Efficient Design of Electricity Market Clearing Mechanisms with Increasing

Levels of Renewable Generation and Carbon Price

by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy in Graduate Program in Environment in the Graduate School of
Duke University

2017

ABSTRACT

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Abstract

Increased use of wind energy in electricity systems can help reduce green house gas emissions and enhance energy security. However, the traditional scheduling and dispatching processes used to ensure the cost-effective and reliable supply of electricity in wholesale energy and ancillary service markets are not designed to deal with wind production uncertainty and variability. The growing variability and uncertainty of wind resources misinforms the scheduling and dispatching processes and ultimately causes economic and environmental inefficiencies. Various approaches have been proposed to integrate the wind uncertainty and variability into the electricity market clearing processes and enhance their economic and environmental efficiency. This dissertation develops a framework that enables quantifying the inefficiencies caused by the wind uncertainty and assessing the economic and environmental efficiency that could be gained by integrating the uncertainty into the market clearing design.

To assess the potential inefficiencies posed by wind uncertainty, three objectives are addressed. (1) Elucidate the incentives that wind uncertainty might create for electricity markets' demand-side participants to develop market manipulation strategies and determine the factors that might contribute to or mitigate such market power. (2) Estimate the economic and environmental costs of wind uncertainty and the improvements that could be achieved by various approaches for integrating the wind

uncertainty into the market clearing design. (3) Investigate how CO_2 pricing policies that affect the priority order of generators in the supply curve and the grid's overall flexibility impact the uncertainty costs and the improvements that could be achieved by integrating the uncertainty into the market clearing design.

First, in order to highlight the opportunities that wind uncertainty creates for the demand-side strategic behavior, this paper explores the effects of allowing large, price-responsive consumers to provide reserves in a power system with significant penetration of wind energy when the market is cleared using stochastic market clearing (SMC). The problem is formulated as a bilevel optimization problem representing a Stackelberg game between the large consumer and the other market participants. The study highlights how a large price-responsive consumer takes advantage of the wind uncertainty and leverages its ramp reserve deployment capability to understate its demand in the day-ahead market (DAM) and reduce the overall day-ahead (DA) and real-time (RT) prices to minimize the total daily cost of purchasing electricity in the DA and RT markets. The study also reveals how wind uncertainty, reserve deployment capacity, and transmission congestion contribute to the market power of large consumers that should be limited to mitigate their market power.

Next, to estimate the economic and environmental inefficiencies of the wind uncertainty, a framework is developed that replicates the operation of wholesale energy market clearing under the traditional design and adjusted designs that indirectly or directly integrate the uncertainty into the market clearing mechanisms. The indirect integration, referred to as augmented deterministic design, maintains the deterministic nature of market clearing mechanisms, i.e., DA unit commitment (DAUC) and economic dispatch (DAED), and deals with the uncertainty through scheduling ramp capability requirements, which are quantified exogenously to the market clearing processes based on the wind uncertainty characterization. The direct integration requires transition to the stochastic market clearing design in which stochastic optimization models are used for direct integration of the wind uncertainty characterization in the DAUC and DAED processes. The stochastic design allows endogenous quantification of the ramp capability requirements and optimizes energy and ramp capability reserve schedules by accounting for the expected cost of recourse actions taken to reconcile the RT balance mismatch caused by the deviation of wind energy producers from their DA production schedules.

The proposed framework resolves the differences of adjusted market clearing designs in terms of pricing, settlement, and reliability management to ensure a fair comparison of their dispatch, economic, and environmental outcomes. The comparative analysis reveals that the augmented deterministic and the stochastic designs enhance the economic and environmental outcomes, yet the stochastic design is superior as it offers more efficient and flexible energy and reserve schedules that are well coordinated with the anticipation of RT wind energy realizations. As a result, the stochastic design's schedules can be adjusted more conveniently and cost-effectively to reconcile the deviations leading to greater operation and startup fuel cost savings; lower cycling of slow producers, higher wind integration and finally lower air emissions. Furthermore, stochastic design offers more efficient prices that reflect the system's operation costs and wind uncertainty more effectively, provide greater remuneration of operational flexibility by producers, and reduce the revenue sufficiency guarantee payments that collectively improve the social surplus to a higher extent with respect to the augmented deterministic design.

