality gap across near-optimal solutions, sorted from worst to best

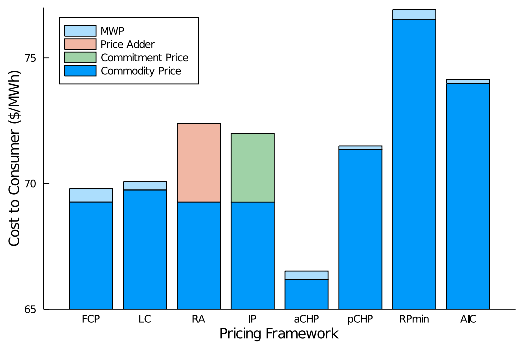
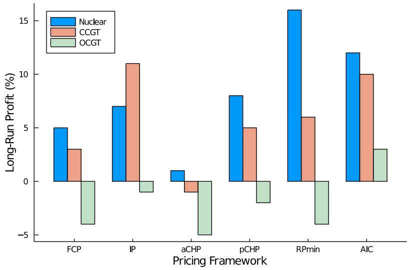


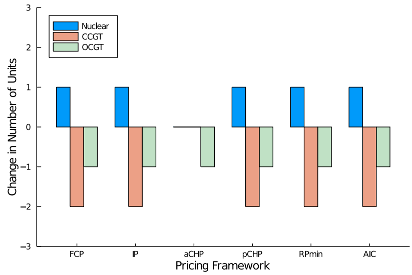
FIGURE 4.3: Base case average cost to consumer at the central planner solution

mixes are driven by demand-set prices, but if one more unit is added, those demand-set prices are now lower, and profits of all generators go down substantially. These high profits for thermal units at adapted mixes can persist even if we allow VRE to be invested endogenously. For example, allowing an incremental wind generator that can be built to any size at no cost for the base case still results in average profits of 22% for OCGTs in the adapted mix for FCP.[5] Additionally, profits vary substantially across pricing frameworks. Profits at the adapted mix are lowest with aCHP. LOC are high across the considered pricing frameworks, with the exception of aCHP, as shown in Figure 4.4(d).

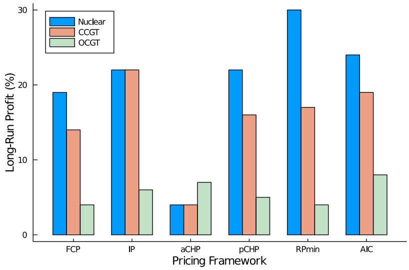
5 Future work may wish to explore if the addition of endogenously invested VRE with energy storage may reduce thermal profits at adapted mixes.



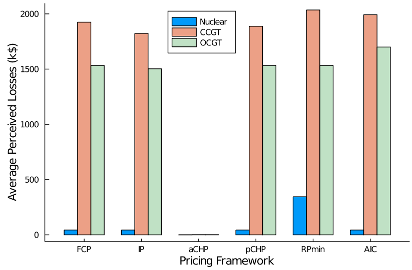
(a) Long-run average profit at CP



(b) Change in units from CP to adapted mixes



(c) Long-run profit at adapted mixes



(d) Perceived losses at adapted mixes

Figure 4.4: Base case results with a 0.001% MIP gap and a 5%-profit bound.

The average cost to consumer differs considerably by pricing framework, with aCHP being substantially lower, as shown in Figure 4.5(a). The magnitude of MWP is also shown in Figure 4.5(a), although their inclusion does not change the adapted mix and negligibly impacts the profits. Note that different adapted mixes may clear different amounts of demand and that average cost to consumer includes payments to VRE. In contrast, to compare across VRE scenarios, the cost to consumers for the consumer surplus is calculated with exogenous VRE and the producer surplus is only reported for thermal generators. We see in Figure 4.5(b) that despite the different adapted capacity mixes, the total social surplus achieved is only very slightly smaller across all pricing frameworks than at the CP solution. However, the transfer from consumer to producer surplus varies substantially by pricing framework. Note that the consumer surplus value is high because it includes the total benefit of cleared demand, most of which is \$10,000/MWh due to the 90% inelastic portion of the demand curve.

The pattern of small changes in social surplus from the CP solution in the adapted mixes but comparably larger changes in consumer surplus is seen across VRE scenarios, profit bounds, and MIP gaps, as seen in Figure 4.6. Across all simulations, aCHP achieves the highest consumer surplus. However, with the smallest MIP gap target (represented by the diamond in comparison to circular markers at 0.001% MIP Gap) the performance of pricing frameworks that rely on the primal solution improve markedly. However, even with small MIP gap targets, RP_{min} and AIC achieve substantially lower consumer surplus. Table 4.6 shows how the average costs to consumers change as a percentage of costs under aCHP for each VRE scenario. In the base case (S100) with a target MIP gap of 0.001%, the average cost to consumers is 8% more expensive than aCHP, while RP_{min} is 22% more expensive. With a target MIP gap of 0%, FCP and aCHP perform equally well by this metric, and RP_{min} is only 13% more expensive. While FCP and aCHP result in nearly identical average costs to consumers for scenarios S75 and S100 under the smallest MIP gap, aCHP still yields more overall consumer surplus, as shown in Figure 4.6(b).

MIP Gap Target 0.001%

	FCP	IP	aCHP	pCHP	RP_{min}	AIC
S25	15%	18%	0%	17%	24%	20%
S50	20%	24%	0%	25%	26%	26%
S75	16%	19%	0%	18%	18%	17%
S100	8%	11%	0%	10%	22%	13%

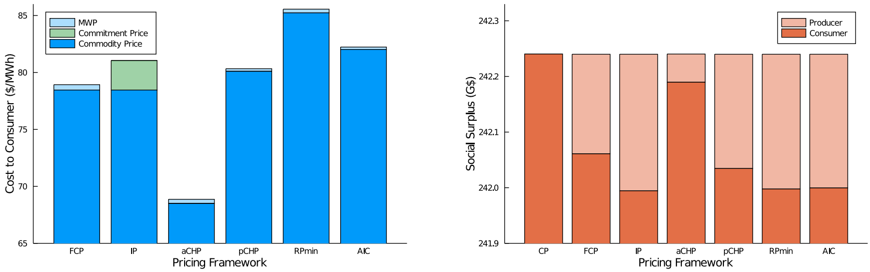
MIP Gap Target 0%

	FCP	IP	aCHP	pCHP	RP_{min}	AIC
S25	2%	3%	0%	5%	13%	9%
S50	6%	6%	0%	6%	17%	13%
S75	-1%	3%	0%	2%	16%	9%
S100	0%	3%	0%	2%	13%	9%

Table 4.6: Change in Average Cost to Consumers as Percentage of aCHP Costs

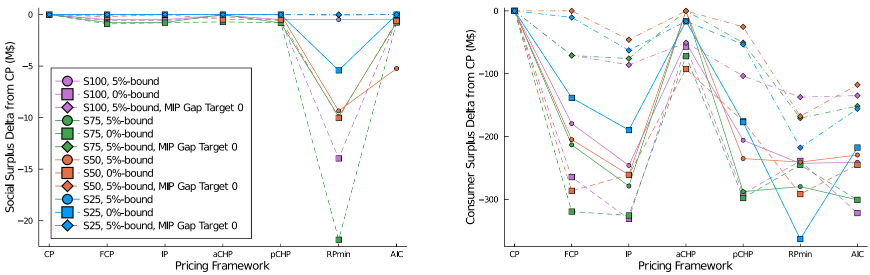
4.4.4 *Varying Levels of VRE Penetration*

As long as the system is allowed to adapt, increasing levels of VRE is not strongly associated with an increase in consumer surplus from the CP benchmark across different pricing frameworks. On the other hand, the gaps in achievable consumer surplus from the CP solution arising from non-convex operations of thermal plants do not appear to substantially decrease with higher shares of VRE either. These results can be seen by comparing across VRE scenarios (indicated by different colors) in Figure 4.6. This is likely due to the total installed capacity of thermal units in the CP solution being equivalent across VRE scenarios, as seen in Figure 4.7.



(a) Average cost to consumer (b) Social surplus

FIGURE 4.5: Base case average cost to consumer and social surplus results with a 0.001% MIP gap and a 5%-profit bound.



(a) Social surplus (b) Consumer surplus

FIGURE 4.6: Social surplus and consumer surplus losses from CP benchmark across all simulations.

Because there is no energy storage in the test case, and there are times at which load is high but VRE production is low, there is no firm capacity value of VRE. The type of thermal capacity built changes, but not the total quantity. The inclusion of significant storage capabilities or VRE penetration sufficient to reliably offset peak net load may change this result, as the total installed thermal capacity may decrease. We find that the aCHP average cost to consumer is generally lower across pricing scenarios and is equivalent with both tested MIP gaps, as shown in Figure 4.8.

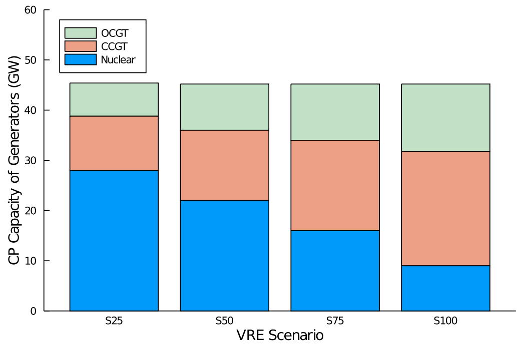


FIGURE 4.7: Total installed thermal capacity at CP solution.

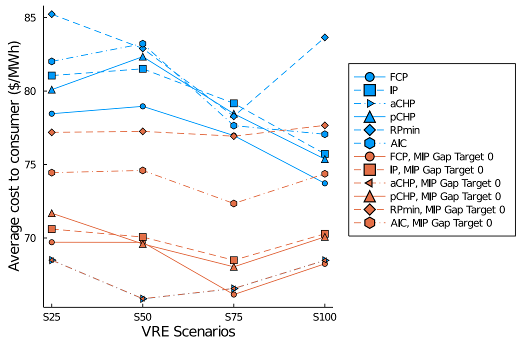


FIGURE 4.8: Average cost to consumer over VRE scenarios with a 5%-profit bound.

4.5 CONCLUSION

We have framed the question of optimal pricing in the long-run in non-convex markets in terms of social surplus achieved and transfer of consumer to producer surplus in adapted long-run market equilibria. We find that aCHP generally achieves the highest social surplus and is also associated with the lowest transfer of consumer to producer surplus. Perhaps surprisingly, FCP is also associated with high social surpluses and high consumer surpluses relative to the CP benchmark provided that a primal solution very close to optimality can be found. Even though transfers of surplus are not monotonic with MIP gap in a non-convex setting, this analysis shows that size of MIP gap can have non-negligible short- and long-run effects. Most pricing frameworks tend to over-compensate inframarginal units, leading to mixes with lower social surplus and a greater transfer of consumer surplus to producer surplus in the long-run. Results also demonstrate that relaxing only a set of online units (pCHP), referred to as "extended LMP" in US markets, performs worse in terms of consumer surplus achieved than relaxations including all units (aCHP). Use of aCHP also has the benefit of being associated with low LOC in the deterministic setting. We also show that the non-convexities issue is not ameliorated with increased VRE so long as optimal overall thermal capacity in the long-run remains unchanged.

We do not find MWP to be significant in long-run well-adapted systems in our case study. This raises questions for further research about how significant MWP are in the context of long-run adapted systems with increased demand elasticity. However, more work should be done to determine if inclusion of no-load costs or a more diverse array of generation technologies might lead to the presence of some of the non-convex features that require MWP for short-run cost recovery in a long-run adapted mix. Additionally, while we know the overall social surplus will be lower than at the CP solution, it would be desirable to explore all lumpy investment market equilibria to see if total producer surplus and its distribution among technology types varies. In this study, we have taken the perspective of a centrally committed market design. Alternatively, a self-committed market design, such as in Europe, in which participants internalize their non-convexities in simple bids is possible. While the dispatch associated with simple bids is likely to be less optimal, further work could attempt to quantify the relative trade-offs.

While aCHP performed best in the scope of this study, it should be noted that good approximations to CHP become more difficult with binding ramping constraints. While prior methods to calculate exact CHP were prohibitively computationally intensive for real-world systems, a new proposal by Andrianesis et al. [106] suggests that exact CHP may be feasible in practice. Transmission constraints, multi-settlement markets, uncertainty, rolling time horizons, and market power concerns may also impact a market operator's preferred pricing framework. While the lack of dependence of CHP on the dispatch solution can be a benefit, the implications of producers being able to estimate the price curve ex-ante should be further explored. Another consideration is that it may not be practical to wait for long-run adaptation since lifetimes of power plants can be decades. Market operators should seek to maximize social surplus in the long-run, but this must be balanced with concerns for consumer surplus during transitional states.

APPENDIX

4.5.1 *Formulation of Price Adders*

Price adders are a way to guarantee short-run cost recovery of all units in lieu of side payments to compensate short-run losses. A price adder ϵ is added on to the commodity price λ^*. We may require that revenue adequacy is guaranteed for each unit over a given horizon, e.g., one day. The problem formulation to determine a revenue adequate (RA) price adder is:

$$\begin{aligned}
\min_{\epsilon} \quad & \sum_{t \in T} \sum_{g \in G} \epsilon_t p_{tg}^* \\
\text{s.t.} \quad & \sum_{t \in T^j} (\lambda_t^{B*} + \epsilon_t) p_{tg}^* - \sum_{t \in T^j} (C_g p_{tg}^* + F_g z_{tg}^*) \geq 0 \quad \forall g \in G, \forall j \in J \\
& \epsilon \geq 0
\end{aligned} \tag{4.24}$$

where p_{tg}^* is the central dispatch decision for production for unit g at time t, C is the variable cost, F is the startup cost, z^* is the fixed startup decision, T^j is a 24-hour interval, and J is the set of days.

[52] propose a method that guarantees short-run revenue adequacy via a price adder ϵ and side payments s called limited compensation (**LC**). Total side payments to compensate short-run losses are limited by a factor α representing a percentage of total commodity market costs. This transfers some of the MWP to a price adder on the commodity price, when binding. The problem formulation is given by:

$$\begin{aligned}
\min_{\epsilon, s} \quad & \sum_{t \in T} \sum_{g \in G} (\epsilon_t p_{tg}^* + s_{tg}) \\
\text{s.t.} \quad & \sum_{t \in T^j} \Big((\lambda_t^* + \epsilon_t) p_{tg}^* + s_{tg} \Big) - \sum_{t \in T^j} (C_g p_{tg}^* + F_g z_{tg}^*) \geq 0 \quad \forall g \in G, \forall j \in J \\
& \sum_{t \in T} \sum_{g \in G} s_{tg} \leq \alpha \sum_{t \in T} \sum_{g \in G} (\lambda_t^* + \epsilon_t) p_{tg}^* \\
& \epsilon, s \geq 0
\end{aligned} \tag{4.25}$$

The base price could also be the commodity price found via a pricing framework that is not already revenue-adequate, e.g., aCHP. RA and LC could also alternatively be formulated to track a target price stream to spread out the adder more evenly and LC could be formulated to prevent a unit from profiting when being compensated for a fixed cost.

4.5.2 *Adapted Mixes Results Table*

	MIP Gap	0.001%		MIP Gap	0.001%		MIP Gap	0.001%		MIP Gap	0.001%	
	Profit Bound	5%		Profit Bound	5%		Profit Bound	5%		Profit Bound	5%	
	VRE	S25		VRE	S50		VRE	S75		VRE	S100	
	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT
FCP	0	0	0	0	0	0	1	-2	-1	1	-2	-1
IP	0	0	0	0	0	0	1	-2	-1	1	-2	-1
aCHP	0	0	0	0	0	0	0	0	0	0	0	-1
pCHP	0	0	0	0	0	0	1	-3	1	1	-2	-1
RPmin	3	-8	1	4	-10	0	4	-10	0	1	-2	-1
AIC	0	0	0	3	-6	-3	1	-2	-1	1	-2	-1
	MIP Gap	0.001%		MIP Gap	0.001%		MIP Gap	0.001%		MIP Gap	0.001%	
	Profit Bound	0%		Profit Bound	0%		Profit Bound	0%		Profit Bound	0%	
	VRE	S25		VRE	S50		VRE	S75		VRE	S100	
	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT
FCP	0	0	0	0	0	-1	1	-3	0	1	-2	-2
IP	0	0	0	0	0	0	1	-2	-2	1	-2	-2
aCHP	0	0	0	-1	1	2	-1	1	2	0	-1	1
pCHP	0	0	0	1	-2	-1	1	-2	-2	1	-2	-2
RPmin	3	-8	1	4	-8	-4	6	-15	-1	6	-15	-1
AIC	0	0	0	1	-3	1	1	-2	-1	1	-2	-2
	MIP Gap	Target 0		MIP Gap	Target 0		MIP Gap	Target 0		MIP Gap	Target 0	
	Profit Bound	5%		Profit Bound	5%		Profit Bound	5%		Profit Bound	5%	
	VRE	S25		VRE	S50		VRE	S75		VRE	S100	
	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT	Nuclear	CCGT	OCGT
FCP	0	0	0	0	0	0	0	0	-1	0	0	-1
IP	0	0	0	0	0	0	0	0	0	0	0	0
aCHP	0	0	0	0	0	0	0	0	0	0	0	-1
pCHP	0	0	0	0	0	0	0	0	0	0	0	-1
RPmin	0	0	0	0	0	0	0	0	-1	0	0	-1
AIC	0	0	0	0	0	0	0	0	0	0	0	0

5

COST RECOVERY WITH VARIABLE RENEWABLE ENERGY

Increasing shares of variable renewable energy (VRE) on the grid requires more flexible operation of other generation technologies. In an ideal energy-only market, prices should adequately compensate flexibility provision. While long-run cost recovery of generators can be achieved in a convex setting with marginal pricing, electricity markets exhibit non-convex costs and require non-convex pricing methods. We investigate how increasing VRE penetration impacts the type of technologies built, their payoffs, social surplus, and price distributions in a long-run resource mix adapted to a number of different non-convex pricing models. We find that non-convex energy-only markets can provide long-run cost recovery for flexible generators even as VRE penetration increases and that the impact of non-convexities decreases with increasing VRE.

5.1 INTRODUCTION

Electricity markets are non-convex due to binary commitment decisions, no-load costs, and minimum operating requirements of generators. More variable renewable energy (VRE) often leads to net load curves with steeper ramps, shorter peaks, and lower minimum values, as illustrated in Figure 5.1. To supply these new net load curves, generators may need to startup and shutdown more often and recover costs from fewer operating hours. This could lead to more instances in which non-convexities matter, and more overall impact of non-convexities on market outcomes. In the long-run, it is important to adequately compensate resources that provide the necessary flexibility to incorporate VRE. However, if resource mixes are allowed to adapt in the long-run, it is unclear if increased VRE will mitigate or exacerbate non-convex market outcomes. We examine how increasing VRE impacts the type of technologies built, their payoffs, overall consumer and producer surplus, and price distributions across a range of installed VRE capacity scenarios with a given stochastic VRE distribution.

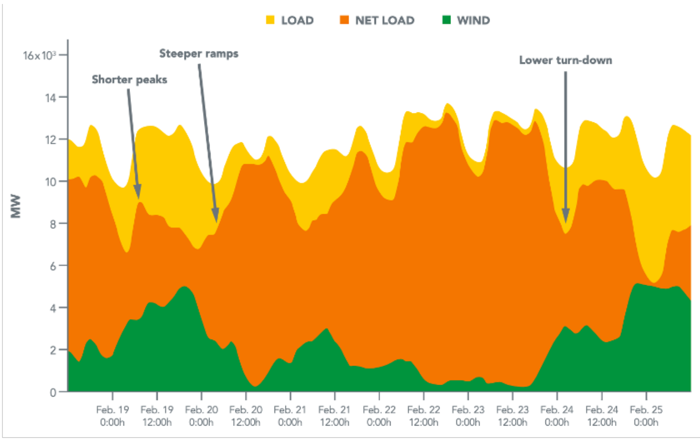


FIGURE 5.1: Variable renewable energy changes the shape of the net load curve. Source: [113]

When investigating the compensation of different types of technologies, it is important to consider the long-run perspective. In the short-run, increased VRE could cause some existing generators to operate at a loss, providing a signal to exit in the long-run. This is a desirable property, as we do not want to support any given resource mix but rather the resource mix that in the long-run meets system needs while maximizing social surplus. Authors in [114] explore how higher wind penetration impacts short-run profits under several non-convex pricing models for a scaled-down static test case resembling PJM, expressing concern that more flexible resources were profiting less under higher wind scenarios. They recommend other market constructs to recover capital costs of flexible generators. However, higher penetration levels of VRE ought to lead to different optimal resource mixes in the long run as retirement and build decisions are made. We must analyze a long-run adapted resource mix to see if flexibility providers are adequately compensated. Reference [14] (Chapter 4) shows long-run adapted systems to several non-convex pricing models as VRE is increased. However, the VRE had no firm capacity credit, i.e., it was not able to reliably offset any thermal capacity due to periods of low VRE generation at times of high demand. Here we expand on the analysis in [14] to examine how different pricing models perform as VRE is able to offset some amount of total thermal capacity in the long-run optimal resource mix.

A challenge is that VRE is stochastic, so even in a convex case we would only expect perfect long-run cost recovery at the optimal resource mix if VRE realizations were as expected. Here we use a scenario-based stochastic capacity expansion model to find a starting resource mix for each VRE installed capacity scenario. Assuming VRE realizations are as expected, we then find resource mixes that represent quasi-break-even solutions for each pricing model. At the adapted long-run resource mixes, we can examine payoffs of generators of different technology types by pricing model and across VRE installed capacity scenarios. How overall consumer surplus differs helps to determine if there is a costly interaction between non-convexities and high VRE. We also examine volatility via price distributions and what payoffs would look like if VRE realizations are not as expected. The analysis allows us to examine whether an idealized non-convex energy-only market can still provide long-run cost recovery for needed flexible generators as VRE increases.

5.2 NON-CONVEX PRICING MODELS

We explore a number of pricing models with details of their implementation given in Table 5.1, where u_g is the commitment status of generator g, u_g^* is the optimal value found in the dispatch problem, and P_g^{max} is the maximum capacity of g. All pricing runs are performed with the assumption that a solution to the market-clearing short-run unit commitment (UC)

Pricing Model	Definition
FCP	$u \in [0,1], \quad u = u^*$
aCHP	$u \in [0,1]$
pCHP	$u \in [0,1], \quad u_g = u_g^* \quad \forall g \in G : u_g^* = 0$
RPM	$u \in [0,1], \quad u = u^*, \quad 0 \leq p_g \leq P_g^{max} u_g \ \ \forall g \in G : u_g^* = 1$

Table 5.1: Pricing Models

dispatch problem, formulated as a mixed integer linear program (MILP), is known.[1] Startup, shutdown, no-load costs, and minimum operating levels yield a non-convex optimal value function for which marginal prices do not always exist. Even where marginal prices can be found, they do not ensure short-run cost recovery (either for variable or startup costs) of optimally dispatched generators (as would be the case in a convex setting). This becomes readily apparent with block-loaded generators that have no ramping abilities and thus can never set the price. The lack of cost recovery with marginal prices of high variable-cost, fast-acting, block-loaded resources is why pricing with non-convexities is referred to in the U.S. as "fast-start pricing" [13], although non-convexities present cost-recovery challenges for all resource types.

Fixed configuration pricing (FCP) can be considered the non-convex analog to locational marginal pricing (LMP), with prices as the dual variables of the power balance constraints after relaxing integrality and fixing the UC status during the pricing run to the optimal values previously found. Approximate convex hull pricing (aCHP) is an approximation to the pricing model proposed by [115] that seeks to find the marginal prices associated with the convex hull of the optimal value function, which is the uniform price associated with the lowest lost opportunity costs (LOC). We can find an approximation with a tight UC relaxation, and this approximation may be exact where ramping constraints are not binding [57]. Partial convex hull pricing (pCHP), in use in a form in MISO [13] relaxes integrality and fixes commitment to optimal values for only a subset of units, e.g., the set of

1 Results for pricing models that depend on the MILP solution may vary based on how close to optimality the UC dispatch problem is solved. We refer to [14] and [111] for further analysis of this dependence.

online units. Finally, relaxed P_{min} pricing (RPM) used in NYISO and several other regions [13] relaxes integrality, fixes commitment to optimal values, and changes the minimum operating capacity required to 0 for some subset of units, e.g., the set of online units.

LOC represents the difference between profits made for a given price following the central dispatch decision and the profits that a generator could make if it chose its own production level based on the given price (its preferred profit). In a convex setting with marginal pricing, LOC does not exist. Make-whole payments (MWP) are a subset of LOC that equal the short-run losses over some time horizon when a generator is scheduled to produce but given the price would prefer not to. MWP are typically resolved on a daily basis, and we follow this convention for each pricing model. However, we note that generators can operate at a short-run loss over a single day while still operating at a short-run profit over a longer time horizon; thus, daily MWP may exceed long-run LOC.

5.3 METHODOLOGY

We analyze a number of installed VRE capacity scenarios, each with an underlying set of VRE realization scenarios. For each installed VRE capacity scenario, we find the central planner's optimal thermal capacity additions using a stochastic capacity expansion model. In a convex setting, the idealized central planner maximizing social surplus chooses the same resource mix as a perfectly competitive market in the long-run with marginal pricing. While our problem is non-convex, this solution provides a starting point to find a resource mix adapted in the long-run to each pricing model. We use an algorithm that iteratively searches nearby resource mixes to find a quasi-break-even solution in which no generator operates at a loss and no new additional generator could enter the market and make a profit.

5.3.1 *Nomenclature*

Indices and Sets

$g \in G$	Set of generators
$G^T \subseteq G$	Set of thermal generators
$G^N \subseteq G^T$	Set of nuclear generators

$G^V \subseteq G$	Set of VRE resources
$t \in T$	Set of time periods (hours)
$l \in L$	Set of demand bids
$\omega \in \Omega$	Set of scenarios

Parameters

C_g	Variable cost (\$/MWh)
F_g	Startup cost (\$)
C_g^{inv}	Annualized investment cost of generator g (\$/yr)
P_g^{min}	Minimum operating capacity (MW)
P_g^{max}	Maximum operating capacity (MW)
M_g^{on}	Minimum on time (h)
M_g^{off}	Minimum off time (h)
R_g	Maximum ramp up/down rate (MW/h)
$\xi_{tg\omega}$	Maximum output for VRE resource (MW)
B_l	Value of demand bid l (\$/MWh)
D_{tl}	Maximum quantity of demand bid l at time t (MW)

Variables

$p_{tg\omega}$	Committed generation for generator g at time t (MW)
$u_{tg\omega}$	(Binary) commitment status for generator g at time t
$z_{tg\omega}$	(Binary) startup decision for generator g at time t
$y_{tg\omega}$	(Binary) shutdown decision for generator g at time t
$d_{tl\omega}$	Amount of cleared demand bid l at time t (MW)
x_g	Binary build decision for each generator $g \in G^T$

5.3.2 *Stochastic Capacity Expansion Model*

We adapt the capacity expansion model from Chapter 4 (also in [14]) to include stochastic VRE generation. Both binary investment decisions and non-convex operational costs contribute to non-convexities, but we can ameliorate the impact of binary investment decisions with a sufficiently large load compared to the size of the generators. Short-run surplus is given as

$$H(x;\xi) = -\sum_{t\in T}\sum_{g\in G}(C_g p_{tg\omega} + F_g z_{tg\omega}) + \sum_{t\in T}\sum_{l\in L} B_l d_{tl\omega} \quad (5.1)$$

The factor Θ scales up expected short-run surplus to an annualized level in objective function (5.2a) that maximizes benefits and minimizes costs, assuming no transmission congestion. Constraint (5.2b) ensures power balance with cleared demand bids. The remaining constraints define operating characteristics of generators, exogenous VRE, and reflect an expectation of one startup cost for nuclear in a year included in investment cost.

$$\min_{x,p,u,z,y,d} \quad \sum_{g\in G} C_g^{inv} x_g - \Theta \mathbb{E}\left[H(x;\xi)\right] \quad (5.2a)$$

s.t.

$$\sum_{g\in G} p_{tg\omega} = \sum_{l\in L} d_{tl\omega} \qquad \forall t \in T, \omega \in \Omega \quad (5.2b)$$

$$0 \le d_{tl\omega} \le D_{tl} \qquad \forall t \in T, l \in L, \omega \in \Omega \quad (5.2c)$$

$$p_{tg\omega} \le P_g^{max} x_g \qquad \forall t \in T, g \in G^T, \omega \in \Omega \quad (5.2d)$$

$$z_{tg\omega} + y_{tg\omega} \le 1 \qquad \forall t \in T, g \in G^T, \omega \in \Omega \quad (5.2e)$$

$$u_{tg\omega} - u_{t-1,g\omega} = z_{tg\omega} - y_{tg\omega} \qquad \forall t \in 2...T, g \in G^T, \omega \in \Omega \quad (5.2f)$$

$$z_{tg\omega} = u_{tg\omega} \qquad \forall t = 1, g \in G^T : g \notin G^N, \omega \in \Omega \quad (5.2g)$$

$$z_{tg\omega} = 0 \qquad \forall t = 1, g \in G^N, \omega \in \Omega \quad (5.2h)$$

$$y_{tg\omega} = 0 \qquad \forall t = 1, g \in G^T, \omega \in \Omega \quad (5.2i)$$

$$z_{tg\omega} + \sum_{t'=t+1}^{\min(t+M_g^{on}-1,T)} y_{t'g\omega} \le 1 \qquad \forall t \in 1...T-1, g \in G^T : M_g^{on} > 1, \omega \in \Omega \quad (5.2j)$$

$$y_{tg\omega} + \sum_{t'=t+1}^{\min(t+M_g^{off}-1,T)} z_{t'g\omega} \le 1 \qquad \forall t \in 1...T-1, g \in G^T : M_g^{off} > 1, \omega \in \Omega \quad (5.2k)$$

$$P_g^{min} u_{tg\omega} \leq p_{tg\omega} \leq P_g^{max} u_{tg\omega} \qquad \forall t \in T, g \in G^T, \omega \in \Omega \tag{5.2l}$$
$$-R_g \leq p_{tg\omega} - p_{t-1,g\omega} \leq R_g \qquad \forall t \in T, g \in G^T, \omega \in \omega \tag{5.2m}$$
$$0 \leq p_{tg\omega} \leq \xi_{tg\omega} \qquad \forall t \in T, g \in G^V, \omega \in \Omega \tag{5.2n}$$
$$p_{tg} \geq 0 \qquad \forall t \in T, g \in G \tag{5.2o}$$
$$u_{tg}, z_{tg}, y_{tg} \in \{0,1\} \qquad \forall t \in T, g \in G^T \tag{5.2p}$$
$$x_g \in \{0,1\} \qquad \forall g \in G^T \tag{5.2q}$$

5.3.3 *Short-Run Dispatch Model*

For a specific realization of VRE, the deterministic short-run dispatch model replaces the objective function (5.2a) with

$$\max_{p,u,z,y,d} \quad \sum_{t \in T} \sum_{l \in L} B_l d_{tl} - \sum_{t \in T} \sum_{g \in G} (C_g p_{tg} + F_g z_{tg}) \tag{5.3}$$

The subset of units G is redefined as only units that were built in the capacity expansion model, $g \in G : x_g = 1$. Constraints (5.2d) and (5.2q) are omitted, as are the scenario indices ω.

5.3.4 *Long-Run Adapted Resource Mixes*

When calculating the long-run adapted resource mix to each pricing model, we assume that VRE realizations occurred exactly as predicted in the stochastic capacity expansion model. Long-run profits are calculated by simulating the short-run dispatch model for each realization of VRE, with results weighted by the probability of each scenario. We use the algorithm given in [14] to find a resource mix that represents a quasi-break-even solution for a given pricing model. The algorithm starts at the central planner resource mix, then iteratively removes unprofitable generators and tests whether building a new generator of a given technology type would be profitable. If the new generator would be profitable, it is added to the model, and the process repeats until a resource mix is found in which no generators are operating at a loss in the long-run and no new generators could enter and make a profit. We select a target profit bound of 5%, meaning the algorithm will stop if all generators are operating within a long-run profit of +/-5%, and generators are only declared to be operating at a loss when profits are below -5%. For this analysis, we assume market power mitigation is sufficient such that LOC beyond MWP do not change bidding behavior.

5.4 RESULTS

5.4.1 *Test Case*

Data for the test case come from the Grid Modernization Lab Consortium's Reliability Test System [38]. In order to decrease the impact of lumpy investment decisions, we scale load and solar generation by a factor of 10 for a representative week. Wind data comes from ERCOT's aggregate generation in 2020 [116]. We test four installed VRE capacity scenarios, differentiated by the wind scalar, as shown in Table 5.2, with the fraction of uncurtailed wind generation ranging from 24% to nearly twice total demand. Within each installed VRE capacity scenario, we explore results for 4 wind realization scenarios drawn from four weeks of different seasons. Distributions of each wind realization scenario are shown in Figure 5.2.

We use candidate generators of four technology types: nuclear, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT), and a gas turbine that is block-loaded, called a fast-start gas turbine (FSGT). These technologies represent base, intermediate, and peaking units.[2] Technical parameters are given in Table 5.3 and cost parameters are given in Table 5.4. Characteristics are adapted from data used in [14] with the addition of the block-loaded FSGT with investment and startup costs 10% lower than OCGT and variable costs 10% higher. We assume 90% of demand at each time period is inelastic (with a benefit of \$10,000/MWh) and 10% of demand is elastic, represented by 200 equally-sized bids descending in price from \$10,000/MWh to \$50/MWh, also as in [14]. We use a profit bound of 5% in the algorithm from 5.3.4 and enforce short-run cost recovery (MWP) over each day.

5.4.2 *Long-Run Resource Mixes*

Results of the stochastic capacity expansion model, the central planner's problem, are given in Figure 5.3. The overall thermal capacity built changes, reflecting a firm capacity credit for wind. With increasing wind, the amount of baseload capacity decreases and the amount of intermediate and peaking capacity increases, reflecting the changing nature of the net load curve. The long-run resource mixes adapted to each pricing model are found using the

2 Note that no energy storage exists in the test system. We wish to test the impact of net load curves with higher ramps, lower turn-downs, and steeper and shorter peaks on generators with non-convex costs.

Inst. Cap.	Wind Scalar	Wind/Demand
S_1	1	0.24
S_2	2	0.47
S_3	4	0.95
S_4	8	1.91
S_n	Wind Realization $\{RS_{n1},...,RS_{n4}\}$	

TABLE 5.2: Scenario Analysis

Tech	Min Output (MW)	Max Output (MW)	Ramp Up/Dn (MW/hr)	Up/Dn time (hr)
Nuclear	900	1000	190	36
CCGT	150	400	320	3
OCGT	50	200	360	0
FSGT	200	200	-	0

TABLE 5.3: Technical Parameters for Thermal Generators

algorithm explained in 5.3.4, and the difference between the adapted mixes and the central planner mix is shown in Figure 5.4. aCHP best supports the central planner resource mix across scenarios, and market solutions tend to favor OCGT over FSGT.

5.4.3 *Generator Payoffs*

Recall that in the convex case, long-run profits for each technology type would be 0%, as the technologies would be able to perfectly adapt (no lumpy investments) and marginal prices always exist. Long-run profits at the adapted mixes are shown in Figure 5.5. At the adapted resource mixes, no generators are making a profit less than 5%, and no new generators could enter and make a profit. aCHP and FCP yield the profits closest to 0%. However, profits are not made uniformly across the horizon of interest; Figure 5.6 shows the long-run profits that would arise if only one of the

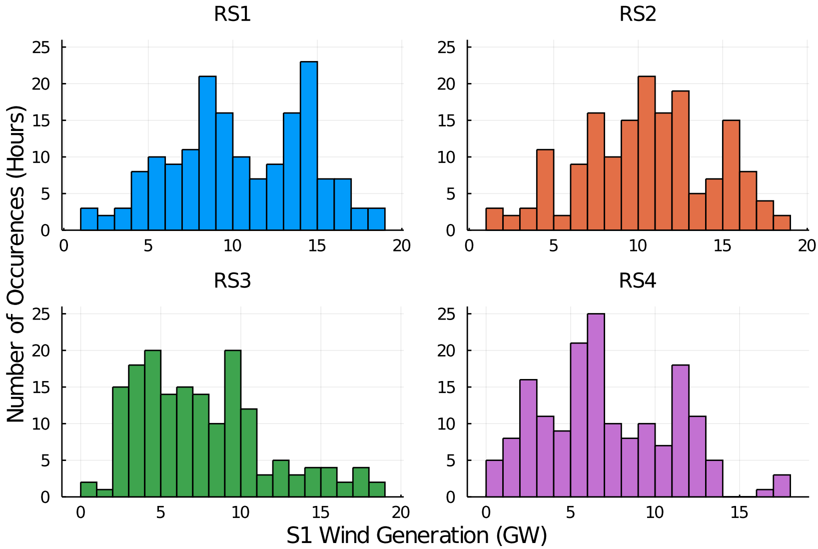


FIGURE 5.2: Distribution of wind realization scenarios

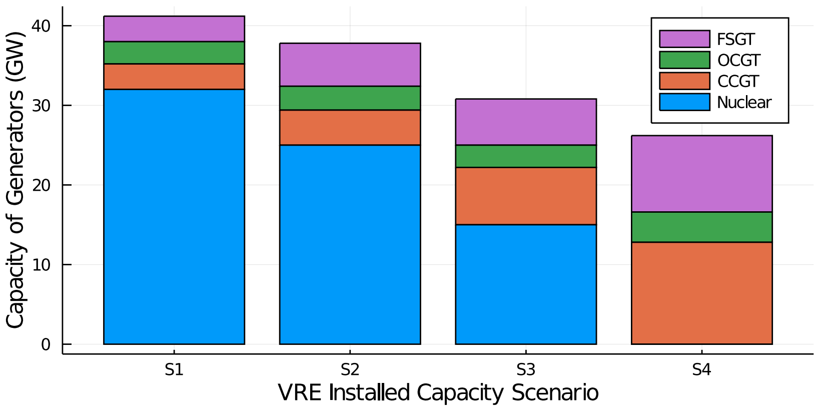


FIGURE 5.3: Installed capacity of technology types in the long-run central planner solution

four VRE realization scenarios occurred. None of the pricing models differ markedly in volatility of profits across the VRE realization scenarios.

Tech	Investment (M$/GW-yr)	Startup (M$)	Variable ($/MWh)
Nuclear	489	1	6.5
CCGT	129	0.06	58.5
OCGT	106	0.01	99.4
FSGT	95.4	0.009	109.34

TABLE 5.4: Cost Parameters for Thermal Generators

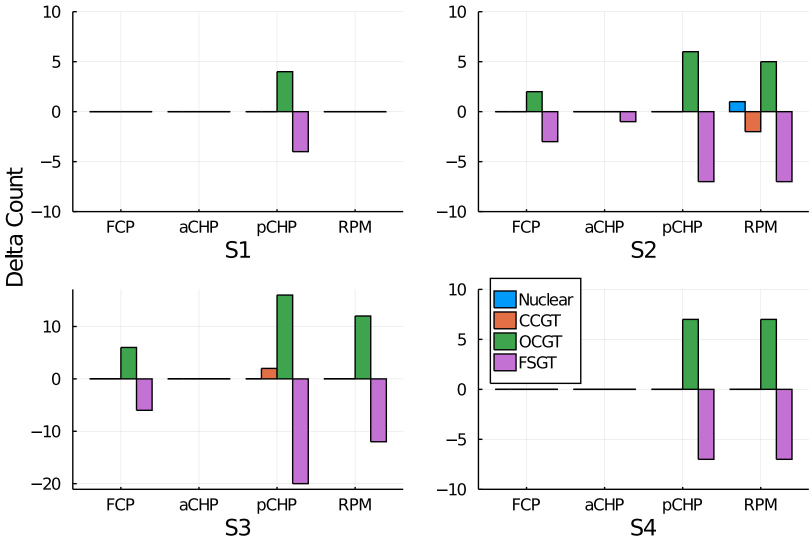


FIGURE 5.4: Difference in number of generators between resource mixes adapted to each pricing model and the long-run central planner solution

5.4.4 *Social Surplus*

Figure 5.7 shows the average cost to consumer (ACC) and the percentage of these costs represented by MWP. Increased VRE offsetting total installed thermal capacity decreases ACC as expected, with aCHP and FCP providing the lowest price. In the long-run adapted mixes, MWP resolved on a daily basis are small and do not show a significant pattern across increasing

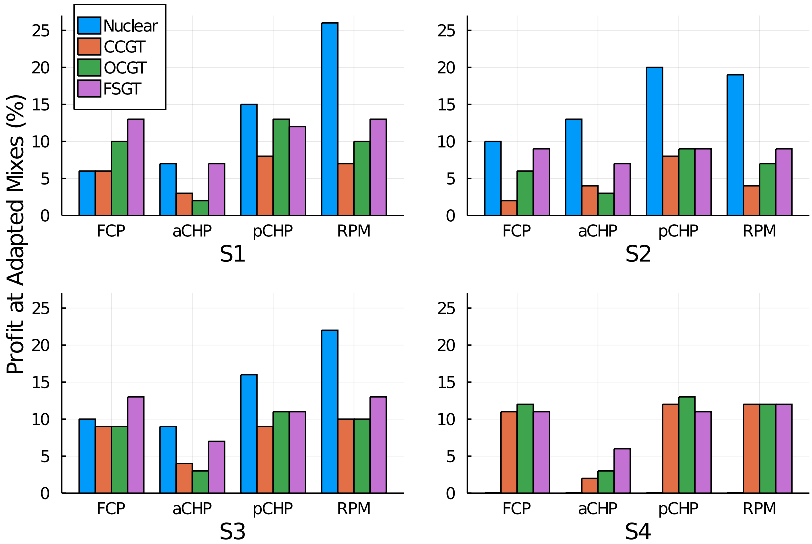


FIGURE 5.5: Average long-run profits at resource mixes adapted to each pricing model

installed VRE capacity.[3] ACC is normalized by MWh served, but the same amount of demand is not necessarily served by each pricing model and installed capacity scenario, so we must also consider social surplus.

Figure 5.8 shows the change in consumer and non-convex generators' producer surplus between adapted mixes and the central planner solution (assuming producers are paid at-cost) as a percentage of total costs to consumer at the central planner solution. Recall that in the convex case in which marginal prices exist and producers can perfectly adapt in the long-run, all social surplus is consumer surplus (as producer profits are 0%). The non-convexitites impose a penalty compared to the convex case as a transfer of consumer surplus to producer surplus.[4] Even as VRE share increases, the profits of generators as a percent of their costs remains similar. However, as

3 Note that aCHP can still have MWP, as it minimizes total LOC, of which MWP are only a subset. MWP here are provided daily, whereas LOC is calculated over the entire horizon.

4 Note that the social surplus only depends on total cleared demand; when the decrease in consumer surplus and the increase in producer surplus are roughly proportional, as here, it indicates the social surplus (and total cleared demand) remains similar between the adapted mixes and the central planner solution. The change is predominantly a transfer from consumer to producer surplus.

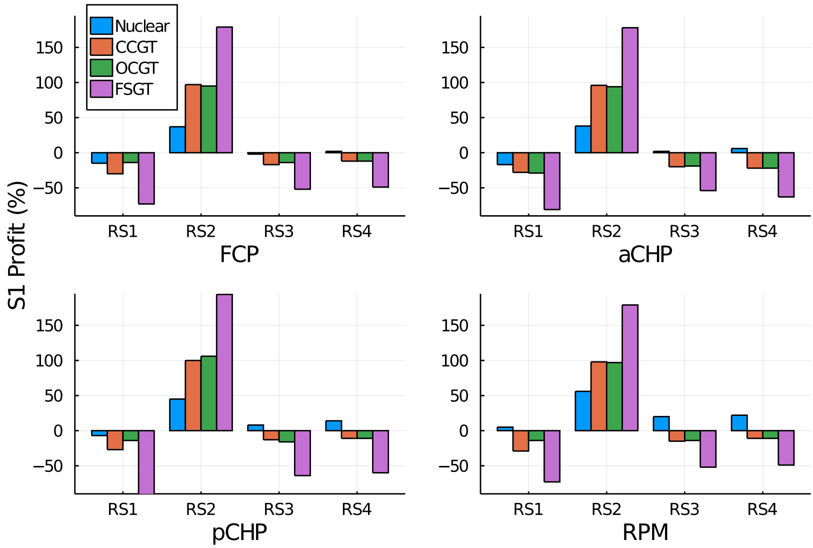


FIGURE 5.6: Average long-run profits under VRE installed capacity S1 if only given VRE realization scenario occurred

seen in Figure 5.9, the impact of these excess profits for generators decreases as a percent of total social surplus with increasing VRE.[5] This is because there are simply less of these generators as VRE increases in the long-run, and the social surplus is increasing as the system is able to incorporate more VRE to serve load.

So far we assume that the presence of LOC (beyond MWP) does not impact generator's truthful bidding of their costs and technical characteristics. However, in reality, LOC may incentivize units to deviate from the centralized dispatch schedule. Recall that in the convex case with marginal pricing, there would be no LOC. In Figure 5.10 we see not only perceived losses (LOC) but also perceived profit after MWP have been given. This is because MWP are resolved on a daily basis, and some units, notably nuclear, occasionally have days in which they operate at a short-run loss, even though over their entire operating horizon they do not operate at a short-run loss. They thus have no LOC over their lifetime and prefer to operate even in the absence of daily MWP, perceiving the side payments as a bonus. Nevertheless, many non-baseload technologies do perceive losses

5 Total social surplus is very high due to inelastic demand's consumer surplus.

beyond MWP at times in which they would prefer to operate given the price but are not scheduled. aCHP minimizes LOC and this is reflected in the substantively lower values of perceived losses across scenarios.