Lastly, the developed market simulation framework is extended to include another adjusted deterministic design, referred to as hybrid deterministic design that uses stochastic optimization for direct integration of the wind uncertainty characterization to the residual unit commitment (RUC) stage. Then the economic and environmental outcomes of alternative market clearing designs are simulated under two carbon-pricing scenarios to evaluate their sensitivity to the introduction of a carbon price that alters the merit order of generation technologies in the supply curve.

The results imply that the stochastic market clearing design is superior to all adjusted deterministic designs. With introduction of a CO_2 price, augmented and hybrid deterministic designs lose their effectiveness due to the shift in merit order of producers. However, stochastic market clearing maintains its superior performance that increases its superiority with respect to adjusted deterministic designs.

In memory of my sister Nahid

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List of Abbreviations

ADMC	……	Augmented Deterministic Market Clearing
ACE	……	Area Control Error
DAE	……	Day-Ahead Economic Dispatch
DAED	……	Day-Ahead Economic Dispatch
DAUC	……	Day-Ahead Unit Commitment
DA	……	Day Ahead
DAM	……	Day-Ahead Market
DMC	……	Deterministic Market Clearing
ED	……	Economic Dispatch
GenCo	……	Generation Company
HDMC	……	Hybrid Deterministic Market Clearing
ISO	……	Independent System Operator
LSE	……	Load Serving Entities
NG	……	Natural Gas
RT	……	Real Time
RTM	……	Real-Time Market
RUC	……	Residual Unit Commitment
RTED	……	Real-Time Economic Dispatch

RTUC	……	Real-Time Unit Commitment
SMC	……	Stochastic Market Clearing
SRUC	……	Stochastic Residual Unit Commitment
SUC	……	Stochastic Unit Commitment
UC	……	Unit Commitment
VER	……	Variable Energy Resources

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1. Introduction

1.1 Background

1.1.1 Electric Power Systems and Regulatory Design

The electric power grid is one of the most complicated manmade systems and the beating heart of a society for economic growth and development. The electricity grids are designed to generate and transfer the electricity as instantly demanded by consumers, and the grid operators manage the generation, transmission, and distribution assets to maintain a safe, reliable, and cost-effective supply of electricity to consumers. However, electricity cannot be effectively stored on a large scale currently, and the power system assets are prone to failures, which together make ensuring a reliable and cost-effective operation of the grid a challenging task demanding sophisticated short-term and long-term planning processes.

Short-term operation planning refers to day to day operation of electricity grids, which maintains the cost-effective balance between supply and demand. Deviating from the balance makes the generators deviate from their nominal operation frequency that might lead to cascaded outages and blackouts if not controlled within the thresholds. The short-term operation includes determining the set of generators that produce the expected demand, optimizing their on/off status trajectory through the day, and dispatching them during the physical consumption/generation. The scheduling and dispatching processes ensure the instantaneous supply of demand at the minimum cost abiding by the thermal limits of transmission lines and physical/thermal constraints of generators under normal and contingency conditions, where contingency refers to the failure of transmission or generation assets or major fluctuation of electricity demand from their expected average outcome. The contingencies and their associated risks are so uncertain that the system operators reserves headroom capacities above planned energy schedules to cover the largest contingency and restore the balance and so the nominal frequency of the grid operation. System operators employ sophisticated computer tools build upon mathematical principles to optimize scheduling resources in the DA and deploying corrective actions during the RT operations and ensure the reliable supply of electricity during real-time operation.

Long-term planning processes serve to optimize the least-cost expansion of supply resource mix and transmission capacity that guarantee the reliable and resilient supply of electricity over a long-term horizon. The long-term expansions consider long-term generation and transmission reserve margins on top of the requirement for meeting the expected demand growth to survive challenges, such as equipment failures, fuel disruptions, and severe weather conditions, without compromising the grid reliability and safety. The investments made in generation and transmission capacity are remunerated so all the capital investments and a fair return on them are covered within the life time of the investments.