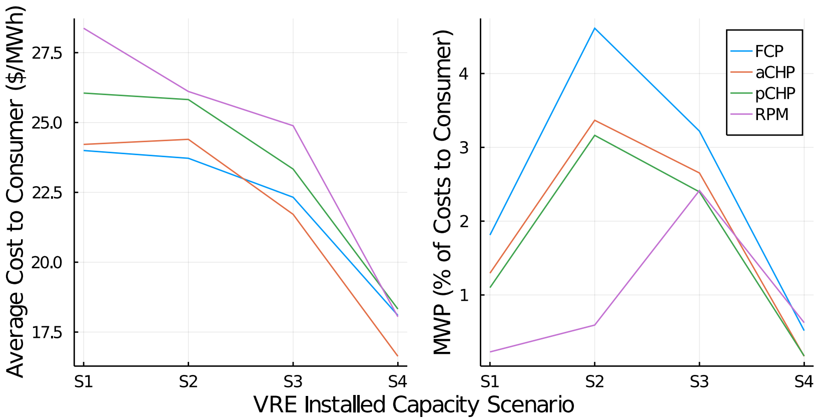


Figure 5.7: Average cost to consumer and daily make-whole payments as a percentage of costs to consumer

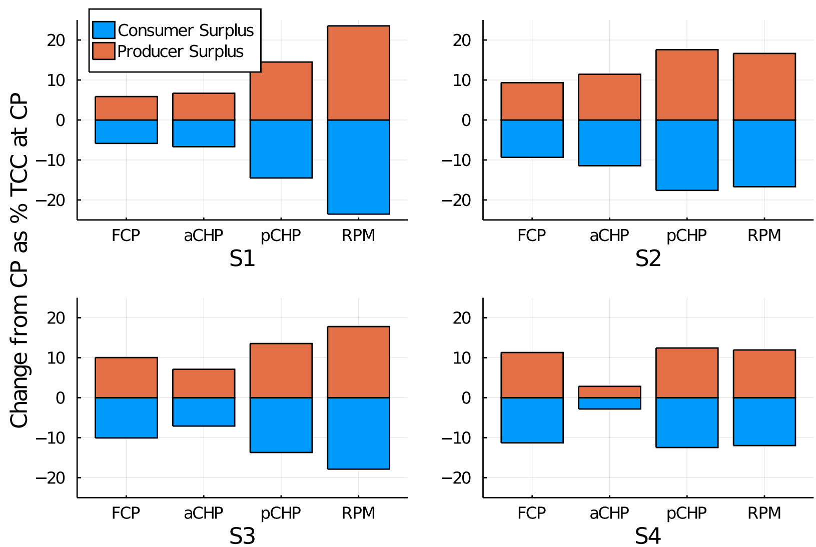


Figure 5.8: Change in surplus from central planner solution as a percentage of total costs to consumer at the central planner solution

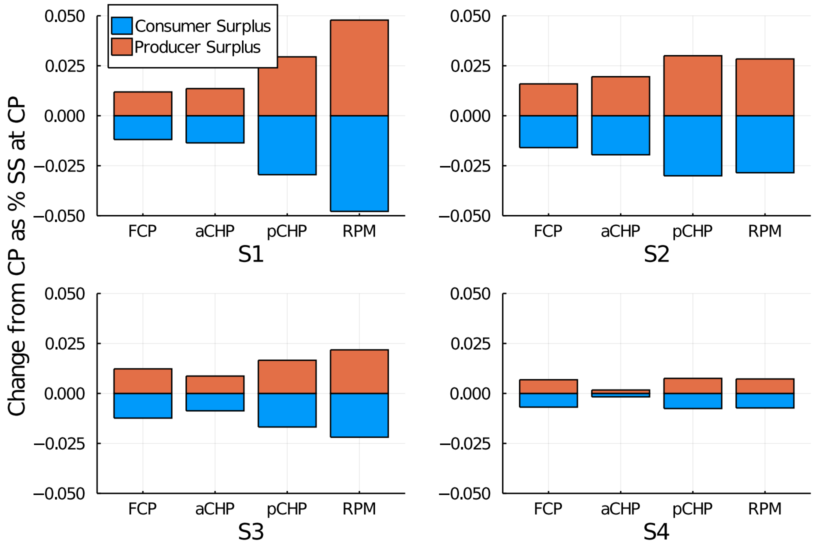


Figure 5.9: Change in surplus from central planner solution as a percentage of social surplus at the central planner solution

5.4.5 *Price Distributions*

Figure 5.11 shows the distribution of prices across pricing models and scenarios. FCP never has price set by the block-loaded unit (as it is never the marginal unit in the pricing run due to its inability to ramp), while RPM has price set by the block-loaded unit most often. aCHP and pCHP have price set higher than the highest marginal-cost unit most often. RPM is implemented for all online units, so the baseload technology most often sets the price, and 0-prices do not appear until substantially more penetration of VRE. In the load duration curve in Figure 5.12, we see that FCP and RPM decrease as a step function based on what generator was marginal, while aCHP and pCHP decrease more gradually, as they are related to the convex hull of the optimal value function.

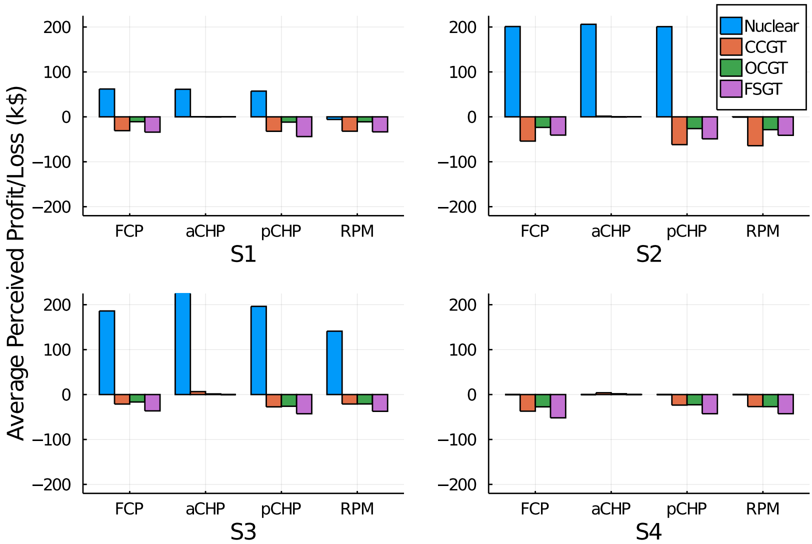


FIGURE 5.10: Average perceived profit/loss after MWP

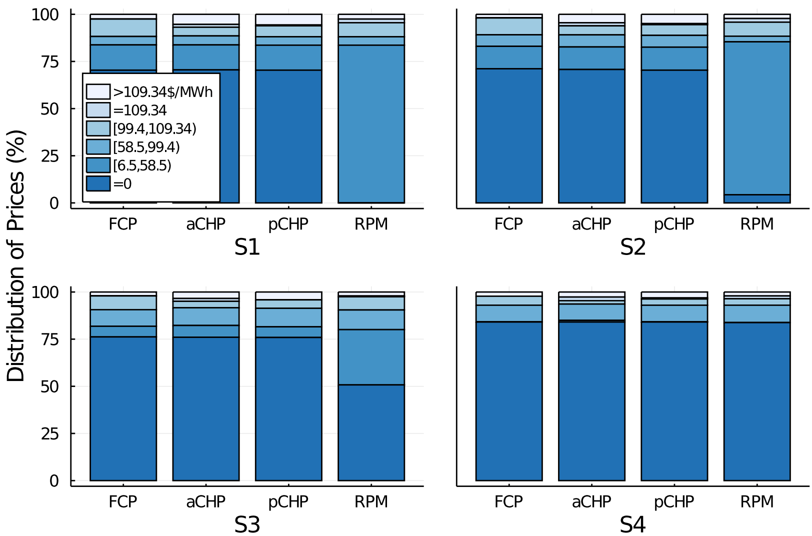


FIGURE 5.11: Distribution of prices for each pricing model and installed capacity scenario

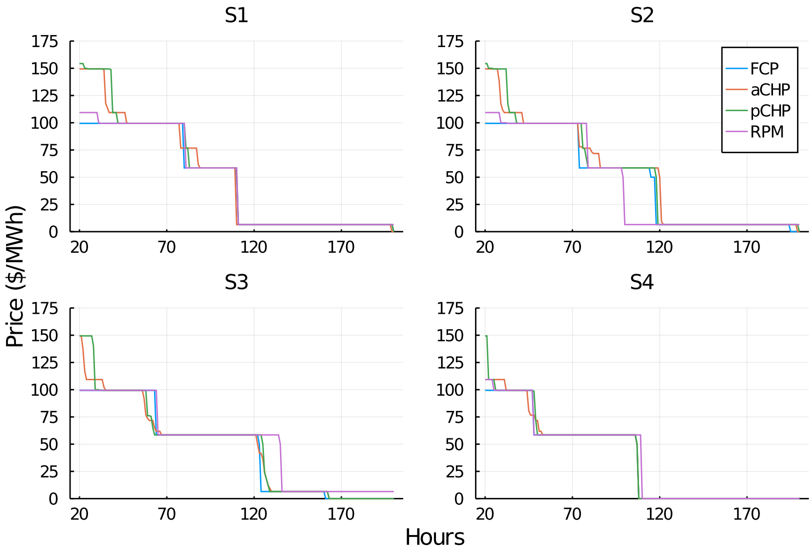


FIGURE 5.12: Price duration curve for highest-priced 20-200 hours

5.5 conclusion

As long as the system is allowed to adapt in the long-run to increased VRE, the issues posed by non-convexities are likely to decrease. Although the amount of excess profit as a percentage of non-convex producer costs may remain similar, fewer non-convex producers decreases the impact of these excess profits as a percentage of overall social surplus. The amount of transfer from consumer to producer surplus across VRE levels is typically lower with convex hull pricing and fixed configuration pricing (or LMP) compared to partial convex hull pricing or relaxed minimum capacity pricing. Convex hull pricing is also most supportive of the central dispatch decision with lowest perceived losses. All pricing models exhibit high profit volatility across wind realization scenarios. While differences exist by non-convex pricing model, idealized energy-only markets can still achieve long-run cost recovery of needed flexible generators even when non-convexities are considered and VRE generation increases, but at the cost of some consumer surplus. The presence of non-convex costs and high VRE does not mean we must necessarily rely on capacity mechanisms for long-run cost recovery. Exact results are dependent on net load profiles and generator characteristics considered, and future work should examine how sensitive conclusions are to different loads, technology characteristics, levels of demand response/elasticity, increasing shares of solar vs wind generation, and the inclusion of energy storage.

Part III

NON-CONVEX PRICING IN THE SHORT-RUN

6

IMPACTS OF NEAR-OPTIMAL SOLUTIONS

We explore the relationship between consumer and producer surplus and optimality gaps in mixed integer linear programming applied to electricity markets. We analyze a long-run adapted resource mix and introduce flexible demand. This allows for comparison of total producer and consumer surplus achieved across near-optimal solutions under different nonconvex pricing models. Results indicate that for pricing models dependent on the primal solution, consumer surplus generally increases (although not monotonically) with increasing optimality and producer surplus correspondingly decreases. Short-run cost recovery is also possible over the operating horizon without make-whole payments for all models examined. These results are highly influenced by scarcity rent from price-setting elastic demand.

6.1 INTRODUCTION

Determining optimal prices in markets with non-convex costs in which optimality gaps in the dispatch decision remain poses a continuing challenge. Since the beginning of the transition to liberalized wholesale electricity markets from vertically integrated utilities, it has been known that optimality gaps that negligibly affect the objective value may nevertheless significantly impact the profitability of individual resources [117]. As Lagrangian relaxation algorithms gave way to tractable algorithms to solve a mixed-integer programming (MIP) formulation, optimality gaps decreased. The move from Lagrangian relaxation approaches to MIP solvers was motivated by the goal of finding better solutions and thus improving social welfare, or social surplus [118]. The question that naturally follows is, how important is finding a solution closer to optimality for MIP solvers in terms of social surplus? System operators typically solve day-ahead markets with unit commitment (UC) within some optimality tolerance, e.g., a 0.1% relative MIP gap in MISO [118].

The volume of surplus transfers among producers resulting from different solutions within the optimality gap is not monotone in the size of the optimality gap, i.e., it does not strictly decrease as the solution approaches optimality [112]. Authors in [112] find in a test system over a 24-hour period with locational marginal pricing that make-whole payments, which ensure units recover all short-run costs, reduce the volatility of intra-producer transfers. It is then explored in [119] whether findings in [112] are still supported over a longer time frame. A daily rolling-horizon with look-ahead UC model is solved in a large test system, obtaining near-optimal solutions at several different MIP gap targets. Producer surplus of individual generators is shown to still vary considerably even with solutions closer to optimality. When including elastic demand, solutions closer to optimality are shown to be closer to the demand cleared in the MIP optimal solution. Authors in [111] examine redistribution of total surplus with inelastic demand in different near-optimal solutions, demonstrating that pricing models that do not depend on the primal UC solution, e.g., convex hull pricing, are associated with smaller wealth transfers.

It is important to distinguish between changes in intra-producer surplus transfers and changes in total producer and consumer surplus. Producer surplus is simply profit, and intra-producer surplus transfer implies that certain producers benefit at the expense of other producers. Total producer surplus, on the other hand, represents the total surplus achieved by producers under a given UC dispatch with a given pricing model. Taking the perspective of a central operator, another concern is the total amount of consumer surplus (the difference between the benefit of cleared demand and payments to producers). Previously in [14] (Chapter 4), we target two different MIP gap tolerances and find that resource mixes adapted in the long-run to different non-convex pricing models can vary based on which target was used. While not explored explicitly, results in [120] similarly suggest an increase in overall consumer surplus as optimality improves.

Instead of primarily focusing on transfers between producers in the short-run as in [112]- [111], we turn our attention to the effect of near optimal solutions on transfers between total consumer and producer surplus in the long-run under different non-convex pricing models. We explore a set of near-optimal solutions across a range of MIP gaps and examine the relationships between consumer and producer surplus in a system with partially elastic demand. We consider only systems in a long-run equilibrium resource mix. This is because in non-adapted mixes, the presence of short-run losses (that are typically compensated by make-whole payments) may be an appropriate signal to exit the market as opposed to an issue arising from non-convex pricing. Analyzing long-run equilibria also allows us to examine not simply short-run profits, but long-run cost recovery of producers. Fixing the underlying resource mix, we then examine near-optimal solutions of the short-run UC dispatch and apply several pricing models. We include scenarios that require daily short-run cost recovery as well as scenarios only enforcing short-run cost recovery over the lifetime of the generator.

6.2 LONG-RUN OPTIMAL RESOURCE MIX

From classical marginal pricing theory, we know that an idealized central planner (CP) maximizing social surplus would choose the same resource mix as a perfectly competitive market with system-wide marginal pricing.[1] At this equilibrium, no units make a profit or loss and all social surplus is consumer surplus. Marginal prices do not exist in markets with non-convex costs, but we can still find a benchmark CP resource mix that maximizes benefit to consumers and minimizes producer costs with a capacity expansion model. We can decrease the impact of lumpy investments by using

1 See [4] for proof of equivalent optimality conditions in the context of electricity markets.

a large test system. Our aim is to solve to a sufficiently small optimality gap such that we find a stable resource mix, acknowledging that because of lumpy investments, we may have more than one long-run equilibrium. In a market with non-convex costs, there may be incentives via profits and losses to move away from this benchmark CP resource mix to a mix that is adapted to a given pricing model. However, because we would like to compare different pricing models across the same set of near-optimal solutions, we keep the same underlying CP resource mix. Below we define the notation and model formulation and refer to Chapter 4 (also [14]) for a more in-depth description.

6.2.1 *Nomenclature*

Indices and Sets

$g \in G$	Set of generators
$G^T \subseteq G$	Set of thermal generators
$G^N \subseteq G^T$	Set of nuclear generators
$G^V \subseteq G$	Set of VRE resources
$t \in T$	Set of time periods (hours)
$l \in L$	Set of demand bids

Parameters

C_g	Variable cost (\$/MWh)
F_g	Startup cost (\$)
C_g^{inv}	Annualized investment cost of generator g (\$/yr)
P_g^{min}	Minimum operating capacity (MW)
P_g^{max}	Maximum operating capacity (MW)
M_g^{on}	Minimum on time (h)
M_g^{off}	Minimum off time (h)
R_g	Maximum ramp up/down rate (MW/h)
$\mathcal{P}_{tg}$	Maximum output for VRE resource (MW)
B_l	Value of demand bid l (\$/MWh)

D_{tl} Maximum quantity of demand bid l at time t (MW)

Variables

p_{tg} Committed generation for generator g at time t (MW)
u_{tg} (Binary) commitment status for generator g at time t
z_{tg} (Binary) startup decision for generator g at time t
y_{tg} (Binary) shutdown decision for generator g at time t
d_{tl} Amount of cleared demand bid l at time t (MW)
x_g Binary build decision for each generator $g \in G^T$

6.2.2 *Capacity Expansion Model*

The factor Θ scales up short-run costs to an annualized level in objective function (6.1a) that maximizes benefits and minimizes costs, assuming no transmission congestion. Constraint (6.1b) ensures power balance with cleared demand bids. The remaining constraints define operating characteristics of generators, exogenous variable renewable energy (VRE), and reflect an expectation of one startup cost for nuclear in a year included in investment cost.

$$\max_{(x,p,u,z,y,d)} \quad \Theta \sum_{t\in T}\sum_{l\in L} B_l d_{tl} - \sum_{g\in G} C_g^{inv} x_g - \Theta \sum_{t\in T}\sum_{g\in G}\left(C_g p_{tg} + F_g z_{tg}\right) \tag{6.1a}$$

s.t.

$$\sum_{g\in G} p_{tg} = \sum_{l\in L} d_{tl} \qquad \forall t \in T \tag{6.1b}$$

$$0 \le d_{tl} \le D_{tl} \qquad \forall t \in T, l \in L \tag{6.1c}$$

$$p_{tg} \le P_g^{max} x_g \qquad \forall t \in T, g \in G^T \tag{6.1d}$$

$$z_{tg} + y_{tg} \le 1 \qquad \forall t \in T, g \in G^T \tag{6.1e}$$

$$u_{tg} - u_{t-1,g} = z_{tg} - y_{tg} \qquad \forall t \in 2...T, g \in G^T \tag{6.1f}$$

$$z_{tg} = u_{tg} \qquad \forall t = 1, g \in G^T : g \notin G^N \tag{6.1g}$$

$$z_{tg} = 0 \qquad \forall t = 1, g \in G^N \tag{6.1h}$$

$$y_{tg} = 0 \qquad \forall t = 1, g \in G^T \tag{6.1i}$$

$$z_{tg} + \sum_{t'=t+1}^{\min(t+M_g^{on}-1,T)} y_{t'g} \leq 1 \qquad \forall t \in 1...T-1, g \in G^T : M_g^{on} > 1 \tag{6.1j}$$

$$y_{tg} + \sum_{t'=t+1}^{\min(t+M_g^{off}-1,T)} z_{t'g} \leq 1 \qquad \forall t \in 1...T-1, g \in G^T : M_g^{off} > 1 \tag{6.1k}$$

$$P_g^{min} u_{tg} \leq p_{tg} \leq P_g^{max} u_{tg} \qquad \forall t \in T, g \in G^T \tag{6.1l}$$

$$-R_g \leq p_{tg} - p_{t-1,g} \leq R_g \qquad \forall t \in T, g \in G^T \tag{6.1m}$$

$$0 \leq p_{tg} \leq \mathcal{P}_{tg} \qquad \forall t \in T, g \in G^V \tag{6.1n}$$

$$p_{tg} \geq 0 \qquad \forall t \in T, g \in G \tag{6.1o}$$

$$u_{tg}, z_{tg}, y_{tg} \in \{0, 1\} \qquad \forall t \in T, g \in G^T \tag{6.1p}$$

$$x_g \in \{0, 1\} \qquad \forall g \in G^T \tag{6.1q}$$

6.3 SHORT-RUN DISPATCH AND PRICING MODELS

6.3.1 *Short-Run Dispatch Model*

Once a capacity mix is fixed, the short-run UC dispatch is solved. This formulation replaces the objective function (6.1a) with (6.2):

$$\max_{(p,u,z,y,d)} \quad \sum_{t \in T} \sum_{l \in L} B_l d_{tl} - \sum_{t \in T} \sum_{g \in G} (C_g p_{tg} + F_g z_{tg}) \tag{6.2}$$

The subset of units G is redefined as only units that were built in the capacity expansion model, $g \in G : x_g = 1$. Constraints (6.1d) and (6.1q) are omitted.

6.3.2 *Pricing Models*

Pricing models are formed from adjustments to the short-run dispatch model after a solution has been found. Prices are found as the dual variables of the power balance constraints from the pricing model runs.

- **Fixed configuration pricing (FCP)**: The binary variables are relaxed and fixed to the values determined in the short-run dispatch model [29]:

$$\{u, z, y\} \in [0, 1] \tag{6.3}$$

$$u, z, y = u^*, z^*, y^* \tag{6.4}$$

  This method is also called locational marginal pricing, although locational prices could be calculated for any of the models and true marginal prices do not exist in the non-convex setting.

- **Convex hull pricing (CHP)**: This method seeks to find the marginal prices corresponding to the convex hull of the non-convex optimal value function, minimizing lost opportunity costs [55]. An approximation that is exact with a tight UC formulation in the case of no binding ramping constraints (see [57]) is to simply relax the binary variables of the short-run dispatch model:

$$\{u, z, y\} \in [0, 1] \tag{6.5}$$

- **Relaxed P_g^{min} operation (RPM)**: The minimum operation level is relaxed such that $0 \leq p_g \leq P_g^{max} u_g \;\; \forall g \in G : u_g^* = 1$. Binary variables are relaxed and fixed to the previously-found optimal values:

$$\{u, z, y\} \in [0, 1] \tag{6.6}$$

$$u, z, y = u^*, z^*, y^* \tag{6.7}$$

  A form of this model relaxing minimum operation for a subset of online units is used in NYISO and several other regions, motivated by block-loaded units being unable to set the marginal price under FCP [13].

6.4 INCENTIVES AND OPTIMALITY GAPS

6.4.1 *Consumer and Producer Incentives*

With market-clearing prices λ and side payments s, we define short-run profit Π, initial short-run profit Π^0, and short-run costs Ξ as follows:

$$\Pi_g := \sum_{t \in T} ((\lambda_t - C_g) p_{tg} - F_g z_{tg} + s_{tg}) \tag{6.8}$$

$$\Pi_g^0 := \Pi_g - \sum_{t \in T} s_{tg} \tag{6.9}$$

$$\Xi_g := \sum_{t \in T} (C_g p_{tg} + F_g z_{tg}) \tag{6.10}$$

We define long-run profits as a percentage of total costs:

$$\pi_g := \frac{\Theta \Pi_g - C_g^{inv}}{\Theta \Xi_g + C_g^{inv}} \tag{6.11}$$

Social surplus is the sum of producer and consumer surplus. Total thermal generator producer surplus is defined as

$$PS := \sum_{g \in G^T} (\Pi_g - \frac{1}{\Theta} C_g^{inv}) \tag{6.12}$$

Total consumer surplus is given by

$$CS := \sum_{t \in T} (\sum_{l \in L} B_l d_{tl} - \sum_{g \in G} \lambda_t p_{tg} - \sum_{g \in G^T} s_{tg}) \tag{6.13}$$

For a pricing model to support the central dispatch decision, the total compensation must be such that no perceived losses exist. Perceived losses are lost opportunity costs (LOC), the difference between what a unit could make given a price if able to schedule its own dispatch (its preferred profit) and what it would make with the same price following the centralized dispatch decision, plus any additional compensation received as side payments. We define initial lost opportunity costs LOC^0 without side payments and final LOC as

$$LOC_g^0 := \max_{u_g, p_g} \quad \Pi_g^0(\lambda^*, u_g, p_g) - \Pi_g^0(\lambda^*, u_g^*, p_g^*) \tag{6.14}$$

$$LOC_g := LOC_g^0 + \sum_{t \in T} s_{tg} \tag{6.15}$$

A subset of LOC^0 is make-whole payments (MWP), the revenue required for short-run revenue adequacy. This occurs when the unit would prefer to not operate at the market-clearing price. MWP are the most common form of side-payment in non-convex pricing and are defined over some time horizon as

$$MWP_g := -\min(0, \Pi_g^0(\lambda^*, u^*, p^*)) \tag{6.16}$$

Typically, MWP are provided as needed on a daily basis. However, there is no a priori reason why a system in a long-run adapted equilibrium should have no units making a loss on any given day. It may be most optimal, for instance, for a unit to suffer a loss one day but gain sufficient inframarginal rent over its operating life to have no long-run losses. Nevertheless, a daily MWP for a market that clears daily may be a necessary incentive for units to bid truthfully and follow market dispatch instructions. For these reasons we use both a typical daily MWP requirement as the default in all pricing models (MWP_D) and alternatively a guarantee of no operational losses over the entire operating horizon (MWP_H).

6.4.2 *Relative MIP Gap*

A relative MIP gap is defined for a minimization problem as the difference between the lower and upper objective bound normalized by the incumbent objective value (the upper bound). If z_P is the primal objective bound and z_D the dual, then

$$\text{MIP gap} := \left| \frac{z_P - z_D}{z_P} \right| \tag{6.17}$$

Relative MIP gaps depend on the problem formulation. Because of this, we must be wary about comparing relative MIP gaps between optimal dispatch problems that do and do not explicitly include benefit of cleared demand in the objective value. For example, let C be a vector of costs associated with the vector of production decisions p and B the benefit of cleared demand d. We then have the objective function

$$\max_{p,d} \quad B^\top d - C^\top p$$

If we assume inelastic demand and that all demand is served, then $B^\top d$ cancels out in the numerator of the associated MIP gap but is still present in the denominator:

$$\left| \frac{C^\top p_D - C^\top p_P}{B^\top d_P - C^\top p_P} \right| \tag{6.18}$$

If $B^\top d$ is large relative to $C^\top p$, then an objective value considering the benefit to demand will result in a much smaller relative MIP gap than an objective value that excludes this term, even though the producer costs are equivalent. The ratio of total benefit to total cost gives some insight as to how much smaller a relative MIP gap to expect.

6.5 RESULTS

6.5.1 *Test Case*

Scenarios are constructed using correlated demand, wind generation, and solar generation profiles from [38]. We scale demand and VRE profiles by a factor of 10, yielding a system with peak load of approximately 47.5GW over the 4 sample weeks selected. Non-coincident peak wind is over 50% of peak load, and non-coincident peak solar is over 25%. VRE is treated as exogenous, and we perform a greenfield capacity expansion for thermal generators of three technology types: nuclear, CCGT, and OCGT, representing base, intermediate, and peaking units. Technical parameters are given in Table 6.1 and cost parameters are given in Table 6.2. Parameters are adapted from data used in [108]. We use partially price-responsive demand assuming 90% of demand at each time interval is inelastic (with a benefit of $10,000/MWh) and 10% of demand is elastic, represented by 200 equally-sized bids descending in price from $10,000/MWh to $50/MWh as in [109], which notes that recent PJM market results indicate such a level of responsive demand may be realistic [121].

Tech	Min Output (MW)	Max Output (MW)	Ramp Up/Down (MW/hr)	Up/Down time (hr)
Nuclear	900	1000	190	36
CCGT	150	400	320	3
OCGT	50	200	360	0

Table 6.1: Technical Parameters for Thermal Generators

Tech	Investment (M$/GW-yr)	Startup (M$)	Variable ($/MWh)
Nuclear	489	1	6.5
CCGT	129	0.06	58.5
OCGT	106	0.01	99.4

Table 6.2: Cost Parameters for Thermal Generators

All models are solved with Gurobi. The capacity expansion model yields a benchmark CP resource mix of 9 nuclear, 57 CCGT, and 67 OCGT units, for a total of 133 thermal units. The generator mix in the CP solution is determined by targeting a MIP Gap of 0 with a time limit, yielding a MIP gap of 0.0003%.[2] Next we use Gurobi's solution pool option to find a set of near-optimal solutions using the short-run dispatch model with a single horizon of 4 weeks, the same as the capacity expansion model.[3] The near-optimal solutions are required to be within 1% of the objective value of the best solution found within a target MIP gap of 0.02%. We find 51 qualifying near-optimal solutions.[4] The ratio of benefit of cleared demand to total producer costs at the best solution with FCP is approximately 200:1, which leads to very small relative MIP gaps. All pricing runs are convex, but calculating lost opportunity costs does require solving additional MIP problems. For these we maintain Gurobi's default MIP gap setting of 0.01%.[5]

6.5.2 *Consumer Surplus and Producer Surplus*

We find that for the pricing models that depend on the primal solution, the total consumer surplus tends to increase with optimality while the total producer surplus tends to decrease, although not monotonically. Figure 6.1 shows how consumer surplus changes with each near-optimal solution ordered from worst to best, with Solution 1 being the best solution found. Results are shown for the pricing models FCP, CHP, and RPM with the default MWP_D as well as the alternative MWP_H. While as expected the relationship is not monotonic, there is nevertheless a significant trend for FCP and RPM, which depend on the primal solution. RPM is found to result in the lowest consumer surplus followed by FCP, with both substantially improving with optimality. CHP yields the highest consumer surplus. Figure 6.2 shows that producer surplus correspondingly trends downward for primal-dependent models as the solution's optimality gap decreases. Note that producer surplus is reported only for thermal units. This trend does

2 Due to the binary build decisions of units of fixed size, it is possible that more than one long-run optimal resource mix exists.

3 We assume perfect foresight so that uncertainty and rolling horizons do not additionally distort producer profits beyond the impact of non-convexities.

4 Gurobi's pool search mode is set such that the solver seeks to find the N best solutions. We specify a high value of N, in attempt to find many qualifying solutions that differ in values for integer variables. However, a diversity criterion is not used.

5 Note that the preferred profit function only includes producer profits and not benefit of cleared demand.

not change if we include MWP_D or if we do not enforce daily short-run cost recovery (MWP_H). Recall that in a convex long-run adapted system there would be no producer surplus. Between the least and most optimal solution found, producer surplus can decrease considerably, e.g., for FCP there is a reduction of 88% between the worst and best solution. Surplus under CHP does not change perceptibly across near-optimal solutions; while the amount of demand cleared and generators online may change between near-optimal solutions, the market-clearing prices found do not since CHP does not depend on the primal solution. We see through the illustration of a sample day in Section 6.5.4 that the different market-clearing prices are a primary driver of differences in surplus between near-optimal solutions for primal-dependent pricing models.

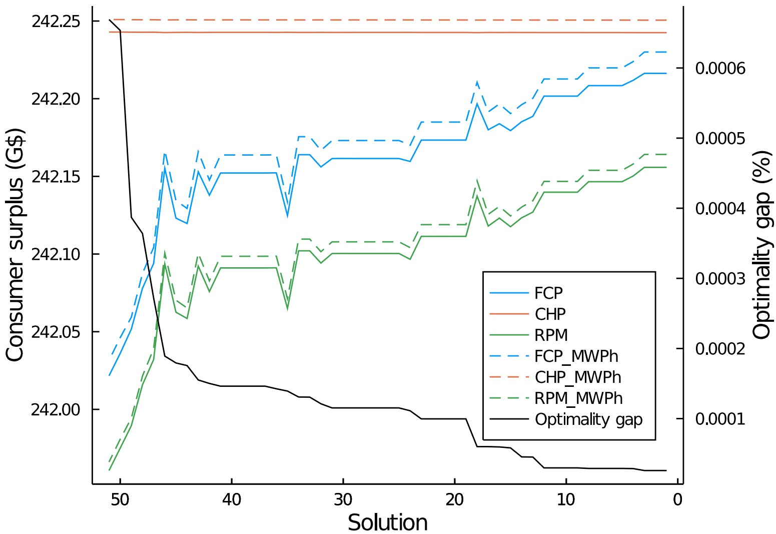


FIGURE 6.1: Consumer surplus and optimality gap across near-optimal solutions by pricing model

6.5.3 *Producer Profits and Incentives*

Short-run revenue adequacy is achieved in all pricing models tested without side payments if enforced over the entire solution horizon (MWP_H). If we instead require short-run revenue adequacy for each day (MWP_D), then side payments in the form of MWP are required. No substantial differences

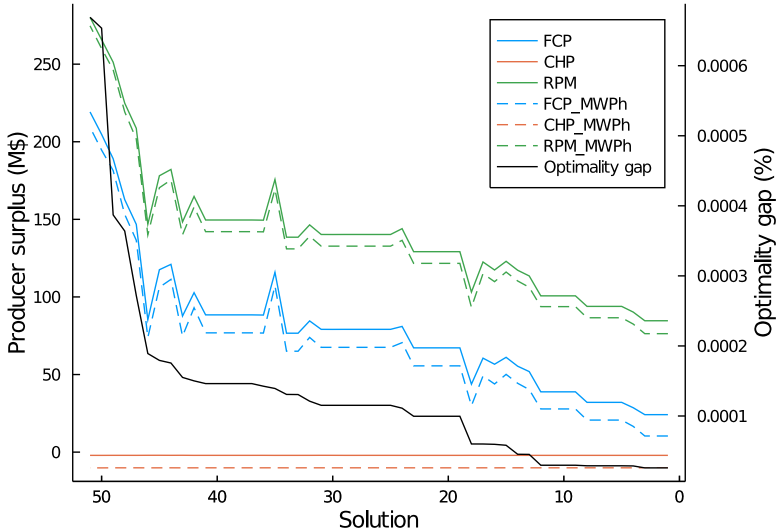


FIGURE 6.2: Long-run producer surplus and optimality gap across near-optimal solutions by pricing model

are seen in MWP for thermal units across near-optimal solutions, as seen in Figure 6.3. When short-run cost recovery is required daily, MWP for RPM are typically lower and less volatile than MWP for FCP. MWP for CHP are consistent across solutions (note that CHP minimizes LOC, not MWP). For primal-dependent pricing models, we see a trend of less extreme LOC as the solution becomes more optimal, illustrated in Fig 6.4. Note that Fig 6.4 displays LOC remaining after any MWP have been transferred, and that perceived losses are shown as negative. CHP with MWP_H yields no LOC, as this method seeks to minimize this incentive to deviate from the schedule. However, if MWP_D are provided, producers actually perceive an excess profit. Producers are thus overcompensated relative to what is necessary for them to be fully incentivized to follow the central dispatch decision. Future work should explore if this issue persists when CHP is calculated on a rolling horizon basis.

By examining long-run profitability by technology type, we can see how near-optimal solutions impact intra-producer wealth transfers. Figure 6.5 shows the average long-run profit of each technology type for the default pricing models (with MWP_D). Recall that in a convex market in long-run equilibrium, no producers would make a profit or loss. Here we see producers making both profits and losses due to lumpy investments, non-convex costs, and also the CP solution not necessarily being the long-run adapted mix for any particular non-convex pricing model. For primal-dependent models FCP and RPM, there is a notable downward trend of profits for all technology types as the solution's optimality improves. This mirrors the trend seen in total producer surplus in Figure 6.2. In this system, the relative profits of technology types do not vary substantially with optimality, but rather uniformly decrease, indicating there is not significant transfer of producer surplus between technology types. CHP provides the closest profits to achieve long-run cost recovery without overcompensation, but the peaking OCGT technology type still suffers a small loss in the long-run. Comparing long-run profits between the MWP_D and MWP_H scenarios in Figure 6.6, we see relatively small changes, as the MWP_D provide only a small amount of additional income.

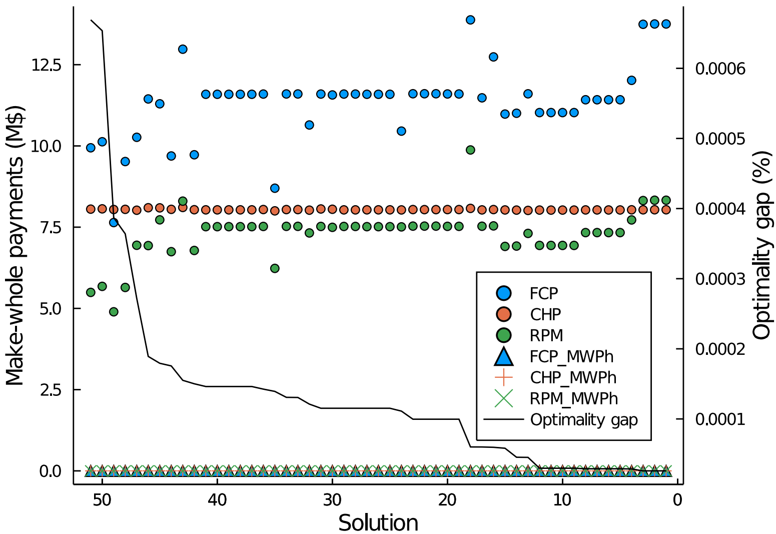


FIGURE 6.3: Make-whole payments across near-optimal solutions

6.5.4 *Comparison of Near-Optimal Solutions*

To understand why near-optimal solutions generally result in superior outcomes in consumer and producer surplus with increasing optimality, it

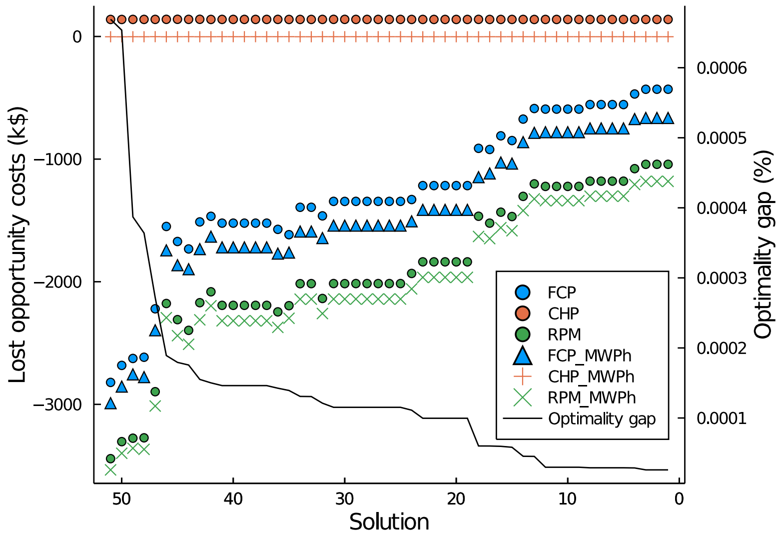


FIGURE 6.4: Remaining lost opportunity costs after transfer of any side payments across near-optimal solutions

is helpful to examine an illustrative day. Figure 6.7 shows the production schedule by technology type and the FCP market clearing price over a single day for the best solution found, Solution 1. Figure 6.8 shows the same for a solution with a higher optimality gap, Solution 50. Figure 6.9 shows the difference in unit commitment decisions and in cleared demand between these two solutions. The production schedules are largely similar. However, the two solutions make slightly different commitment decisions, leading to different levels of cleared demand and different prices in several evening hours, given in Table 6.3. In these hours, the price is being set by the elastic portion of demand in both solutions. Because Solution 1 clears a higher level of demand than Solution 50, the price is lower. This results in higher consumer surplus both from the higher benefit of cleared demand and the lower market clearing price. Conversely, producers receive less compensation than under Solution 50, which is less optimal and has a higher total producer surplus. The effect of the decreased production in Solution 50 is overpowered by the large increase in price, leading to an overall increase in producer surplus compared to Solution 1. Demand elasticity is an important driver of the magnitude of these results. In a long-run equilibrium setting with sufficiently price-responsive demand,

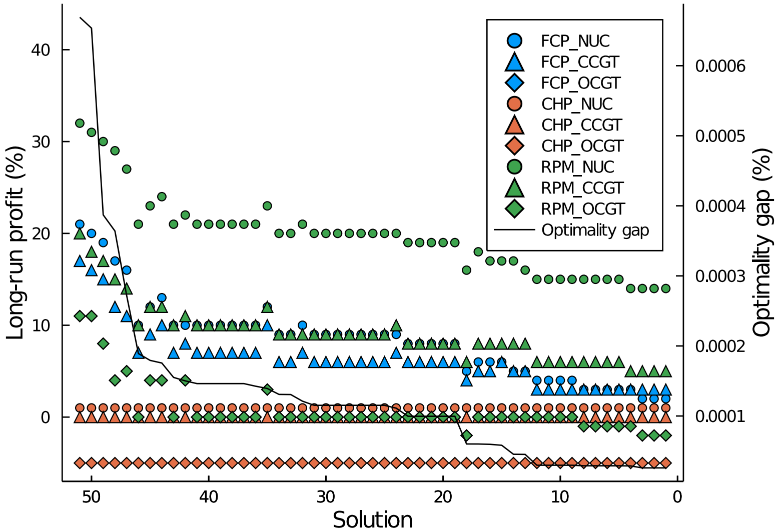


Figure 6.5: Long-run profits as percent of overall costs by technology type with MWP_D

demand sets the price fairly often, leading to many opportunities in which suboptimal commitment decisions might lead to lower cleared demand and thus higher market-clearing prices.

FCP ($/MWh)		
Hour	Solution 1	Solution 50
17	58.5	300.0
18	99.4	1200.0
19	250.0	1550.0
20	150.0	1000.0

Table 6.3: Comparison of market-clearing prices

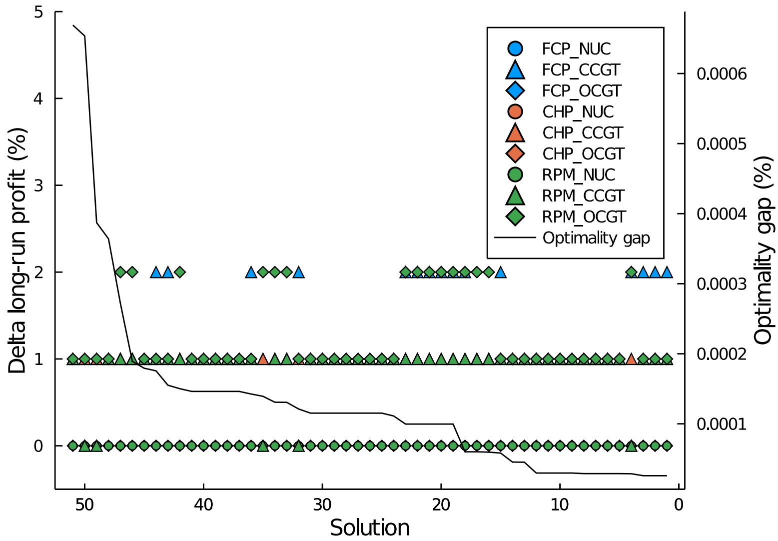


FIGURE 6.6: Long-run profits percentage point delta between MWP_D and MWP_H cases

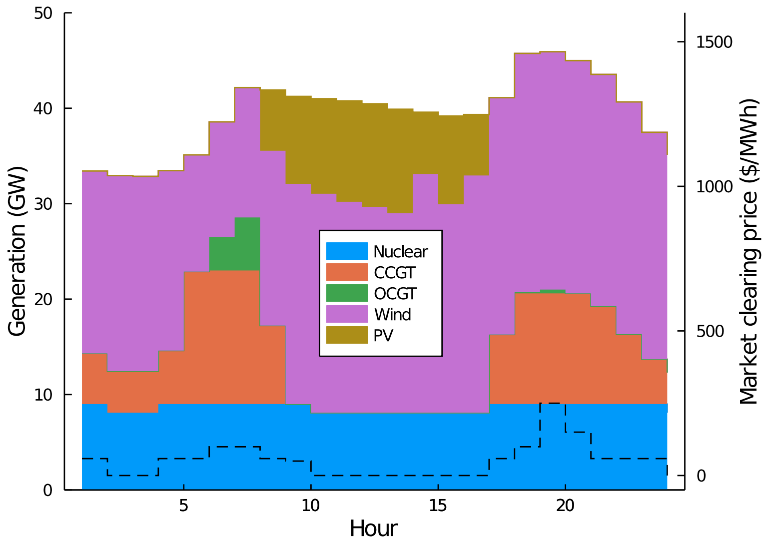


FIGURE 6.7: Production by technology type and FCP market-clearing price for Solution 1

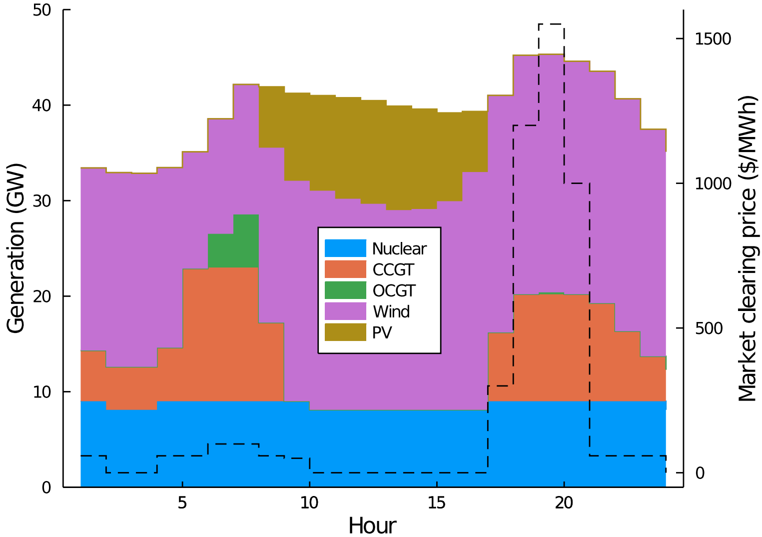


FIGURE 6.8: Production by technology type and FCP market-clearing price for Solution 50

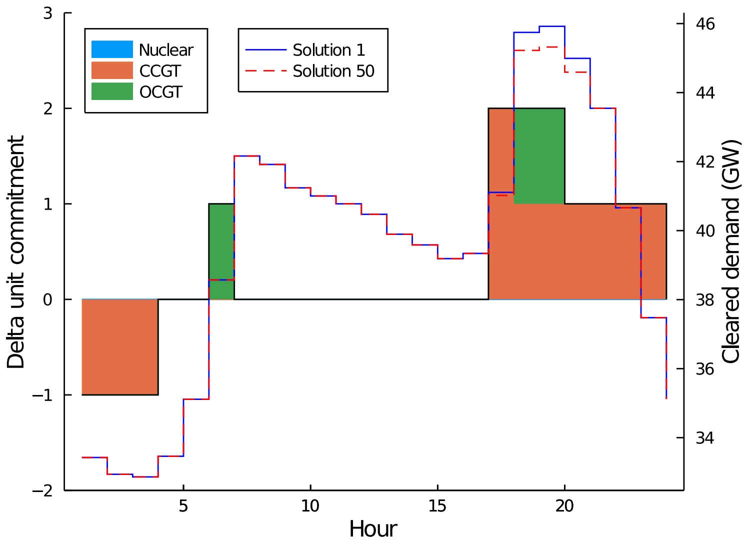


FIGURE 6.9: Difference between unit commitment and cleared demand in Solution 1 and Solution 50

6.6 CONCLUSION

We compare several non-convex pricing models with the goal of determining to what extent it is worth pursuing smaller MIP gaps in electricity market-clearing algorithms from a social welfare perspective and how this conclusion varies by pricing model. Using a long-run adapted resource mix with price-responsive demand, we find a non-monotonic but nevertheless significant trend in changes in consumer and producer surplus with optimality gap of the UC dispatch decision for some pricing models. For pricing models dependent on the primal solution, such as locational marginal pricing, consumer surplus generally increases with increasing optimality and producer surplus correspondingly decreases. These results are influenced highly by scarcity rent from price-setting elastic demand. Convex hull pricing does not depend on the primal solution, yielding a high consumer surplus across near-optimal solutions. We also find that short-run cost recovery can be achieved over longer time horizons without any make-whole payments in a long-run adapted system. This finding raises the question of to what extent make-whole payments in real-world markets are necessary for long-run cost recovery or if they may distort the important economic signal to exit in the long-run that negative profits provide.