Although the above principles have governed the operation and planning of electricity grid over most of the last century, their implementation demonstrates various regulatory designs across the globe. The dominant designs include regulated monopoly/utility and electricity markets. The regulated utility design, a single company controls the generation, transmission, and distribution systems and is solely responsible for delivering electricity to retail consumers. In this design, the electricity rates paid by retails consumers are regulated by the utility commissions to cover all operation and capacity expansion costs for reliable operation of the grid and the return on their capital investments. The other design introduces competition to the electric power sector through market mechanisms, where different assets are owned by various entities, and their services are priced in auctions or through contracts. In this design, the daily operational processes for generation and transmission of the electricity are administered by a non-profit organization called Independent System Operator (ISO), where electricity is treated like a commodity and traded between wholesale producers (GenCOs) and consumers (LSEs) of electricity. A major feature of the energy markets is that the resulting prices, used to settle the energy transactions between wholesale producers and consumers, do not reflect the capacity expansion costs, referred to as "missing money problem". To address this issue, ISOs can procure their long-term supply resource capacity requirements in capacity markets. In capacity markets, ISOs auction their long-term supply resource reserve margin requirement to create a long-term price signal for attracting investments required to guarantee the adequate supply of power to consumers. In fact, the capacity market demand emulates the long-term capacity expansion requirement and the corresponding payment the remuneration process for covering the capital investment costs in the regulated utility design.

1.1.2 Short-Term Operation in Electricity Markets

Electricity markets provide several trading floors for wholesale consumers/producers to buy/sell their electric energy demand/supply that differ in their time window and administration. The major chunk of energy is traded through forward bilateral contracts or futures markets months ahead of physical consumption/generation. These forward markets are designed to be liquid and provide effective hedging opportunities to market participants against the risk of RT energy and fuel price volatilities. The remaining energy is traded in a two-period mechanism, including DA and RT markets, called deterministic market clearing. DAM is a financial market with no binding commitment for physical delivery of energy, which runs daily and optimize schedules of resources for the next day schedules with hourly resolution. RTM is a physical spot market which is run for single periods with sub-hourly intervals between a few minutes to an hour ahead of RT operation in which market participants can trade their deviations from the DA commitments/projections and deliver them during the RT grid operations. ISO administers both the DAM and RTM and the physical grid operations in RT.

In the DAM and RTM, on top of the energy trade, the ISO procures those ancillary service requirements that ensure the grid reliability. Only a set of ancillary services are procured in the DA and RT markets. Below is the full list of ancillary services as defined by Federal Energy Regulatory Commission (FERC) [1], and whether there are incorporated into the DA and RT market clearing or not as presented in [2].

Scheduling, system control, and dispatch service: this service is required to schedule resources and control the flow of power into, out of, or through a control area and is provided by the operator of the control area, i.e. ISO or Regional Transmission Operator (RTO).

Reactive power and voltage control service: this service is required to keep the voltage levels within the acceptable limits; it is offered on a cost-based service which is not included in the DA or RT market clearing cost/welfare functions.

Energy Imbalance Service: this is the service provided by RTM that resolves the deviations from forward and DA market schedules.

Regulation and frequency response service: regulation reserve is provided to balance the fast variations in load or generation, or more generally the area control error (ACE), occurring in between the RTM clearing intervals. Regulation reserve requirements are scheduled and priced in both up and down directions in both DA and RT markets. Frequency response service is the second-to-second droop response of generator's governors to frequency deviations from its nominal value. Frequency response is neither priced nor paid cost-based rates.

Synchronized and non-synchronized operating reserves: Synchronized or spinning reserve refers to extra unloaded capacity which could be deployed within a short amount of time from the unscheduled failure of a generator or any other disruption to supply. Synchronized reserve requirements are scheduled and priced in both DA and RT markets. Non-synchronized or supplemental reserves is extra generation capacity which is not online, but it can synchronize to the grid in a short time to compensate the generation failure after the spinning reserves are loaded.