In the long-run, excess producer profits or losses associated with higher MIP gaps in some non-convex pricing models may distort the optimal resource mix away from the central planner mix. Chapter 4 (also [14] provides evidence that the relationships between surplus and optimality gap hold for each pricing model in systems that are long-run adapted to each pricing model. There is also a trade-off between a desire to show a realistic test case with a large range of generator types and characteristics with the desire to perform an analysis in a long-run adapted equilibrium. Additional analysis is needed to examine if these results hold for a more diverse set of resources and over rolling horizons and multi-settlement markets. Further work may also employ a diversity criterion to ensure there is a good representation of the variety of near-optimal solutions that are possible. Finally, the impact of different demand elasticities on results should be explored. As energy and capacity market designs become more scrutinized with growing shares of VRE, there is a greater need to understand the role of near-optimal solutions and non-convex costs in electricity markets. This work provides some evidence that, particularly with the inclusion of price-responsive demand, small improvements in optimality may have significant positive effects on overall consumer and producer surplus.

7

AUCTION DESIGN AND INCENTIVE COMPATIBILITY

The system operator's scheduling problem in electricity markets, called unit commitment, is a non-convex mixed-integer program. The optimal value function is non-convex, preventing the application of traditional marginal pricing theory to find prices that clear the market and incentivize market participants to follow the dispatch schedule. Units that perceive the opportunity to make a profit may be incentivized to self-commit (submitting an offer with zero fixed operating costs) or self-schedule their production (submitting an offer with zero total cost). We simulate bidder behavior to show that market power can be exercised by self-committing/scheduling. Agents can learn to increase their profits via a reinforcement learning algorithm without explicit knowledge of the costs or strategies of other agents. We investigate different non-convex pricing models over a multi-period commitment window simulating the day-ahead market and show that convex hull pricing can reduce producer incentives to deviate from the central dispatch decision. In a realistic test system with approximately 1000 generators, we find strategic bidding under the restricted convex model can increase total producer profits by 4.4% and decrease lost opportunity costs by 2/3. While the cost to consumers with convex hull pricing is higher at the competitive solution, the cost to consumers is higher with the restricted convex model after strategic bidding.

7.1 INTRODUCTION

Price formation efforts in wholesale electricity markets are premised on assumptions of competitive market behavior such that all participants are price takers in the spot market. In short, the consequence is that offers submitted to the ISO reflect the actual marginal cost of each resource and the market clearing price is set by the marginal cost of the highest cost offer that the ISO accepts. The impact of these assumptions can be widespread: for example, studies on long-term investment often take this aspect of the spot market for granted. It is therefore important to critically assess whether wholesale electricity price formation policies currently support competitive behavior in the spot markets.

A growing literature on non-convex pricing has highlighted the absence of uniform market-clearing prices in practical wholesale electricity market scheduling problems [14], [51], [105], [109]. In addition to marginal production costs, conventional thermal generators also have avoidable fixed costs relating to their start-up, shut-down, and operating status, and opportunity costs related to minimum production level when they are online and the minimum up-time or down-time between start-up and shut-down decisions. The issue of non-convexities arises in markets that solve a mixed integer liner program (MILP) called the security constrained unit commitment (SCUC) problem to efficiently schedule conventional thermal generators during the day-ahead market [122], which is commonly implemented in the United States. An alternate market design in which participants attempt to internalize their non-convex costs in block orders (leading yet still to a non-convex problem for the market operator) is common in Europe [58]. It is typically not possible to determine a uniform market clearing price where all market participants are able to maximize their profit by following the socially optimal production schedule determined by the system operator.

The system operator solves an optimization problem with the operating constraints of the units and calculates uniform prices that are charged to all participants in the auction. Payments typically also include side payments to individual units to ensure that they suffer no short-run losses from following the central dispatch decision. However, ensuring no short-run losses does not guarantee that units will have no lost opportunity costs. Lost opportunity costs are the difference between a generator's preferred profit achieved when producing to maximize its profit in response to the price and the profit achieved when following the system operator's socially-optimal dispatch schedule. While the exercise of market power by offering untruthful bids is a concern in many markets [47], we show that that these lost opportunity costs may motivate market participants to bid strategically to improve their outcomes by offering their desired production quantity at zero cost. A generator in a non-convex market is able to exercise market power by self-committing/scheduling.

An ideal pricing mechanism achieves four properties. First, it achieves market efficiency by maximizing social welfare and resulting in an outcome from which no participant wishes to unilaterally deviate. Second, participants should recover their variable costs (although not necessarily their fixed capital costs) in the short-run. Third, it is revenue adequate. The amount of revenue recovered from consumers is at least as great as the amount of revenue paid to suppliers. Finally, the ideal pricing mechanism is incentive compatible: participants do best when offering their true preferences or costs. Each producer maximizes its own payoff by bidding its true supply costs, and no participants have an incentive to exercise market power by bidding strategically.

If the market is convex, i.e., the optimal value function seen by the market operator is convex, and participants must bid their true costs, then pricing at marginal cost yields an outcome that achieves market efficiency, cost recovery, and revenue adequacy. No participant faces a lost opportunity cost. The optimality conditions for the equilibrium market problem in which each participant seeks to optimize its individual benefit and the system operator's optimization problem seeking to optimize social welfare are equivalent, and thus the social-welfare maximizing outcome is the same as the market outcome. However, if the market is not perfectly competitive, it is possible for participants to bid strategically and increase their payoffs. Thus, marginal pricing does not guarantee incentive compatibility if the operator has imperfect information and producers can increase their supply offers above their true costs. In fact, no market-clearing mechanism ensures all four properties at the same time [40], [41]. A trade-off must be made, and alternative pricing methods may achieve different properties. While it is possible to ensure incentive compatibility with the the Vickrey–Clarke–Groves (VCG) mechanism, in which truthful bidding is the dominant strategy [44], revenue adequacy is no longer guaranteed, although strategies have been proposed to reduce the market operator's budget deficit [44], [45].

If a market has non-convex costs, often no uniform price can be found that supports the market operator's schedule, resulting in significant lost opportunity costs. A number of methods for pricing in the presence of non-convexities have been proposed. Authors in [29] propose relaxing integrality and fixing binary variables to the previously-found optimal values, a method we will call fixed configuration pricing (FCP). This can result in instances in which the generator that sets the price does not have the highest variable costs, and thus the price may decrease as demand increases. Lost opportunity costs may be high, i.e., generators may not be incentivized to follow the central dispatch decision. Another proposal by [55] called convex hull pricing (CHP) seeks to find a uniform price that minimizes lost opportunity costs. There is evidence this approach improves long-run incentives [14], [51], [109], [123], while [106] propose a new computationally tractable method using Dantzig-Wolfe decomposition to find exact convex hull prices.

While attention in incentive compatibility discussions is primarily given to economic offers [124]–[126], non-convex markets raise the possibility of increasing payoffs by submitting zero-cost supply offers for the desired level of production. A stylized test case proposed in [120], [127], replicated in Section 7.4, demonstrates that market power in non-convex markets can be exercised by self-committing. Some Nash equilibria strategies include zero-cost supply offers.

In electricity markets, the phenomenon of self-committing or self-scheduling by submitting offers below actual costs is widespread. A self-commitment is when a generator indicates to the system operator that it wishes to be dispatched at least at its minimum operating level regardless of the market price. From the operator's perspective, this equates to submitting an offer with zero costs up to the minimum operating level. Similarly, a self-schedule entails submitting an offer with zero costs up to the desired dispatch quantity. Self-commitment and self-schedules constitute approximately 40% of the energy market offers in the PJM market [128]. We can characterize a self-commitment or self-schedule offers as benign or adverse, depending on whether it reduces market efficiency. Benign offers may be submitted if a resource's startup or notification time exceeds the window of the 24-hour day-ahead market, to avoid transaction costs of gathering cost information for units that are very likely to be dispatched, or because of take-or-pay fuel contracts that render some portion of the generator's output a sunk cost. However, an adverse offer would result in greater profits in expectation for a generator than if the generator had submitted an economic bid reflective of its true costs. It is unclear how many (if any) adverse self-commitments and self-schedules exist, as such a strategy may be difficult to detect by conventional market power mitigation software. Nevertheless, adverse self-commitment and self-schedules could result in lower market efficiency if they cause the system operator to find a suboptimal dispatch decision due to the distorted costs. To disincentivize inefficient behavior, generators that self-commit or self-schedule are typically not eligible for make-whole payments. Notably, the type of units found to strategically self-commit in [127] share similar characteristics to the coal generators that often self-commit in reality [129], namely that they are "inflexible, relatively expensive, and mostly profitable" [127].

Authors in [120], [127] demonstrate the ability of generators to strategically self-commit in a stylized test system with a single operating time period. The question remains as to whether generators could determine optimal strategies in a more realistic system with many different generator attributes across a multi-period optimization horizon. Self-commitment and self-scheduling allows "out-of-merit" resources to enter the SCUC solution yet remain profitable; each out-of-merit commitment and dispatch may cause a cascading change in market prices and the commitment and dispatch of other resources in the market. The outcome cannot be be explicitly modeled by individual participants in realistically sized markets. To avoid this issue, we show that market agents can implicitly identify profitable self-commitment and -scheduling strategies via simple reinforcement learning algorithms, i.e., without using a sophisticated model for how an agent's self-commitment or self-scheduling will affect the SCUC solution. We investigate the ability of participants to learn to improve outcomes by self-scheduling or self-committing via a reinforcement learning algorithm in a large-scale test system over an operating day, simulating a day-ahead market. We examine two competing pricing models, showing that the ability of generators to adversely self-commit or self-schedule is decreased with convex hull pricing.

7.2 PRICING MODELS

A simple unit commitment problem with variable cost C, startup cost F, production p, and commitment status u linked to startup decision z with inelastic demand is formulated as:

$$\min_{u, p \in \mathcal{P}} \quad \sum_{t \in T} \sum_{g \in G} (C_g p_{tg} + F_g z_{tg}) \tag{7.1a}$$

$$\text{s.t.} \quad \sum_{g \in G} p_{tg} = D \quad \forall t \in T \tag{7.1b}$$

$$u \in \{0, 1\} \tag{7.1c}$$

where $\mathcal{P}$ is the set of operating constraints.

For a price signal λ^* to incentivize an agent to follow the system operator's dispatch decision p^*, the production quantity must solve a function that maximizes each generator's profits given λ^*:

$$\max_{p_g, u_g} \quad \Pi_g(\lambda^*, p_g, u_g) \quad \forall g \in G \tag{7.2}$$

With market-clearing prices λ, variable costs C, startup costs F, startup decision z linked to commitment status u, and side payments s, initial short-run profit Π^0 and final short-run profit Π are defined as:

$$\Pi_g^0 := \sum_{t \in T} ((\lambda_t - C_g) p_{tg} - F_g z_{tg}) \tag{7.3}$$

$$\Pi_g := \Pi_g + \sum_{t \in T} s_{tg} \tag{7.4}$$

Perceived losses are lost opportunity costs (LOC), the difference between what a unit could make given a price if able to schedule its own dispatch (its preferred profit) and what it would make with the same price following the centralized dispatch decision, plus any additional compensation received as side payments. We define initial lost opportunity costs LOC^0 without side payments and final LOC as:

$$LOC_g^0 := \max_{u_g, p_g} \quad \Pi_g^0(\lambda^*, u_g, p_g) - \Pi_g^0(\lambda^*, u_g^*, p_g^*) \tag{7.5}$$

$$LOC_g := LOC_g^0 + \sum_{t \in T} s_{tg} \tag{7.6}$$

Provided the unit could choose to not produce, a subset of LOC^0 is make-whole payments (MWP), the revenue required for short-run cost recovery.

This occurs when the unit would prefer to not operate at the market-clearing price. MWP are typically determined for the same timescale at the day-ahead market, i.e., for each 24-hour period:

$$MWP_g := -\min(0, \Pi_g^0(\lambda^*, u^*, p^*)) \tag{7.7}$$

Prices cannot be derived directly from the unit commitment problem without relaxation. The method proposed in [29] fixes the binary variables in the to their optimal values and then computes prices λ from the Lagrangian multipliers of the resulting linear program. We call this method fixed configuration pricing (FCP).

$$\min_{u,p \in \mathcal{P}} \quad \sum_{t\in T}\sum_{g\in G}(C_g p_{tg} + F_g z_{tg}) \tag{7.8a}$$

$$\text{s.t.} \quad \sum_{g\in G} p_{tg} = D \quad \forall t \in T \quad : \lambda_t \tag{7.8b}$$

$$u = u^* \tag{7.8c}$$

$$u \in [0,1] \tag{7.8d}$$

An alternative model seeks to find the uniform price that minimizes lost opportunity costs, deriving prices from the convex hull of the optimal value function. In convex hull pricing (CHP), prices are determined by solving the Lagrangian dual of the UC problem. Approximate CHP (aCHP) can be calculated by identifying a close approximation of the convex hull of the primal UC problem [57]. If a good approximation can be found, aCHP prices λ are given by simply relaxing the binary variables:

$$\min_{\{u,p\} \in \mathcal{P}} \quad \sum_{t\in T}\sum_{g\in G}(C_g p_{tg} + F_g z_{tg}) \tag{7.9a}$$

$$\text{s.t.} \quad \sum_{g\in G} p_{tg} = D \quad \forall t \in T \quad : \lambda_t \tag{7.9b}$$

$$u \in [0,1] \tag{7.9c}$$

7.3 METHODOLOGY

7.3.1 *Unit Commitment Model*

The unit commitment problem to be solved in each iteration is given below. The short-run profit for each generator g is:

$$\Pi_g^0 := \sum_{t \in T} (\lambda_t p_{tg} - \sum_{s \in S} C_{gs} \rho_{tgs} - H_g u_{tg} - F_g z_{tg}) \tag{7.10}$$

Nomenclature

Indices and Sets

$g \in G$	Set of generators
$G^T \subseteq G$	Set of thermal generators
$G^V \subseteq G$	Set of VRE resources
$t \in T$	Set of time periods (hours)
$s \in S$	Set of offer steps

Parameters

C_{gs}	Variable cost in offer step s (\$/MWh)
F_g	Startup cost (\$)
H_g	No load cost (\$)
P_g^{min}	Minimum operating capacity (MW)
P_{gs}^{max}	Maximum operating capacity of offer step s (MW)
M_g^{on}	Minimum on time (h)
M_g^{off}	Minimum off time (h)
R_g^+	Maximum ramp up rate (MW/h)
R_g^-	Maximum ramp down rate (MW/h)
$\mathcal{P}_{tg}$	Maximum output for VRE resource (MW)
D_t	Maximum quantity of demand bids at time t (MW)
U_g^{init}	Initial status of generator (Binary)

Variables

p_{tg}	Committed generation for generator g at time t (MW)
ρ_{tgs}	Generation for generator g in offer step s at time t (MW)
u_{tg}	(Binary) commitment status for generator g at time t
z_{tg}	(Binary) startup decision for generator g at time t
y_{tg}	(Binary) shutdown decision for generator g at time t
n_t	Non-served energy at time t (MW)

Formulation

$$\min_{(p,\rho,u,z,y)} \quad \sum_{t\in T}\sum_{g\in G}\left(\sum_{s\in S}(C_{gs}\rho_{tgs}) + H_g u_{tg} + F_g z_{tg}\right) + \sum_{t\in T} n_t \tag{7.11a}$$

s.t.

$$\sum_{g\in G} p_{tg} + n_t = D_t \qquad \forall t \in T \tag{7.11b}$$

$$\sum_{s\in S} \rho_{tgs} = p_{tg} \qquad \forall t \in T, g \in G \tag{7.11c}$$

$$z_{tg} + y_{tg} \leq 1 \qquad \forall t \in T, g \in G^T \tag{7.11d}$$

$$u_{tg} - u_{t-1,g} = z_{tg} - y_{tg} \qquad \forall t \in 2, ..., T, g \in G^T \tag{7.11e}$$

$$z_{tg} = u_{tg} \qquad \forall t = 1, g \in G^T : U_g^{init} = 0 \tag{7.11f}$$

$$z_{tg} = 0 \qquad \forall t = 1, g \in G^T : U_g^{init} = 1 \tag{7.11g}$$

$$z_{tg} + \sum_{t'=t+1}^{\min(t+M_g^{on}-1,T)} y_{t'g} \leq 1 \qquad \forall t \in 1, ..., T-1, g \in G^T : M_g^{on} > 1 \tag{7.11h}$$

$$y_{tg} + \sum_{t'=t+1}^{\min(t+M_g^{off}-1,T)} z_{t'g} \leq 1 \qquad \forall t \in 1, ..., T-1, g \in G^T : M_g^{off} > 1 \tag{7.11i}$$

$$P_g^{min} u_{tg} \leq p_{tg} \qquad \forall t \in T, g \in G^T \tag{7.11j}$$

$$\rho_{tgs} \leq P_{gs}^{max} u_{tg} \qquad \forall t \in T, g \in G^T, s \in S \tag{7.11k}$$

$$0 \leq p_{tg} \leq \mathcal{P}_{tg} \qquad \forall t \in T, g \in G^V \tag{7.11l}$$

$$p_{tg} \geq 0 \qquad \forall t \in T, g \in G \tag{7.11m}$$

$$u_{tg}, z_{tg}, y_{tg} \in \{0,1\} \qquad \forall t \in T, g \in G^T \tag{7.11n}$$

$$x_g \in \{0,1\} \qquad \forall g \in G^T \tag{7.110}$$

We assume generators can ramp up to or down from P^{min} during startup or shutdown. We use tight UC constraints in attempt to better approximate the convex hull of the optimal value function when relaxing binary variables [130]. Ramping constraints are implemented as the two-period ramp inequalities proposed in [131]:

$$p_{tg} \leq p_{t-1,g} + (P_g^{min} + R_g^+)u_{tg} - P_g^{min}u_{t-1,g} - R_g^+ z_{tg} \qquad \forall t = 2,...,T, g \in G^T \tag{7.12}$$

$$p_{t-1,g} \leq p_{t,g} + (P_g^{min} + R_g^-)u_{t-1,g} - P_g^{min}u_{t,g} - R_g^- y_{tg} \qquad \forall t = 2,...,T, g \in G^T \tag{7.13}$$

Let $P_g^{MAX} = \sum_{s \in S} P_{gs}^{max}$, the maximum capacity of generator g. We implement the following constraints from [132] that serve only to tighten the UC formulation:

$$p_{tg} \leq P_g^{MAX}u_{tg} - (P_g^{MAX} - P_g^{min})y_{t+1,g} \qquad \forall t = 1, g \in G^T \tag{7.14}$$

$$p_{tg} \leq P_g^{MAX}u_{tg} - (P_g^{MAX} - P_g^{min})z_{t,g} - (P_g^{MAX} - P_g^{min})y_{t+1,g} \qquad \forall t = 2,...,T-1, g \in G^T : M_g^{on} \geq 2 \tag{7.15}$$

$$p_{tg} \leq P_g^{MAX}u_{tg} - (P_g^{MAX} - P_g^{min})z_{t,g} \qquad \forall t = T, g \in G^T \tag{7.16}$$

$$p_{tg} \leq P_g^{MAX}u_{tg} - (P_g^{MAX} - P_g^{min})z_{t,g} \qquad \forall t = 2,...,T-1, g \in G^T : M_g^{on} < 2 \tag{7.17}$$

$$p_{tg} \leq P_g^{MAX}u_{tg} - (P_g^{MAX} - P_g^{min})y_{t+1,g} \qquad \forall t = 2,...,T-1, g \in G^T : M_g^{on} < 2 \tag{7.18}$$

7.3.2 *Offer Strategies*

In order for generators to bid strategically, the no load costs, startup costs, and variable cost in each offer step are further indexed by t. Generators can choose between three different offer strategies:

- **Economic**: The generator submits its true costs and is eligible for make-whole payments.
- **Self-commit**: For each time period in which the generator wishes to self-commit, it submits an offer with zero startup and no-load costs, and no variable costs up to P^{min}. Variable costs beyond the minimum generation level are submitted economically. The generator is not eligible for make-whole payments.
- **Self-schedule**: For each time period in which the generator wishes to self-schedule, it submits an offer with zero startup and no-load costs, and no variable costs up to the desired dispatch quantity p^*_{tg}. Variable costs above $P^m in$ are retained as economic offers, i.e., a generator is willing to be scheduled above its preferred schedule but submits an offer at its true cost. If a generator wishes to be scheduled for $p^*_{tg} < \sum_{s=1,...,S^*} \rho_{tgs}$, then the variable cost of generation C_{gS^*} is submitted for offers between p^*_{tg} and $\sum_{s=1,...,S^*} \rho_{tgs}$. The generator is not eligible for make-whole payments.

We refer to strategic bids collectively as self-schedules or self-commits. This method of defining self-schedules and self-commits guarantees that no matter how many generators bid strategically, the system operator's problem is still feasible. Note that the only side payments generators can receive are make-whole payments in the case of an economic bid. Lost opportunity costs are never explicitly compensated, and doing so may create a revenue adequacy problem for the system operator. If lost opportunity costs were paid in full, under convex hull pricing there would be an incentive to submit arbitrarily large bids of zero price that must be accepted entirely if at all [58]. Future research could use the approach outlined here to include non-truthful cost offers exaggerating marginal costs as additional strategies.

7.3.3 *Greedy Algorithm*

The generators' problem of choosing what offer strategy to bid is a multi-armed bandit problem. In a multi-armed bandit problem, a set of discrete choices results in uncertain, random payoffs. The bandit (gambler) seeks to find a strategy that maximizes payoff. Each generator must determine how to bid based on the profitability of each strategy determined in previous outcomes, which depends on the offer strategies of other generators. One method to solve the multi-armed bandit problem is via the greedy reinforcement learning algorithm [133], [134]. Drawing from a history of prior outcomes, the greedy algorithm chooses the best strategy in expectation with probability α and chooses a strategy at random with probability $1 - \alpha$.

In the first iteration of the simulation, all generators bid economically, representing the competitive market solution. Afterwards the generators explore other strategies randomly with probability $1 - alpha$. If the expected payoff is equivalent between a strategic bid and an economic bid, the generator defaults to bidding economically.

7.3.4 *Exponential Smoothing*

The expected profit of a strategy is calculated via exponential smoothing with parameter η. Let x be a vector of values to be smoothed indexed by t of length T. The expected value of x is s_T, where s_t is calculated as:

$$s_1 = x_1 \tag{7.19}$$

$$s_t = \eta x_t + (1 - \eta) s_{t-1} \quad \forall t \geq 2 \tag{7.20}$$

In order to determine when in a multi-period optimization horizon to self-commit or self-schedule, a generator must determine an expected price stream for a given strategy. To calculate the expected prices, the price λ_t in a given period is exponentially smoothed across all iterations in which the generator chose the given strategy.

7.3.5 *Adverse Bidding Test*

We define a strategic bid as adverse if bidding strategically increases the expected profits of a generator. For an adverse bidder, either $\overline{X}_{selfcomm} - \overline{X}_{eco} > 0$ or $\overline{X}_{selfsched} - \overline{X}_{eco} > 0$. Note that an adverse bid may result in an increase in total production costs and thus a decrease in market efficiency, but it may also represent a transfer of profits among generators without impacting the total social surplus achieved. The payoffs a generator makes are influenced not only by its bidding decision but the bidding decisions of the other generators. A generator may learn to bid strategically based on profits achieved due to the bidding strategy of others. To determine if a strategic bidder is actually able to increase its profits via its own offer strategy, we use the an unequal variance two-sample t-test, also known as Welch's t-test.

Welch's t-test tests the null hypothesis that two sets of samples come from distributions with equal means against the alternative hypothesis that the distributions have different means. Like Student's t-test, it assumes the sample means being compared are normally distributed, but unlike Student's t-test, it does not assume that the populations have equal variances. It is more reliable than Student's t-test when the samples have unequal variances and unequal sample sizes [135].

The test statistic t is defined as:

$$t = \frac{\Delta\overline{X}}{s_{\Delta\overline{X}}} = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{s^2_{\overline{X}_1} + s^2_{\overline{X}_2}}} \tag{7.21}$$

$$s_{\overline{X}_i} = \frac{s_i}{\sqrt{N_i}} \tag{7.22}$$

where $\overline{X}_i$ and $s_{\overline{X}_i}$ is the sample mean and its standard error, s_i is the corrected sample standard deviation, and N_i is the sample size. In the analysis that follows, we use a p-value of 0.05.

7.4 ILLUSTRATIVE TEST CASE

Authors in [120], [127] propose a stylized test case in which the Nash equilibria strategies can be found analytically. We use this test case for three scenarios: a single-period case $|T| = 1$ with demand profile D_1, a multi-period case with $|T| = 10$ and constant demand profile D_1, and a multi-period cast $|T| = 1$ with fluctuating demand profile D_2. The case consists of 3 types of generators with characteristics given in Table 7.1.

Gen. $i \in \{1, ..., 5\}$	P_{hi}^{min} (MW)	P_{hi}^{max} (MW)	C_{hi} (\$/MWh)
GEN1$_i$	25	25	15
GEN2$_i$	0	25	10
GEN3$_i$	0	25	25

TABLE 7.1: Illustrative test case generator characteristics

Generators types GEN2 and GEN3 are convex with only a marginal cost, while type GEN1 is block-loaded, making the optimal value function of this system non-convex. Let the demand level be $225 + \epsilon$ MW, where $\epsilon > 0$ and negligibly small.

Under the FCP model, the price is \$25 for the socially optimal solutions in which any 4 GEN1s are committed as well as for any integer solution in which less than 4 of the 5 GEN1s self-commit. If all 5 GEN1s self-commit, the price decreases to \$10, and the total actual production costs to serve load increase, leading to a decrease in market efficiency. If 4 of the 5 GEN1s are committed, the 5^{th} has a LOC of $-\$250$, as it would prefer to be committed given the price of \$25.[1] If all GEN1s self-commit and the price drops to \$10, then each suffers a loss, with a payoff of -\$125. Let γ_{hi} be the probability that a generator self-commits. Assuming there is no collusion, the mixed strategy Nash equilibrium can be found analytically to be $\gamma_{1i} = 0.831$ $\forall i \in \{1, ..., 5\}$ [120]. There are also five fixed asymmetric strategies in which 4 of the 5 generators self-commit and one does not. In contrast, under the CHP model, the price is \$15, and the GEN1s have no incentive to self-schedule, as their profits are always 0.

We replicate the above example and show that the simulations converge on one of the Nash equilibria with fixed asymmetric strategies. The single-period scenario $|T| = 1$ has demand profile D_1. Removing all constraints in (7.11) for which $t > 1$, we simulate the market using greedy $\alpha = 0.9$ and exponential smoothing $\eta = 0.05$ over 2000 iterations.

Recall that the first iteration is the competitive solution in which all generators bid economically. Figure 7.1 shows that actual total producer costs do not increase above the competitive solution once strategic bidding is allowed. The system operator never selects a suboptimal solution due to the strategic bidding. The generators are also not able to increase total producer profits by strategic bidding. Since demand is inelastic and all demand is served, no increase in producer profits implies no increase in the cost to consumers, shown in Figure 7.2. When all GEN1s self-commit/schedule, the price drops to \$10 and no make-whole payments are required, leading to lower costs to consumers and lower producer profits in these iterations.

The number of times each generator selects each offer strategy over the simulation period is shown in Figure 7.3. Under the FCP model, 4 of

1 The convention used here is to display LOC as the perceived profit or loss. A perceived loss is negative. A perceived profit is possible if a side payment was given in excess of perceived losses, e.g., if CHP were calculated over a different time period than MWP.

the 5 GEN1s learn to self-commit (or, equivalently, self-schedule, as the unit is block-loaded) while the GEN1_1 learns to bid economically. GEN1s collectively self-commit/schedule 78.4% of the time over the final 1000 iterations. A number of GEN2s self-commit or self-schedule more than the random exploratory probability $(1 - \alpha)/3$. However, this does not mean that they learn to strategically bid because they are necessarily able to influence the price. A GEN2 may bid strategically and see a bigger payoff (or bid economically and see a smaller payoff) incidentally because of the behavior of GEN1s in that iteration. However, no GEN2 obtains mean profits self-committing or self-scheduling that are statistically significantly greater than the mean profits from bidding economically.

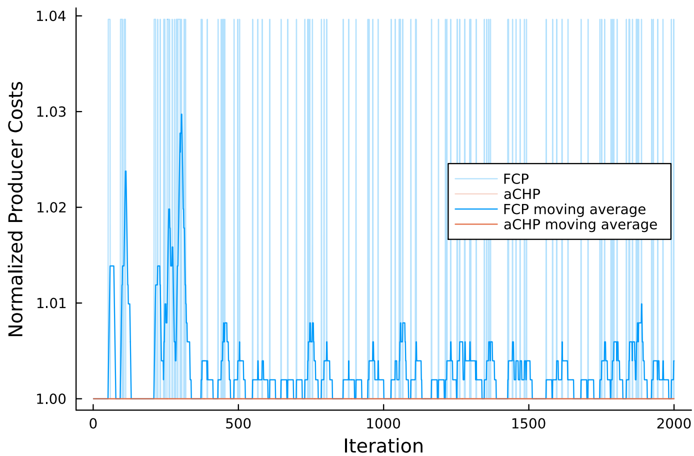


FIGURE 7.1: $|T| = 1$, D_1 Total actual production cost normalized by production cost at the competitive solution in which all generators bid economically. Higher producer costs indicate the system operator selected a suboptimal solution due to strategic bids.

A generator is said to be an adverse strategic bidder if it profits in expectation from bidding strategically rather than bidding economically in a statistically significant manner. Either $\overline{X}_{selfcomm} - \overline{X}_{eco} > 0$ or $\overline{X}_{selfsched} - \overline{X}_{eco} > 0$ and the p-value from the corresponding Welch's t-test is > 0.05. Table 7.2 and Table 7.3 show the number of adverse strategic bidders under the FCP and aCHP models. For the FCP model, 4 of the GEN1s are statistically significant adverse strategic bidders, while 0 of the GEN2s are. Under the aCHP model, no generators pass the statistical significance test.

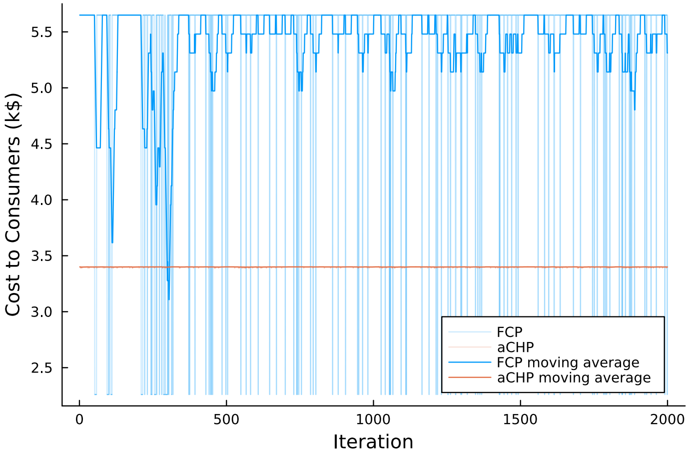


Figure 7.2: $|T| = 1$, D_1. Cost to consumers for each pricing model over iterations.

	Number		
	$\overline{X}_{eco} < (\overline{X}_{selfsched}$ OR $\overline{X}_{selfcomm})$ and $p < 0.05$		
Gen. $i \in \{1,...,5\}$	$\|T\| = 1$, D_1	$\|T\| = 10$, D_1	$\|T\| = 10$, D_2
$GEN1_i$	4	4	5
$GEN2_i$	0	0	3
$GEN3_i$	0	0	0

Table 7.2: Adverse Strategic Bids (FCP)

Excess profit is defined as the difference for strategic generators between the mean profit for the strategic bidding strategy with the highest payoff (either $\overline{X}_{selfcomm}$ or $\overline{X}_{selfsched}$) and $\overline{X}_{eco}$, the mean profit when bidding economically. The total excess profit among all adverse strategic bidders is shown as a percentage of the total producer profits in the competitive solution in which all generators bid economically for each pricing model in Table 7.4. Note that it is typically not possible for generators to realize their excess profit simultaneously, but this figure gives a sense of the magnitude of the profit opportunity for strategic bidders in the market. Excess profits under FCP are 24.4%, while there are no excess profits under aCHP.

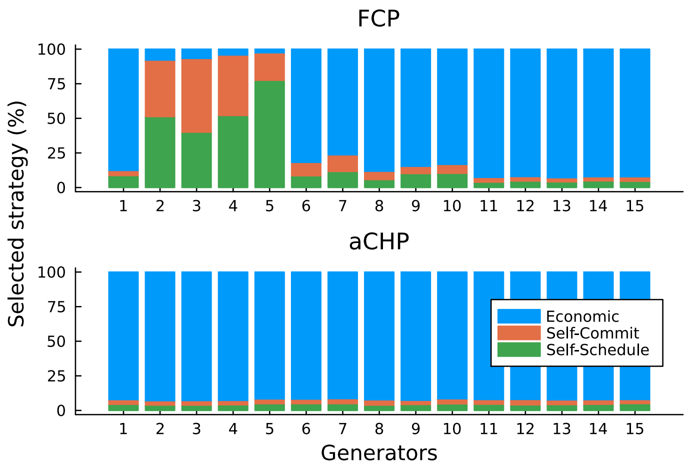


FIGURE 7.3: $|T| = 1$, D_1. Percent of iterations that a generator chose each offer strategy.

Figure 7.4 shows the profit duration curve for generators at the competitive solution and the mean profits made in simulation with each bidding strategy. In the competitive solution, all GEN2s are committed and make the highest profits \$(25-10)$(D_1 + \epsilon)$, while 4 of the GEN1s are committed and make a profit \$(25-15)$(D_1 + \epsilon)$, with 1 GEN1 not committed and making no profit. One GEN3 is committed to clear demand ϵ but makes no profit. Under the aCHP model, all generators have the same payoff as under the competitive solution regardless of bidding strategy, with the exception of the marginal GEN3 that discovers self-committing or self-scheduling will entail a loss.

	Number		
	$\overline{X}_{eco} < (\overline{X}_{selfsched}$ OR $\overline{X}_{selfcomm})$ and $p < 0.05$		
Gen. $i \in \{1,...,5\}$	$\lvert T\rvert = 1$, D_1	$\lvert T\rvert = 10$, D_1	$\lvert T\rvert = 10$, D_2
GEN1$_i$	0	0	0
GEN2$_i$	0	0	3
GEN3$_i$	0	0	0

TABLE 7.3: Adverse Strategic Bids (aCHP)

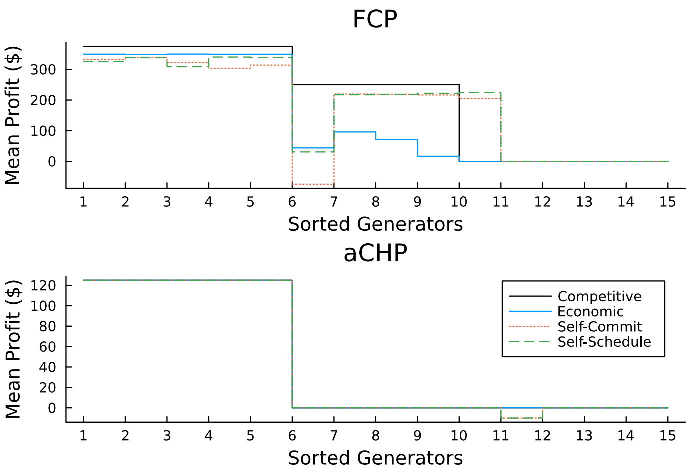


FIGURE 7.4: $|T| = 1$, D_1 Profit duration curve. Generators are sorted by profit achieved in the competitive outcome in which all generators submit economic bids. The mean profit achieved for each strategy in simulation is also shown.

	Total excess profit (% competitive profits)		
Pricing Model	$\lvert T\rvert = 1$, D_1	$\lvert T\rvert = 10$, D_1	$\lvert T\rvert = 10$, D_2
FCP	24.4%	20.9%	13.6%
aCHP	0%	0%	0.08%

TABLE 7.4: Adverse Strategic Bids Payoffs

For FCP, the GEN2s do best by bidding economically, but suffer a loss in expectation compared to the competitive solution due to GEN1 strategic behavior sometimes lowering the price to $10 from $25. A profit transfer takes place among the GEN1s, in which a generator that is committed in the competitive solution and profits is shut out by the other four generators' strategic behavior.

Next, we expand this market into a multi-period market, assuming no binding ramping constraints. The market has constant demand D_1 of 225 + ϵ, where $\epsilon = 1$ MW, yielding the same price possibilities as the prior example. The competitive prices and the prices found in simulation with strategic bidding are shown in Figure 7.6.

While the learning behavior shown in Figure 7.5 appears different than when $|T| = 1$, Tables 7.2 and 7.3 show that the number of statistically significant adverse bidders in each pricing model is equivalent. A different asymmetric Nash equilibrium is found in which GEN14 bids economically and all others bid strategically. GENS1s collectively self-commit/schedule 78.5% of the time over the final 1000 iterations and excess profits shown in Table 7.4 are similar to $|T| = 1$.

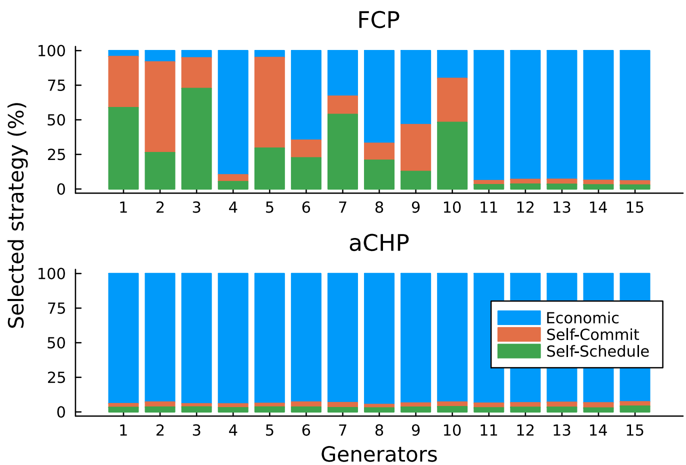


FIGURE 7.5: $|T| = 10$, D_1. Percent of iterations that a generator chose each offer strategy.

Next we vary the demand, with demand profile D_2 shown in Figure 7.7 and $|T| = 10$. This yields the competitive and strategic bidding prices shown in Figure 7.8. The lost opportunity costs for aCHP are lower than FCP, as shown in Figure 7.9.

The total producer costs normalized by the costs in the competitive solution are shown in Figure 7.10. Strategic bidding with FCP can increase actual producer costs by over 1.5%, but on average only increases costs slightly ($< 0.5\%$).

Figure 7.11 shows the percent of iterations each generator chose each strategy. The number of adverse bidders is again shown in Tables 7.2 and 7.3. Under FCP, GEN1s all are adverse strategic bidders, collectively self-

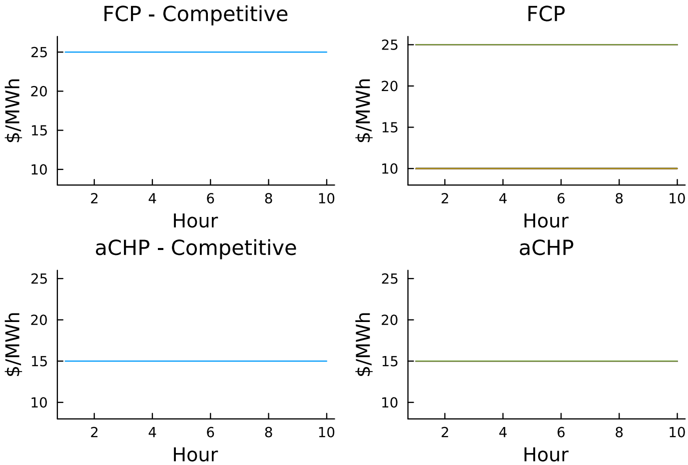


Figure 7.6: $|T| = 10$, D_1. Prices attained under the competitive solution in which all generators bid economically and prices attained over all iterations of strategic bidding.

committing/scheduling 64.7% of the time over the final 1000 iterations. GEN2s collectively self-schedule or self-commit 62.0% of the final 1000 iterations. All 5 GEN1s are statistically significant adverse bidders, but only 3 of the 5 GEN2s are. Self-committing is profitable for 2 GEN2s but self-scheduling is profitable for 3. Under aCHP, 3 GEN2s also learn to profitably bid strategically by self-scheduling, but the payoff is very small. The total excess profit as a percentage of the competitive profits for FCP is 13.6%, while it is only 0.08% for aCHP, shown in Table 7.4. The profit duration curve at the competitive solution is shown in Figure 7.12. While the mean profits vary little under aCHP no matter the offer strategy, the mean profits attained for each strategy under FCP vary considerably.

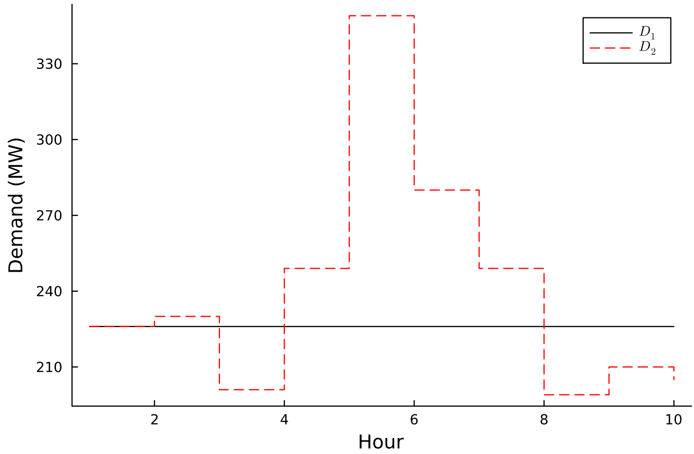


Figure 7.7: Demand profiles.

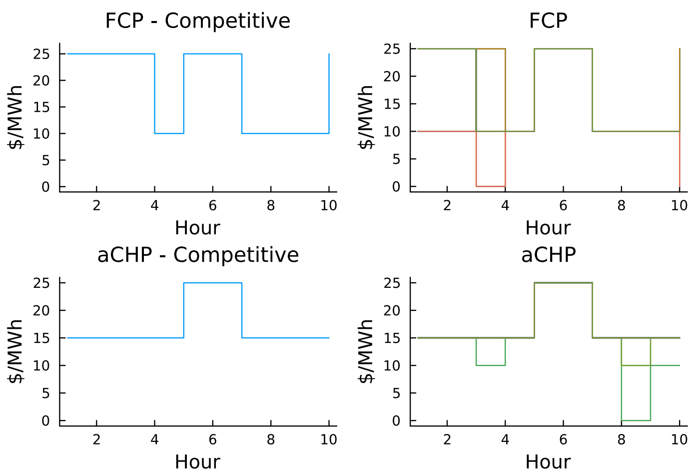


Figure 7.8: $|T| = 10$, D_2. Prices attained under the competitive solution in which all generators bid economically and prices attained over all iterations of strategic bidding.

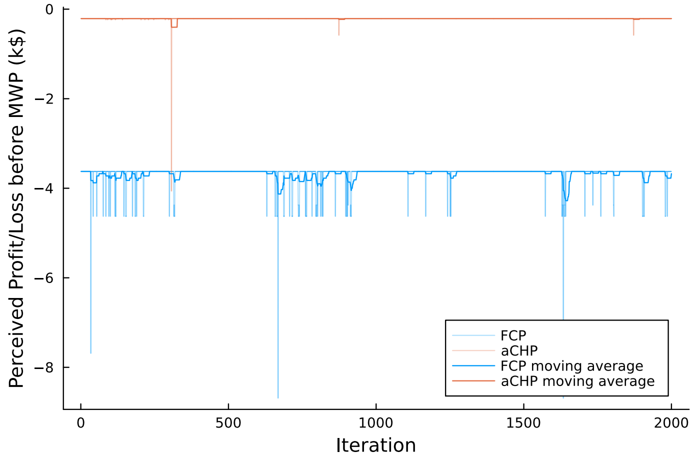


FIGURE 7.9: $|T| = 10$, D_2. Lost opportunity cost displayed as perceived profit or loss before MWP.

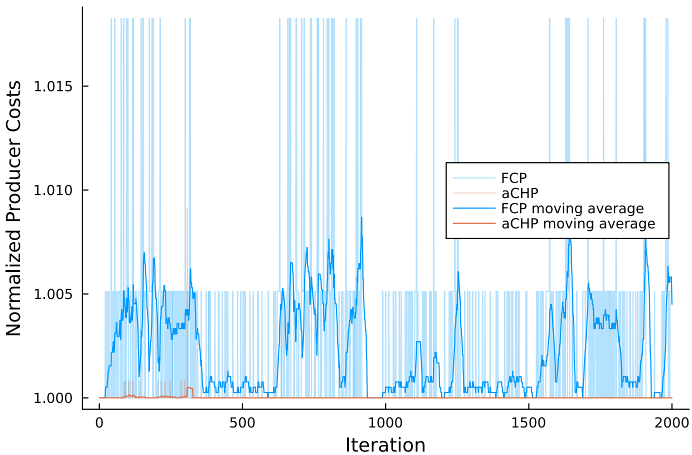


FIGURE 7.10: $|T| = 10$, D_2 Total actual production cost normalized by production cost at the competitive solution in which all generators bid economically.

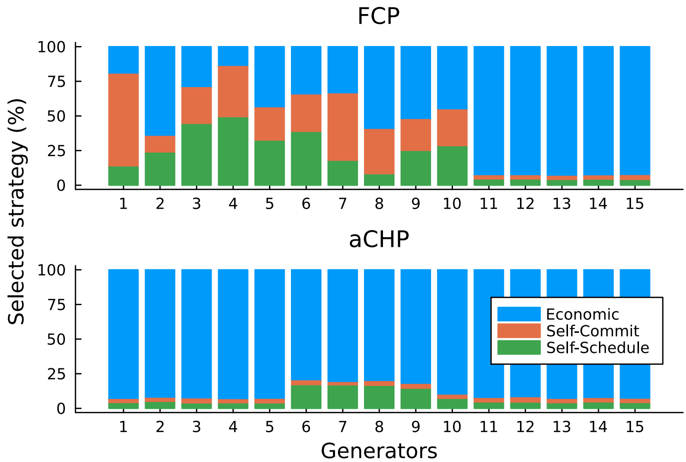


FIGURE 7.11: $|T| = 10$, D_2. Percent of iterations that a generator chose each offer strategy.