Load following is another service which according to the FERC order 888 [1], his service is the action to follow the general trending load pattern within the day provided on the energy schedules optimized by the economic dispatch which clears the DA and RT markets. However, with the variable energy resources (VER) on the rise, the following reserves coming with the energy schedules may not suffice for following the trending net load pattern [2].

1.1.3 Energy and Ancillary Service Market Design

In all U.S. electricity markets, energy and ancillary services are jointly cleared in a two-settlement system. Two-settlement system refers to the fact that DA and RT markets are cleared separately such that the chosen day-ahead energy schedules/transactions are determined regardless of the deviations that occur in RT and their associated costs.

In the day-ahead market, the producers submit their supply offers and consumers their bids for energy. Qualified producers and consumers submit their offers for supplying ancillary services, including regulation and operating reserve requirements. Then a two-stage scheduling process is performed to determine the DA energy and reserves schedules that minimize the cost of supplying energy demand and meeting the regulation and contingency reserves requirements based on the offers/bids submitted by the market participants. In the first stage of the cost-minimization process, a security-constrained unit commitment model determines the start-up and shut-down (commitment) transition trajectory of the generators, and then the hourly energy and reserves schedules and prices are determined in the security-constrained economic dispatch model on the basis of the frozen commitment schedules. The unit commitment and economic dispatch models include a direct current (DC) representation of the transmission grid that enables considering nodal energy balance constraints and regional reserve requirements constraints.

In current systems, these models tend to be deterministic in nature, scheduling resources to meet some single expected value of key input variables across the scheduling interval. The primary tools through which these deterministic models can handle the variability and uncertainty around the expected average condition are regulation and contingency reserves. However, these requirements are not designated to manage wind production forecast uncertainty and variability, and the requirement targets are set by static rules of thumb without accounting for wind production uncertainty and variability [3].

In the RTM, market participants submit new bids/offers that reflect how their RT production/consumption realization deviate from their DA schedules. Another two-stage cost minimization is conducted in RT to reconcile the mismatch between the real-time supply and demand based on the RT market participants' offers/bids.

Energy prices are based on the marginal price theory [4], and since they are calculated on a nodal basis, they are referred to as the Locational Marginal Price (LMP).

The LMP represents the marginal cost of serving an additional MW of load at any specific load. The DA energy LMP at each node is equivalent to the dual variable of the corresponding nodal balance constraint in the linear economic dispatch optimization problem. RT LMP is the dual variable of the nodal balance constraint in the RT economic dispatch problem that reflects the marginal cost of correcting RT supply or demand deviations. Due to Lumpiness/Non-convexity of the least-cost function arising from unit commitment (which is mixed-integer programming problem), the LMPs only reflect the variable cost of energy production or equivalently do not reflect the commitment costs of generators (i.e. the startup and no load costs).

The DA and RT reserves prices are determined on a regional basis. They are equivalent to the marginal cost of one MW increase in the requirement represented by the dual variable of the set of reserves requirements constraints.

After the DA market, all DA transactions are settled at the DA prices; consumers pay the ISO for their energy DA demand at the DA nodal prices and producers receive payments from ISO for their scheduled generation at their respective LMP. Similarly, all RT transactions are settled at the RT LMP. All market participants with deviations from the DA schedules receive or make payments to the ISO at the RT LMP. Although the RTM is run in sub-hourly intervals, the settlement process is run hourly based on average hourly RT LMP. At the end of each day, if the producers' daily profits are negative, the ISO grants them uplift payments that make them whole to their daily operation costs. The uplift payments occur mainly due to the DA and RT prices that do not reflect the commitment costs.

1.1.4 Wind Energy Characteristics and its Implications for Market Clearing Design Efficiency

The traditional energy and ancillary market clearing is not inherently designed to deal with the increasing variability and uncertainty of wind energy resources. In the traditional design, the uncertainty and variability on key inputs are managed using ancillary services, regulation and operation reserves. However, none of these reserves are designed to deal with the challenges associated with wind uncertainty. Also, the following reserves that inherently come with energy schedules are not adequate to follow the uncertainty on wind energy's hourly and sub-hourly trending pattern.

Wind energy's variability affects balancing operation of the grid at different time scales. It increases second-to-second fluctuations that could be managed by increasing the regulation reserve requirements. Also, it increases the ramping requirements for following the net load trending patterns between hourly and sub-hourly intervals. The ramping requirements could be cost-effectively managed if the scheduling and dispatch processes were fed with perfect information about RT wind energy. However, the lack of such information misleads the commitment and dispatch of electricity generators distorting the economic and environmental outcomes of the DA and RT electricity markets.

In absence of flexible demands, the system operator relies on conventional generators' flexibility to follow the growing fluctuations and fast ramps of wind energy production during RT operation. However, wind production uncertainty impairs the system operator's ability to utilize the generators' flexibility in an optimal and cost-effective manner. Since the DA wind predictions are currently highly inaccurate [5], the uncertainty around the DA wind energy misinforms the DA market outcomes leading to suboptimal DA schedules that could be operationally infeasible and insufficient for correcting the RT deviations from DA schedules and ramping needs. As only a limited set of producers are nimble enough to respond to ISO's high speed redispatch and commitment adjustment instructions, the information gap between the DA and RT markets increases the operation costs and divergence between DA and RT prices. The inefficient commitment of resources and distorted prices lead to windfall profits for some generators and financial loss for other producers. It can also damage the settlement of energy transactions among producers and consumers that ultimately degrade the overall level of welfare in the market and create incentives for manipulative behavior by the market participants.

1.1.5 Alternative Market Clearing Designs for Integrating Wind Uncertainty

Various adjustments have been proposed for integrating wind uncertainty characterization into the market clearing design to overcome the distortions caused by DA wind uncertainty, such as DA flexible ramp requirements [6]–[8], stochastic unit commitment (SUC) [9]–[12], and stochastic market clearing (SMC) [13]–[15]. The aim of all these market clearing enhancements is to ensure DA energy schedules are supplemented with sufficient ramp-feasible headroom capacities to cost-effectively follow the RT wind energy trending pattern. While DA ramp products and SUC maintain the deterministic nature of the market clearing design, implementing SMC requires changing the conventional auction and bidding design elements common between the deterministic designs.

Ramp requirements are market-based products ensuring the DA and RT schedules are supplemented with sufficient and ramp-feasible amounts of up and down headroom capacity to follow the ramping uncertainty of wind and solar energy resources or more generally the net load [7], [8]. SUC is a modification to the DA scheduling process, in which DA commitments are optimized by a stochastic programming model, which accounts for the decision tree of wind production uncertainty and minimizes the DA operation costs and the expectation RT balancing costs. The SUC's commitments directly includes the uncertainty characterization into the unit commitment process and commits sufficient and ramp feasible capacity to follow wind variations under any RT realizations of wind. Another alternative for using the SUC to integrate the wind uncertainty into the market clearing design is to implement it in the residual/reliability unit commitment (RUC) phase which is conventionally run after the DA market clearing ends [11]. Unlike the above adjustments that partially incorporate wind uncertainty into the DA market clearing processes, SMC includes the wind uncertainty in both unit commitment and economic dispatch processes. SMC aggregates all the benefits of the above-mentioned approaches. Unlike SUC and SRUC that only affect the commitment of generators, SMC not only optimizes the accounts for the uncertainty in the commitment process, it optimizes the energy and ramp capability reserves and internalize the associated costs of uncertainty in the DA energy prices.

1.2 Dissertation Objectives and Outline

Understanding the implications of wind production uncertainty and how the uncertainty characterization should be integrated into the market clearing mechanisms is essential to cost-effective achievement of the CO_2 mitigation targets. The main contribution of this dissertation is developing a new framework, called Electricity Market Simulation Tool (EMST), that enables evaluating various designs for wholesale energy and ancillary service market clearing that integrate the wind production uncertainty characterization into different stages of the DAM clearing. This framework is used to provide a comprehensive and fair picture of the economic and environmental distortions caused by the wind uncertainty and conducting a fair assessment of the enhancements that could be achieved by the alternative market clearing designs. The dissertation organization is presented below.