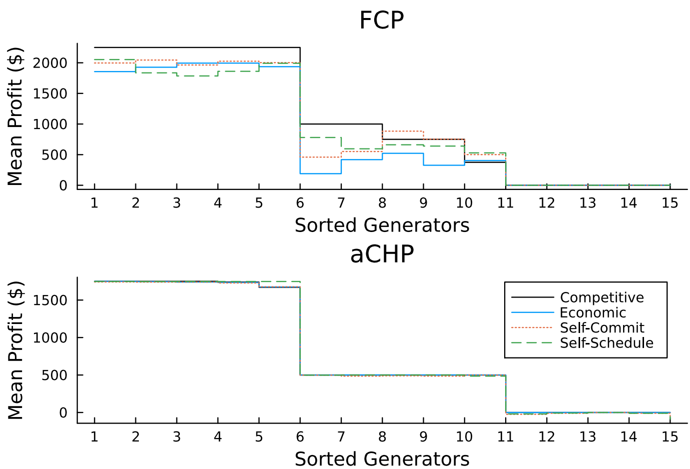


FIGURE 7.12: $|T| = 10$, D_2 Profit duration curve. Generators are sorted by profit achieved in the competitive outcome in which all generators submit economic bids.

7.5 LARGE-SCALE TEST CASE

7.5.1 *Data*

Data for the large-scale test system come from a benchmark library curated and maintained by the IEEE PES Task Force on Benchmarks for Validation of Emerging Power System Algorithms [136]. We simulate several days from the FERC test cases [137], [138]. Generator data are based on the publicly available unit commitment test instance from the Federal Energy Regulatory Commission (FERC) consisting of approximately 1000 generators with load and wind data based on publicly available data from PJM. Each case includes an aggregated variable renewable energy (VRE) generator. This is a wind profile that is scaled to be 2% of annual load in the low wind scenarios and 30% in the high wind scenarios. Transmission constraints are omitted due to lack of data availability but are an important avenue for future research.

Generators have up to 12 offer steps S, and marginal costs in each offer step were calculated from cumulative costs in each offer step. Block loaded units are assumed to have no no-load costs. The variable cost from 0 to P^{min} is assumed to be the same variable cost as in the first offer step above P^{min}, with the remainder as no-load cost. If this is infeasible (e.g., if the no-load cost would be negative), there is assumed to be no no-load cost, and the variable cost between 0 and P^{min} is the cumulative cost to produce at P^{min} divided by P^{min}.

The three cases considered are shown in Table 7.5. FERC1 and FERC3 are high wind cases, while FERC 2 is the low wind version of FERC1. While no resource mixes in these test cases are adapted in the long-run to the demand profiles, we expect FERC2 is especially poorly adapted because of the large increase in wind capacity, i.e., many thermal resources in this system ought to be incentivized to exit the market. FERC1 and FERC2 are a summer day and FERC3 is a winter day. Table 7.5 lists the maximum aggregate wind generation and maximum demand over the 24-hour period.

7.5.2 *Results*

All optimizations are solved to a MIP gap of 0.01% with a horizon of 24 hours with no look-ahead. Transmission constraints and reserve requirements are omitted. Since demand is considered as inelastic and all demand

	FERC1	FERC2	FERC3
Date	2015-07-01	2015-07-01	2015-02-01
Max Demand	112.6 GW	112.6 GW	103.7 GW
Thermal Generators	978 (177.5 GW)	978 (177.5 GW)	934 (180.7 GW)
VRE Generators	1 (1.2 GW)	1 (18.2 GW)	1 (4.5 GW)

TABLE 7.5: FERC Test Cases

is cleared without any non-served energy, the MIP gap reflects total producer costs. Note the convention that if a generator is neutral between bidding strategically or bidding economically at a given iteration in the simulation period based on expected profit, the generator defaults to bidding economically. The first iteration is the competitive solution in which all generators bid economically. The simulation is run with greedy $\alpha = 0.9$ and exponential smoothing $\eta = 0.05$ over 1000 iterations.

Results for FERC1 demonstrate that generators are able to learn to bid strategically in a way that increases producer profits and the cost to consumers. Figure 7.13 shows that while the cost to consumers changes negligibly with aCHP when generators can self-commit or self-schedule, the cost to consumers under FCP rises. At the competitive solution, the cost to consumers with FCP is 1.2% lower than with aCHP. However, the mean cost to consumers for FCP in the final 500 iterations is 0.76% higher than the mean cost to consumers for aCHP in the final 500 iterations. The average cost to consumers under FCP settles at approximately 2% higher with strategic bidding than the competitive solution, as shown in Figure 7.14. Under FCP, total producer profits increase on average in the final 500 iterations by 4.4% compared to the competitive solution, as shown in Figure 7.16. The efficiency of the system operator's solution with strategic bidding can decrease with strategic bids, but only very slightly, as shown in Figure 7.15. Note that each iteration only solves to a MIP gap of 0.001%, so some iterations can also achieve slightly lower producer costs than the competitive solution in the first iteration.

Figures 7.19 and 7.20 show the market share of each strategy per iteration in terms of number of units and total MW bidding each offer strategy. For FCP, generators that self-commit or self-schedule represent 38.8% of the total thermal generator capacity on average in the final 500 iterations. For

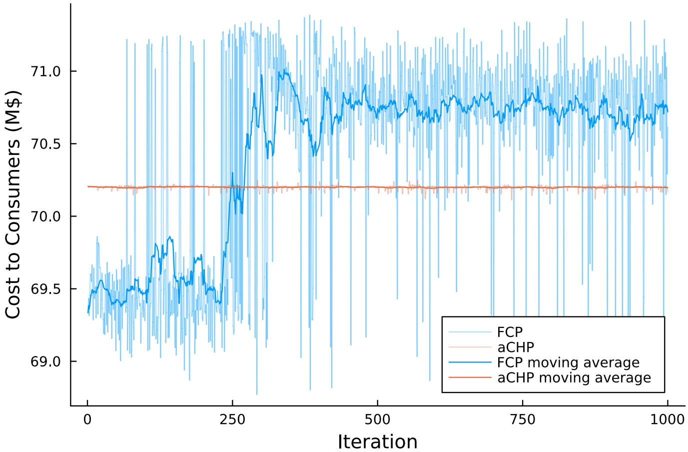


FIGURE 7.13: FERC1. Cost to consumers for each pricing model over iterations. Average costs to consumers under FCP rise during the simulation to be greater than costs to consumers under aCHP.

aCHP, 18.3% of available MW self-commit or self-schedule on average in the final 500 iterations.

However, not all generators that bid strategically profit because of their strategy; some randomly learn to bid strategically due to the behavior of other generators that influence the price. Tables 7.6 and 7.8 show the number of statistically significant adverse strategic bidders for each pricing model, and Tables 7.7 and 7.9 show the total MW represented by these adverse strategic bidders. Under FCP, generators representing 24.7% of thermal capacity profit by either self-scheduling or self-committing. Under aCHP, this number is 13.9%. Total excess profits for adverse bidders are given in Table 7.10. Excess profits are defined in Section 7.4 as the difference for strategic generators between the mean profit for the strategic bidding strategy with the highest payoff (either $\overline{X}_{selfcomm}$ or $\overline{X}_{selfsched}$) and $\overline{X}_{eco}$, the mean profit when bidding economically. Total excess profits for FCP are 0.73% of FCP competitive profits, while total excess profits for aCHP are only 0.01% of aCHP competitive profits.

Figure 7.17 shows the total MWP required for cost recovery in each iteration. The aCHP model has higher prices in the competitive solution in the first iteration, and thus has lower MWP requirements. Since generators

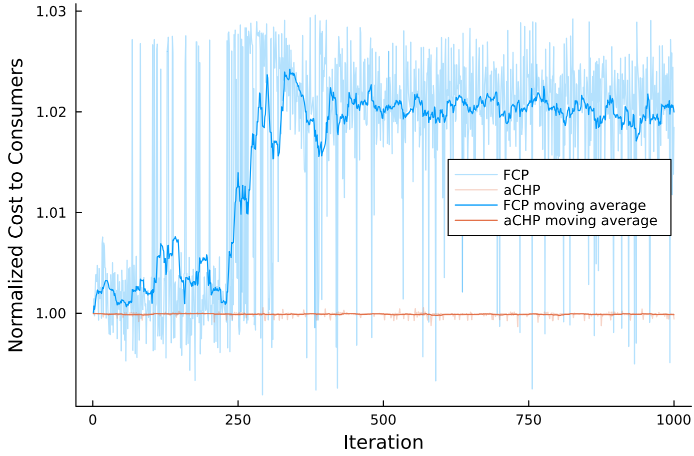


FIGURE 7.14: FERC1. Cost to consumers over iterations normalized by cost to consumers at the competitive solution in which all generators bid economically for each pricing model.

in FCP learn to strategically bid to increase the price, MWP fall over iterations. When generators are learning to increase their profits by bidding strategically, they are learning to decrease LOC. Figure 7.18 shows that while LOC has no trend for aCHP, LOC under FCP decreases over the iterations.

The prices found with strategic bidding vary far more under FCP than under aCHP, leading to increased profit potential. Competitive prices and the range of prices found via strategic bidding for each pricing model are shown in Figure 7.21.

The profit duration curve under competitive conditions and deviations from this curve for each generator under each bidding strategy are shown in Figures 7.22 and 7.23. For FCP, many generators benefit from the allowance of strategic bidding and resulting higher prices even if they cannot themselves impact the price. Typically it is generators that were already highly profitable under competitive conditions that have the highest payoffs under strategic conditions. For aCHP, there is no additional profit potential relative to competitive profits, and some potential for losses, indicating that aCHP incentives generators not to self-schedule if they could impact the price. Figures 7.24 and 7.25 show the deviation from competitive profits

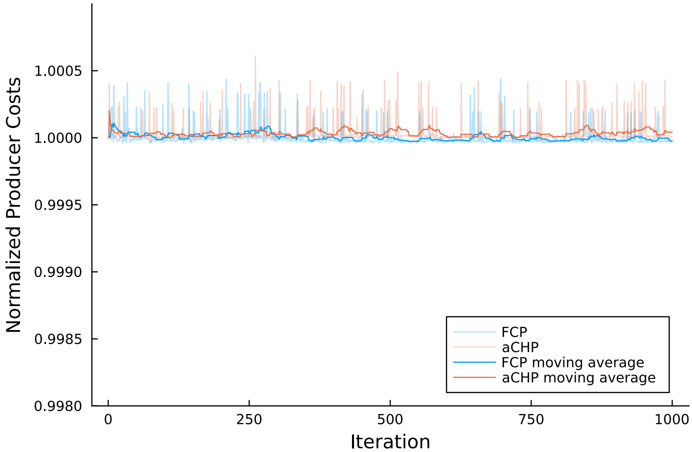


Figure 7.15: FERC1. Total actual production cost normalized by production cost at the competitive solution in which all generators bid economically. Production cost at the competitive solution varies for FCP and aCHP.

for statistically significant adverse bidders. Under FCP, again the generators with the highest competitive profits benefit the most from bidding strategically. Under aCHP, there is little to no increased payoff relative to competitive conditions (note the different axis scale in Figure 7.25). Because adverse generators are determined based on the expected payoff of a strategic bid compared to economic bids while other generators are also bidding strategically instead of the payoff in competitive conditions, some of the deviations from competitive profits are negative.

The zero-marginal cost VRE generator also benefits from the higher profits induced by strategic thermal generators under FCP. Figure 7.26 shows the total profit achieved under CHP changes negligibly, but the total profit achieved under FCP grows as the thermal generators determine optimal strategic bidding strategies.

FERC2 is the same case as FERC1 except a large quantity of wind was added. This means the resource mix is far from the long-run adapted resource mix, so we would expect to see less opportunity for profits for thermal generators, and that less thermal generators overall will be committed. FERC3 is another low wind case, but on a winter instead of summer day.

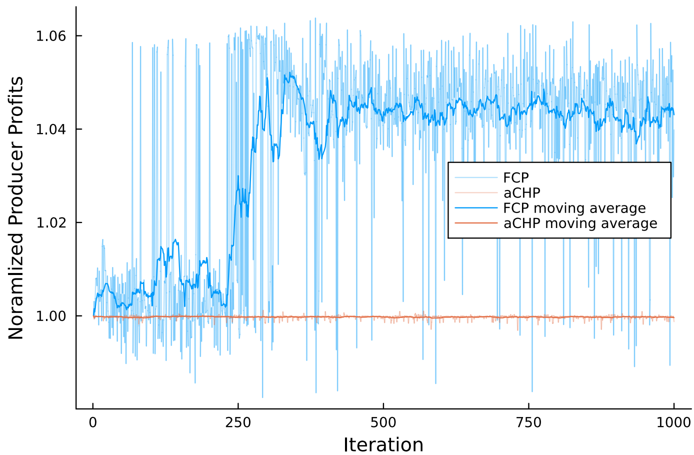


FIGURE 7.16: FERC1. Total producer profits normalized by profits at the competitive solution in which all generators bid economically for each pricing model.

Tables 7.6 and 7.8 show the number of statistically significant adverse strategic bidders for each pricing model, Tables 7.7 and 7.9 show the total MW represented by these adverse strategic bidders, and Table 7.10 shows the total excess profit. Under FCP, FERC2 with has a similar amount of MW that are statistically significant adverse bidders as FERC1 (23.9% vs 24.7%), but the total excess profits are lower (0.09% vs 0.73%). FERC3 has a higher share of MW as adverse bidders at 37.2%, and total excess profits of 0.60%. The MW of adverse bidders for aCHP is lower than FCP in both cases, and

	Number of Generators		
	$\overline{X}_{eco} < (\overline{X}_{selfsched}$ OR $\overline{X}_{selfcomm})$ and $p < 0.05$		
Strategy	FERC1	FERC2	FERC3
Self-Commit	90 (9.2%)	61 (6.2%)	94 (10.1%)
Self-Schedule	82 (8.4%)	66 (6.7%)	103 (11.0%)
Total (Unique)	119 (12.2%)	93 (9.5%)	136 (14.6%)

TABLE 7.6: Adverse Strategic Bids (FCP)

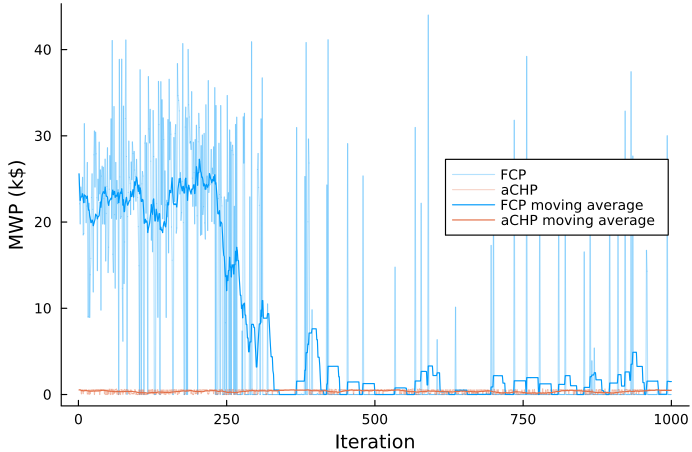


Figure 7.17: FERC1. Make-whole payments required for short-run cost recovery by pricing model.

the excess profits for both is 0.00%, i.e., the payoffs from strategic bidding, while statistically significant, are very small.

While the normalized cost to consumers under FCP in FERC2 only increases by approximately 0.05% (Figure 7.27), the normalized cost to consumers in FERC3 increases by approximately 1.5% (Figure 7.28). The increase in normalized producer profits for FERC2 shown in Figure 7.31 is also lower than in FERC1 (less than 1% vs 4.4%), while the average increase in FERC3 in the final 500 iterations is 2.9%, shown in Figure 7.32.

	Generator Capacity (GW)		
	$\overline{X}_{eco} < (\overline{X}_{selfsched}$ OR $\overline{X}_{selfcomm})$ and $p < 0.05$		
Strategy	FERC1	FERC2	FERC3
Self-Commit	32.8 (18.5%)	28.6 (16.1%)	50.7 (28.0%)
Self-Schedule	30.2 (17.0%)	29.4 (16.6%)	50.4 (27.9%)
Total (Unique)	43.9 (24.7%)	42.4 (23.9%)	67.3 (37.2%)

Table 7.7: Adverse Strategic Bids (FCP)

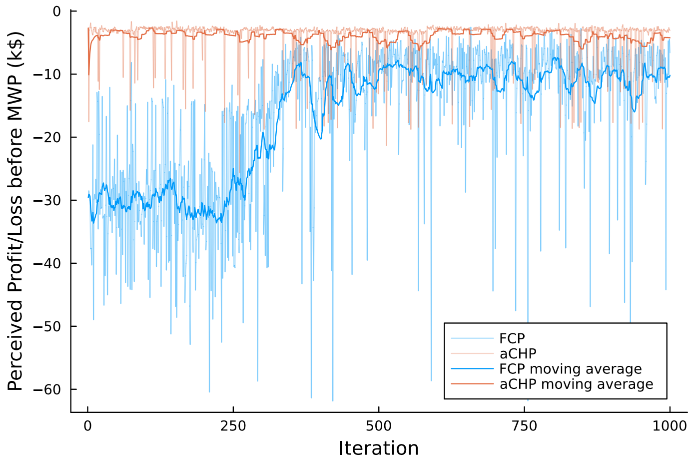


FIGURE 7.18: FERC1. Lost opportunity cost displayed as perceived profit or loss before MWP. Generators under FCP learn to bid strategically so as to lower LOC.

The LOC in the competitive solution for FCP is far lower in FERC2 and FERC3 compared to FERC1, and there is no trend of decreasing LOC with learning as with FERC1. Figures 7.29 and 7.30 show LOC for FERC2 and FERC3. The market share of each offer strategy for FERC2 and FERC3, shown in Figures 7.33 and 7.34, are similar to those found in FERC1. The range of prices found under FCP with strategic bidding varies more and reaches higher values in FERC3 than FERC2, as shown in Figures 7.35 and 7.36. The peak price in particular varies more for FERC1 and FERC3 than FERC2, with significant added wind.

	Number of Generators		
	$\overline{X}_{eco} < (\overline{X}_{selfsched}$ OR $\overline{X}_{selfcomm})$ and $p < 0.05$		
Strategy	FERC1	FERC2	FERC3
Self-Commit	39 (4.0%)	19 (1.9%)	16 (1.7%)
Self-Schedule	63 (6.4%)	37 (3.8%)	26 (2.8%)
Total (Unique)	90 (9.2%)	47 (4.8%)	35 (3.7%)

TABLE 7.8: Adverse Strategic Bids (aCHP)

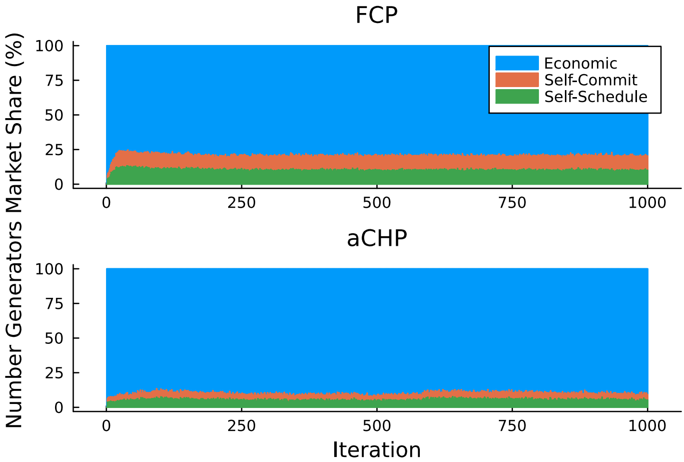


Figure 7.19: FERC1. Market share of each offer strategy per iteration as percentage of generators bidding each strategy.

	Generator Capacity MW		
	$\overline{X}_{eco} < (\overline{X}_{selfsched}$ OR $\overline{X}_{selfcomm})$ and $p < 0.05$		
Strategy	FERC1	FERC2	FERC3
Self-Commit	9.2 (5.2%)	6.1 (3.4%)	3.4 (1.9%)
Self-Schedule	19.0 (10.7%)	12.4 (7.0%)	7.3 (4.0%)
Total (Unique)	24.7 (13.9%)	14.0 (7.9%)	9.8 (5.4%)

Table 7.9: Adverse Strategic Bids (aCHP)

	Total excess profit (% competitive profits)		
Pricing Model	FERC1	FERC2	FERC3
FCP	$236.0k (0.73%)	$32.7k (0.09%)	$204.2k (0.60%)
aCHP	$2.6k (0.01%)	$1.0k (0.00%)	$1.4k (0.00%)

Table 7.10: Adverse Strategic Bids Payoffs

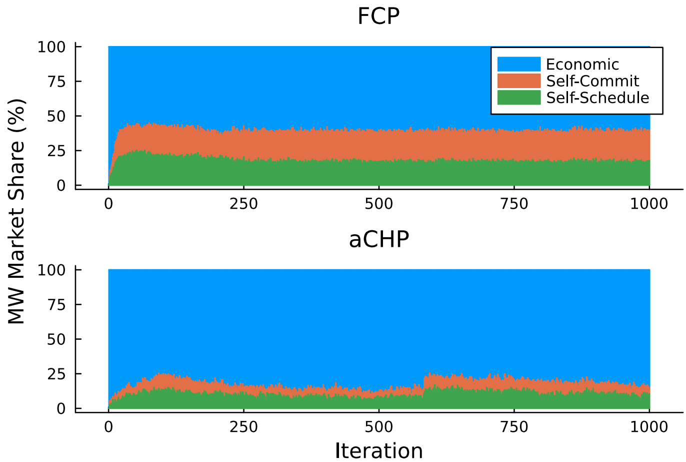


FIGURE 7.20: FERC1. Market share of each offer strategy per iteration as percentage of MW of total thermal generator capacity bidding each strategy.

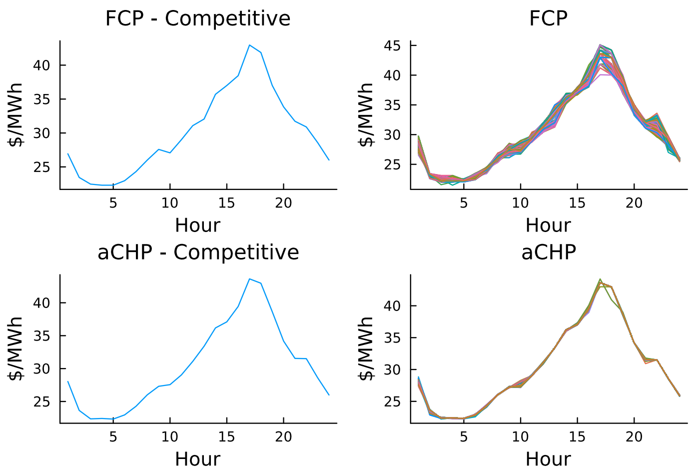


FIGURE 7.21: FERC1. Prices attained under the competitive solution in which all generators bid economically and prices attained over all iterations of strategic bidding.