Chapter 2 focuses on the opportunities that wind uncertainty creates for manipulative behavior of large price-responsive consumers of electricity when the DAM is cleared using SMC. The study elucidates the strategies that the large price-responsive consumer use to leverages its reserve provision capability for manipulating the DA and

RT market prices and ultimately minimizing its electricity procurement expenses. The study also clarify the major factors contributing to the large consumer's market power that could be limited to mitigate its ability to exercise its market power.

Chapter 3 and 4 address the implications of wind uncertainty in competitive electricity markets. Chapter 2 introduces the Electricity Market Simulation Tool (EMST) and how various deterministic and stochastic scheduling and pricing tools are combined in various deterministic and stochastic designs to deal with wind uncertainty. This chapter also clarifies the fundamental differences of the deterministic and stochastic designs in terms of bidding and pricing of resources, settling energy and reserves transactions, and ensuring the reliability requirements. I develops a framework that enables a fair comparative analysis of various market clearing designs investigated in this dissertation. The developed framework runs the system simulation for a year on a scaled version of PJM to elucidate how ramp products and SMC improve the economic and environmental performance of the market clearing design and how their differences in terms of scheduling and pricing resources affect their outcomes. The comparative analysis also casts light on how deterministic and stochastic designs remunerate the flexibility provided by generators.

Chapter 4 extends the framework developed in Chapter 3 to include another adjusted deterministic design, called hybrid deterministic market clearing (HDMC) design that adds ramp products to the DA market clearing and uses stochastic optimization in the RUC stage. Including HDMC allows evaluating the upper bound on economic and environmental enhancements that can be achieved by integrating the DA wind uncertainty characterization in a deterministic market-clearing framework. This chapter also investigates the economic and environmental performance of the adjusted deterministic and stochastic designs in a scenario that CO2 emissions are priced. This is particularly important as a CO_2 price alters the merit order of producers in the supply curve and influences the grid's flexibility in responding to intermittency and uncertainty of wind energy resources, and the effectiveness of adjusted designs in overcoming the resulting dispatch and price distortions.

2. Strategic Demand-side Response to Wind Power Integration

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2.1 Abstract

This paper explores the effects of allowing large, price-responsive consumers to provide reserves in a power system with significant penetration of wind energy. A bilevel optimization model represents the utility maximization problem of a large consumer, subject to a stochastic day-ahead co-optimization of energy and reserves that a system operator would solve to clear the market while considering wind power uncertainty. An examination of the market outcomes from both an illustrative and a large-scale study using this model allows analysis of a) the effects of the type of behavior of the large consumer (i.e., strategic vs competitive), b) limits on the amount of reserves it is allowed to provide, and c) variability and accuracy of characterization of wind power uncertainty.

2.2 INTRODUCTION

2.2.1 Background and Motivation

Increased elasticity of electricity demand is deemed to have multiple system's benefits including facilitation of integration of renewables. Similarly, it is generally accepted that allowing price responsive consumers to provide ancillary services may further improve market outcomes. However, it is possible that any positive effects may be counteracted by the strategic behavior of large consumers able to manipulate the market, particularly when they have the flexibility to provide balancing services (up and down reserves) to the grid. This impact can be even more significant under high penetration of wind energy resources which increases the need for real-time balancing services.

2.2.2 Aim and Approach

The aim of this paper is to investigate the extent to which an elastic large consumer, denoted "strategic consumer", can exercise its market power in an energy-only, wind-integrated electricity market. We define a strategic consumer as an entity that either owns large loads in different locations of the electricity grid or a non-profit aggregator that submits purchase bids on behalf of its loads. These entities, by definition, are obliged to serve their loads while having control over their consumption through diverse instruments. Examples of such an entity are large corporations with industrial plants like aluminum, steel, and ferro alloys production plants; liquefied air companies; motor vehicle manufacturing companies; pulp, paper, and paperboard mills; etc.

We develop a stochastic complementarity model (based on a bilevel optimization problem) representing the optimal bidding strategy of the strategic consumer, considering wind power production uncertainty and endogenous formation of clearing prices of electricity. The proposed bilevel programming approach includes an upper-level (UL) problem, representing expected utility maximization of the strategic consumer (as the only player behaving strategically), constrained to a lower-level (LL) problem, representing actual day-ahead market (DAM) clearing and balancing operation of the grid. The UL problem depends on clearing prices coming from the LL problem, and the LL problem is influenced by day-ahead bidding curves determined in the UL problem. The strategic consumer owns large number of loads that do not need to be fully supplied.

The considered pool in this paper is cleared one day prior to power delivery on an hourly basis. The pool clearing algorithm is a single-period network-constrained auction, which is recast as a two-stage stochastic programming problem to incorporate the integration of wind power producers and the uncertainty of their production. The first stage of this model represents the actual DAM clearing and the second stage models the balancing operation of the system for different realizations of wind power production. Indeed, DAM decisions are made accounting for expected balancing cost of the system due to uncertain wind fluctuations. Depending on the real-time realization of wind power production, up or down reserves are deployed to balance generation and demand during the real-time operation of the system. Reserve deployment refers to changes in energy generation/consumption levels of units/loads between the first (day-ahead) and second (balancing) stages. Units/loads reserve a part of their generation/consumption capacity, called reserve capacity, in the day-ahead stage to be converted to energy in the balancing stage, offsetting wind power variations. The rationale of the stochastic market clearing model is investigated using a generic mathematical framework in [14]. The stochastic market clearing model has generally two main differences with respect to the existing deterministic models traditionally used in the electricity markets: 1) estimation of the reserve requirements and 2) dispatch of energy and deployment of reserves. In deterministic market clearing models, reserve requirements are input parameters reflecting a target that system's operators pre-specify based on reliability criteria and without any consideration of the current costs of such services and/or updated information on the uncertainty and variability of intermittent energy resources. In contrast, in a stochastic market clearing model reserve requirements are endogenously determined through simulating the balancing operation of the system under different scenarios. The second difference between the stochastic and deterministic modeling stems from the dispatch of energy and reserves. The stochastic model provides an optimal pre-positioning of generating units and loads to manage the uncertain events in the balancing stage of the system. Consequently, and different from the deterministic modeling, stochastic models would not necessarily schedule all the day-ahead forecasted wind power production in the DAM, and instead, would schedule a level of wind power production determined after considering its variability and uncertainty, and the costs and availability that required reserves for managing it [13], [14], [16]–[19]. The pricing scheme of the stochastic model is proved to ensure generation cost recovery and revenue adequacy in expectation. A lossless dc representation of the network is embodied in both stages of the pool clearing algorithm so both day-ahead and balancing prices are locational marginal prices (LMPs).

2.2.3 Literature Review and Contributions

One thread of research related to this work is concerned with demand-side bidding strategy in electricity markets. Most literature in this domain regards electricity purchasers as price takers. For instance, references [20]–[22] optimize the bidding strategy of a price-responsive retailer, with different responsiveness levels to electricity prices.

Similarly, [23], [24] optimize the contracting policies for energy purchase of an energy buyer participating in forward and day-ahead markets using stochastic programming models. In addition, [25] designs the robust electricity procurement strategy of a large consumer in a DAM and a subsequent adjustment market using information gap decision theory. However, very little attention has been paid to the strategic demand-side bidding with endogenous formation of electricity prices. [26] proposes a non-linear programming approach (where optimality of its solution is not guaranteed) for the optimal bidding strategy of a retailer procuring electricity in the

DAM and several subsequent intra-day markets. The retailer's impact on the clearing prices is represented through its residual offer curves in each market. [27] proposes a complementarity bilevel model for deriving strategic bidding curves of a large consumer, supplying its demand in a day-ahead pool, under the uncertainty of supply offer curves of producers.