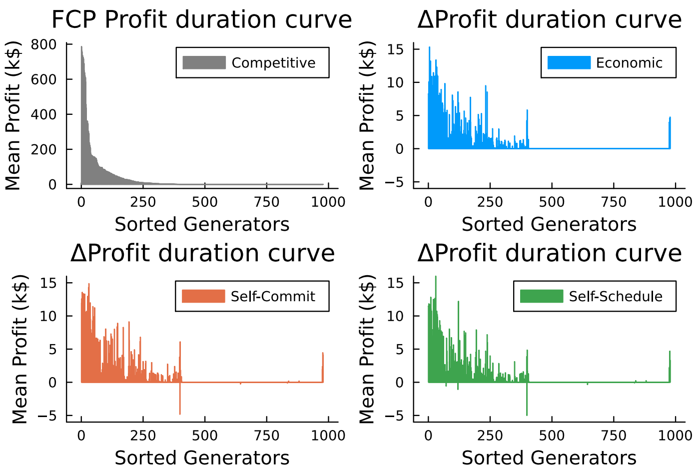


FIGURE 7.22: FERC1. Profit duration curve and deviations for FCP. Generators are sorted by profit achieved in the competitive outcome in which all generators submit economic bids. The difference between the mean profit achieved for each strategy in simulation and the profit achieved at the competitive solution is shown.

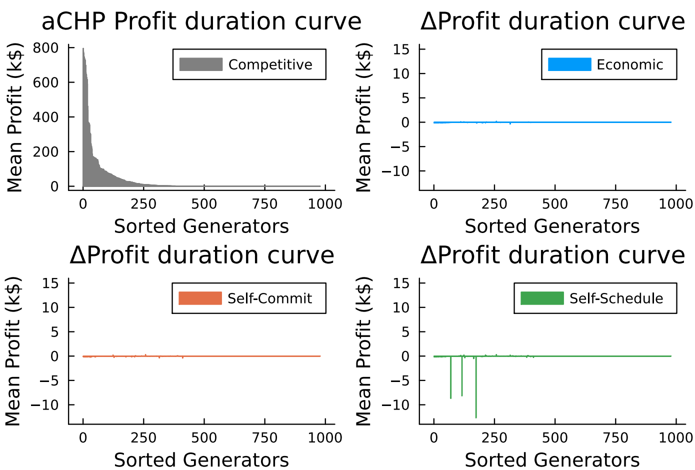


FIGURE 7.23: FERC1. Profit duration curve and deviations for aCHP. Generators are sorted by profit achieved in the competitive outcome in which all generators submit economic bids. The difference between the mean profit achieved for each strategy in simulation and the profit achieved at the competitive solution is shown.

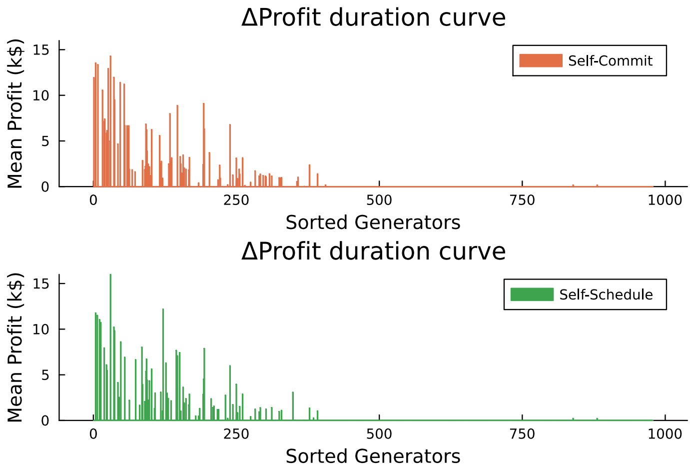


FIGURE 7.24: FERC1 (FCP). Deviations from the competitive solution profit duration curve for statistically significant adverse generators. Generators are sorted by profit achieved in the competitive outcome in which all generators submit economic bids. The difference between the mean profit achieved for each strategy in simulation and the profit achieved at the competitive solution is shown only for adverse generators.

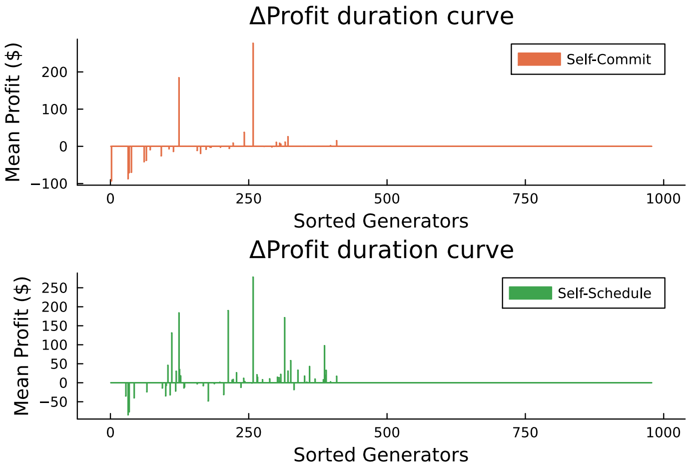


FIGURE 7.25: FERC1. (aCHP). Deviations from the competitive solution profit duration curve for statistically significant adverse generators. Generators are sorted by profit achieved in the competitive outcome in which all generators submit economic bids. The difference between the mean profit achieved for each strategy in simulation and the profit achieved at the competitive solution is shown only for adverse generators. Adverse generators are determined based on the expected payoff compared to economic bids in simulation, not payoff in the competitive solution, so Δ may be < 0.

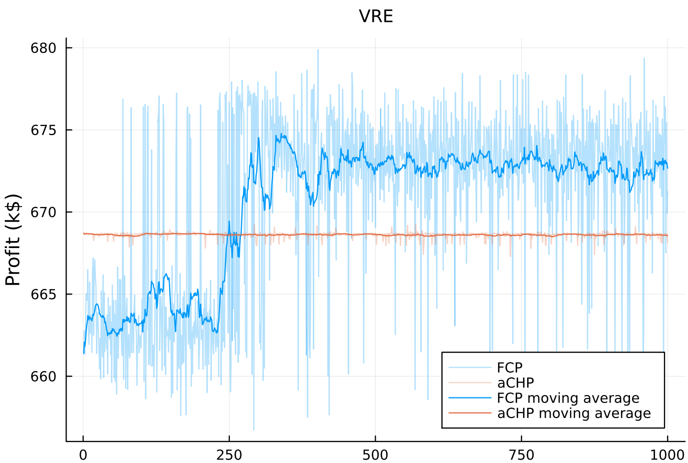


FIGURE 7.26: FERC1. Aggregate profit of VRE generators over iterations.

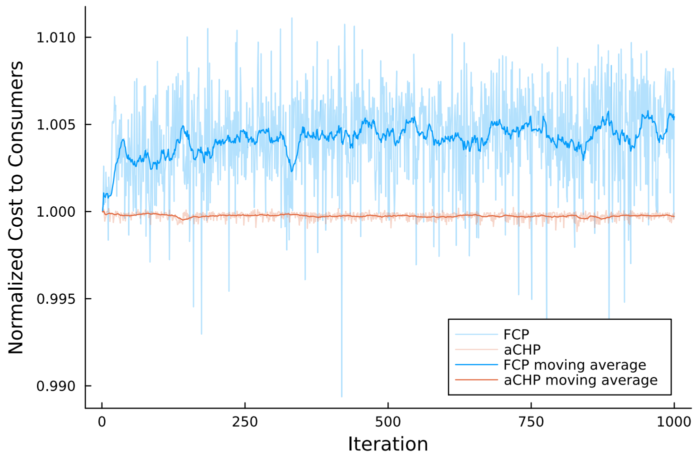


FIGURE 7.27: FERC2. Cost to consumers over iterations normalized by cost to consumers at the competitive solution in which all generators bid economically for each pricing model.

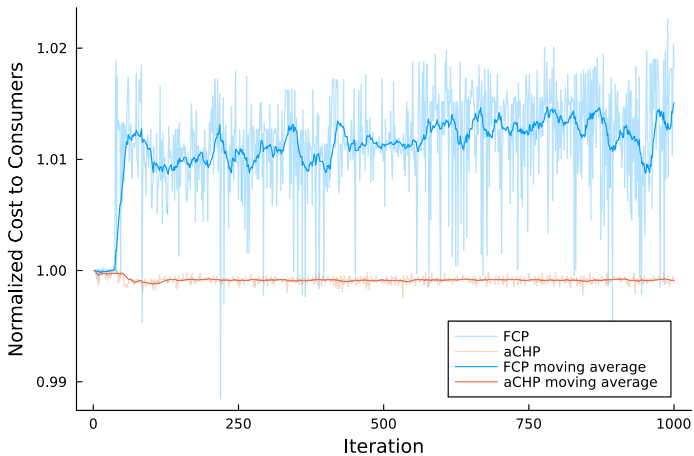


FIGURE 7.28: FERC3. Cost to consumers over iterations normalized by cost to consumers at the competitive solution in which all generators bid economically for each pricing model.

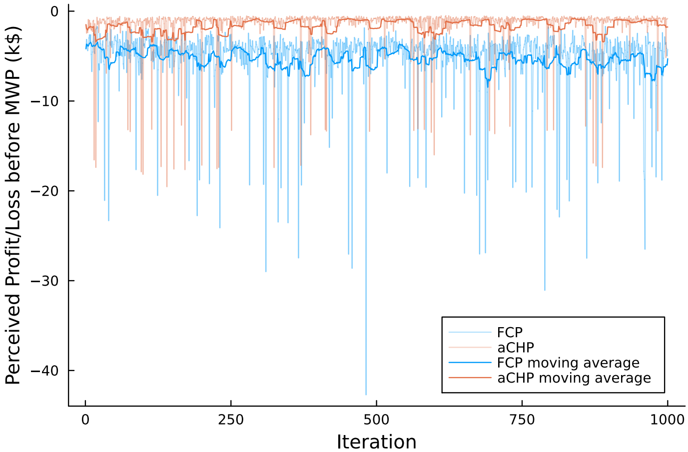


Figure 7.29: FERC2. Lost opportunity cost displayed as perceived profit or loss before MWP.

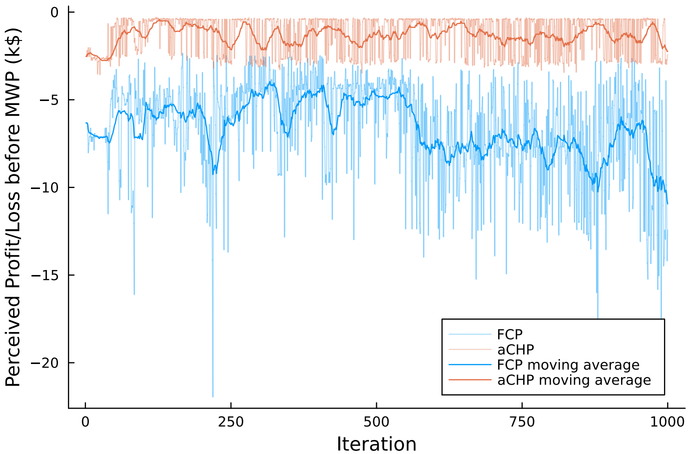


Figure 7.30: FERC3. Lost opportunity cost displayed as perceived profit or loss before MWP.

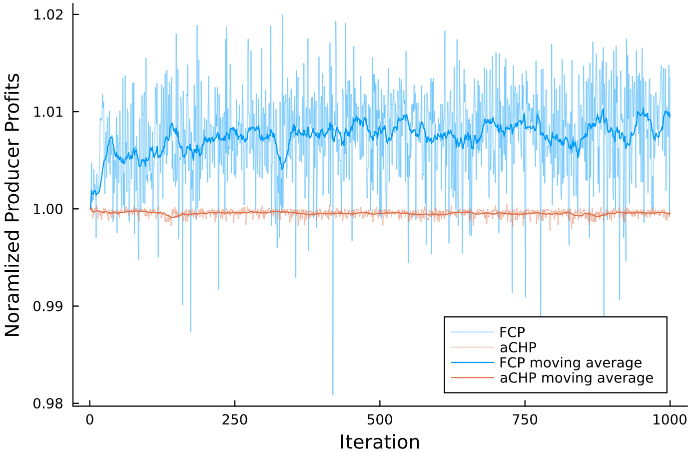


FIGURE 7.31: FERC2. Total producer profits normalized by profits at the competitive solution in which all generators bid economically for each pricing model.

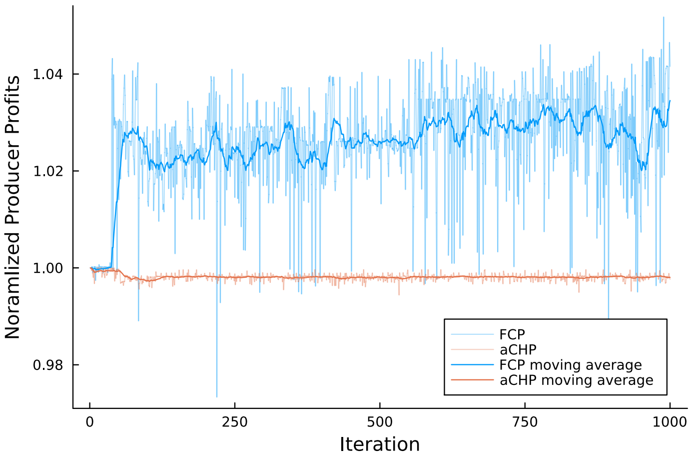


FIGURE 7.32: FERC3. Total producer profits normalized by profits at the competitive solution in which all generators bid economically for each pricing model.

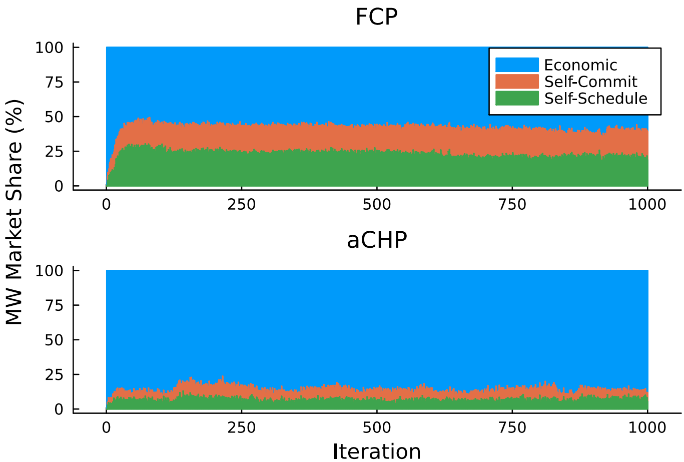


Figure 7.33: FERC2. Market share of each offer strategy per iteration as percentage of MW of total thermal generator capacity bidding each strategy.

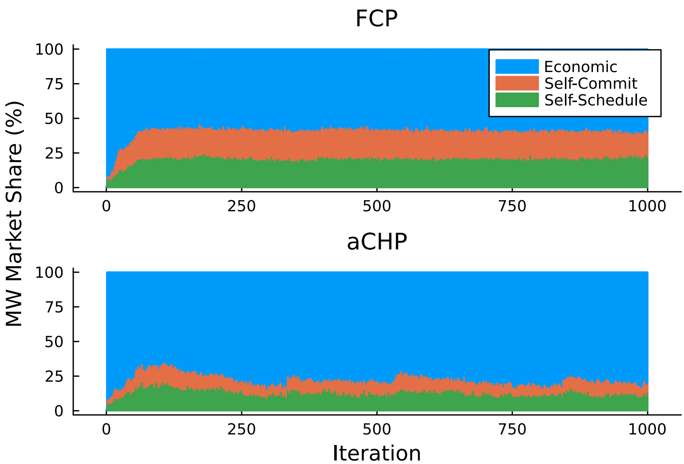


Figure 7.34: FERC3. Market share of each offer strategy per iteration as percentage of MW of total thermal generator capacity bidding each strategy.

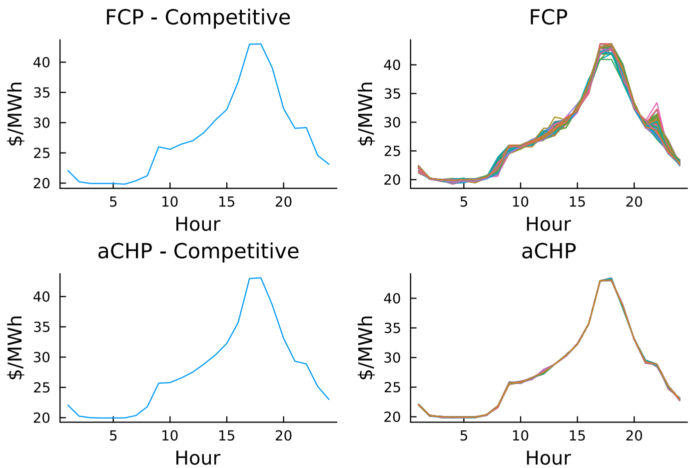


FIGURE 7.35: FERC2. Prices attained under the competitive solution in which all generators bid economically and prices attained over all iterations of strategic bidding.

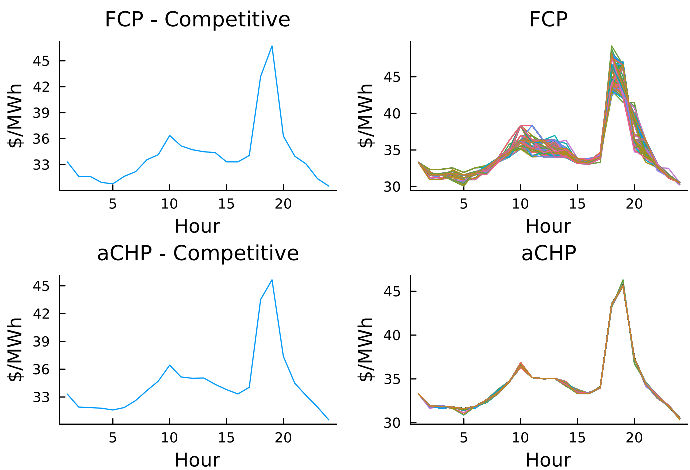


FIGURE 7.36: FERC3. Prices attained under the competitive solution in which all generators bid economically and prices attained over all iterations of strategic bidding.

7.6 CONCLUSION

In a market with non-convex costs, market power can be exercised by self-committing/scheduling. In electricity markets that permit self-commitment and self-scheduling, generators can learn to bid strategically to increase their profits using reinforcement learning without knowledge of the costs or strategies of other generators. While the FCP pricing model provides incentives to adversely (to the market) self-commit or self-schedule, convex hull pricing provides minimal incentives to deviate from the socially-optimal dispatch solution.

Using a realistic test system, we find that when LOC is high under FCP, generators can learn to bid strategically to increase their profits and lower LOC. In one test case strategic bidding decreased total system LOC under FCP by approximately 2/3. Generators who are able to adversely self-commit or self-schedule to increase their profits tend to be generators who were already highly profitable under competitive conditions. However, many generators benefit from the higher prices induced by strategic generators. In our simulations, approximately 40% of thermal generating capacity under FCP learned to self-schedule or self-commit, similar to the levels in markets today. Importantly, we are finding this behavior without the presence of long lead time scheduling constraints or take-or-pay fuel contracts that are typically used to explain this behavior. Of this amount, between 24%-38% across cases increased their payoff by bidding strategically rather than bidding economically in a statistically significant manner while other generators were bidding strategically. Cost to consumers under aCHP is higher in competitive conditions, but cost to consumers under FCP is higher in strategic conditions. Producer profits increased in cases with low wind 2.9% and 4.4% respectively, while they increased in a case with significant added wind (and thus less profit potential for the same resource mix of thermal generators) only 1%.

The ability of generators to adversely self-commit or self-schedule depends on the number and characteristics of the generators in the system. If there is significant excess thermal generation capacity, the profit potential is lower. More work is needed to explore how different resource mixes and net load profiles influence the potential for adverse self-commitments and self-scheduling.

Future work should consider how transmission constraints and reserve requirements may impact the ability of participants to benefit from strategic bidding. Future work should also explore how other non-convex pricing methods currently used by system operators in the United States (see [13]) may create incentives for adverse self-commitments and self-schedules.

While the induced higher profits by strategic bidding benefit all committed generators, generators who are successful adverse bidders tend to be generators who were already highly profitable under competitive conditions. This could in the long-run bias investment decisions, leading to a resource mix that does not maximize social welfare.

8

CONCLUSION

8.1 SUMMARY

A number of challenges in electricity markets may potentially lower the social surplus and consumer surplus achieved from the theoretical ideal. Chapter 3 shows that improvements made to calculations of transmission congestion in zonal pricing still result in a large welfare gap. However, even with nodal pricing, marginal pricing as a market clearing mechanism does not have the desired economic properties of being able to clear the market while providing a dispatch solution from which no generator has an incentive to deviate. This is due to the technical characteristics and commitment costs of generators that result in a non-convex optimal value function.

Prices are not meant to support the existing resource mix but rather to provide optimal signals for entry and exit in the long-run, and Chapter 4 explores how different non-convex pricing models can lead to different long-run resource mixes. These different resource mixes and pricing models result in different levels of consumer surplus, with the restricted convex model and convex hull pricing, a method that minimizes lost opportunity costs, providing the least overcompensation to inframarginal units. Chapter 5 examines how increasing shares of variable renewable energy impact the cost recovery of flexible units in a non-convex setting. Long-run cost recovery is still possible for flexibility providers, but there is a penalty to consumers relative to the convex case that is proportional to the amount of non-convex resources in the system.

Chapter 6 finds that better near-optimal solutions can improve outcomes for consumers when demand is flexible. Finally, Chapter 7 examines the incentives of market agents to bid strategically by offering zero-cost bids when they face lost opportunity costs. Via a reinforcement learning algorithm, agents can learn to self-schedule or self-commit to increase profits without explicit knowledge of the costs or strategies of other agents. In a realistic test system, adverse bids under the restricted convex pricing model increased total producer profits substantially, while convex hull pricing preserved the profits made at the competitive market solution and resulted in a lower cost to consumers.

8.2 OUTLOOK

We are at a time of transition in which massive investments in low-carbon electricity generating capacity must be made to achieve goals of net zero carbon emissions by mid-century. Electricity market design must adapt to significant increases in the shares of zero-marginal cost variable renewable energy. Whether or not the future decarbonized electricity market design includes long-term reliability obligations, the most efficient design will be built around efficient energy prices. As fossil-fuel resources are displaced by low-carbon resources, the findings in this dissertation can guide system operators in understanding how price formation impacts the transition, and to what extent energy markets can signal enough of the right kind of resources to be built for reliability needs. With more systems considering implementing nodal pricing, this work demonstrates the gap between nodal pricing and the theoretical ideal of convex markets and offers paths forward for system and market operators.

This dissertation addresses how inaccurate representation of the transmission network and treatment of non-convexities influences market efficiency. The nature of non-convexities is such that conclusions can often not be drawn universally, and more work is needed to determine the magnitude of impacts in different regions. However, the approach outlined in this thesis can be used to consider long-run impacts of different pricing models as more variable renewable energy and flexible demand enter the system. The cumulative impact of non-convexities on market inefficiency may decrease as thermal resources retire; alternatively, the impact may increase if new technologies are adopted that require their own modeling approach with integrality. The findings in this body of work make a case for the adoption of convex hull pricing, which has become computationally tractable with recent advances in decomposition algorithms. It also sheds light on the importance of incorporating price-responsive, flexible demand. As the energy sector transitions to a low-carbon future, it will become more important that energy markets provide price signals that not only enable efficient operation but also signal optimal investment decisions.

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