Complementarity modeling, or specifically bilevel optimization has been applied before to different electricity market problems. This technique has been used to study the offering strategy of a producer [28], the offering strategy of investor-owned storage units [29], the bidding strategy of a large consumer participating in day-ahead markets [27], strategic generation investment [30], [31], transmission expansion planning [32], [33], vulnerability assessment [34], yearly generation maintenance scheduling [35], and yearly transmission maintenance scheduling [36]. Among these papers, [27] is the only one investigating the strategic behavior of a large price-responsive consumer through complementarity modeling. However, [27] determines the strategic day-ahead bidding curves without considering the benefits the strategic consumer can obtain from provisioning balancing services. Moreover, [27] also leaves out of the analysis the uncertainty of wind power production and its impacts on provision of balancing services and other market outcomes determining the benefits of the strategic consumer. To fill these gaps, this paper extends the model presented in [14] in three ways: a) it allows demand-side resources to provide reserves, b) it accounts for the benefits of this provision in the determination of the bid of the strategic consumer, and c) it accounts for the uncertainty on wind power generation and its impacts on the strategic consumer's ability to manipulate the market to its benefit. To the best of our knowledge, our approach of using a two-stage stochastic market clearing model in the lower-level program of a complementarity model to determine the day-ahead dispatch of energy and reserves under wind power uncertainty is the first of its kind. None of the previous works have addressed the impacts of the participation of the strategic consumer on the reserve provision and the impacts of wind power production uncertainty on the design of this consumer's day-ahead bidding strategy. Accordingly, the contributions of this paper are threefold:

1) A two-stage stochastic complementarity model that derives an optimal bidding strategy for a large strategic consumer in an electricity market (including day-ahead trading stage and real-time operation) under wind power production uncertainty, and demand-side reserve provision.

2) A transformation of the proposed stochastic complementarity model into an equivalent mixed-integer linear programming (MILP) problem.

3) Use of the proposed model to explore the effects of allowing large consumers to participate in the reserve's market under uncertainty on wind-power production.

2.2.4 Organization

The remainder of the chapter is organized as follows. Section 3 presents features and assumptions of the proposed strategic bidding model. Mathematical formulation of the model, including the bilevel model, its corresponding Mathematical Program with

Equilibrium Constraints (MPEC) and its equivalent MILP are described in Section 4. Section 5 provides and discusses the results from case studies. Section 6 concludes the paper.

2.3 Model Features and Assumptions

The main modeling features and assumptions of this paper are as follows:

1) The strategic consumer bids strategically the demand of load in the DAM at a price B_q^S, while offers competitively its reserve deployment at U_q^S which is identical to its marginal utility.

2) Each load and each generating unit offers both up and down reserves at an identical price. This assumption is made due to lack of data on offer prices, nevertheless if it was revised to consider asymmetrical offer prices for the up and down reserves it is unlikely the conclusions of this paper would change.

3) All loads/generating units submit their energy bids/offers to the DAM, while only flexible loads/generating units offer reserve deployment in the balancing stage.

4) Among all potential uncertainties, only wind power production uncertainty is taken into account and characterized through a finite set of plausible scenarios.

5) Scheduled wind production in the DAM for each wind farm is limited to the expected wind power production of that wind farm.

6) Since the clearing algorithm of the pool is a single-hour auction, the inter-temporal constraints of generating units and loads are not considered.

7) Only one single bidding/offering block is considered for each load/generating unit.

8) Only competitive loads are considered for involuntarily load curtailment in the balancing stage so that they are paid for their curtailed load at their value of lost load (VOLL).

9) The supply side is assumed to be perfectly competitive so all generating units submit their marginal costs and their respective offers.

2.3 Model Formulations

This section presents the notation, the formulation of the bilevel model, and the corresponding MPEC in nonlinear and linear forms.

2.3.1 Notation

2.3.1.1 Indices

q Index for loads of the strategic consumer running from 1 to N_q.

l Index for loads of competitive consumers running from 1 to N_l.

g Index for generating units running from 1 to N_g.

k Index for wind farms running from 1 to N_k.

n, m Indices for buses running from 1 to N, and from 1 to M, respectively.

ω Index for wind power scenarios running from 1 to N_ω.

2.3.1.2 Sets

D^S Set of loads of the strategic consumer.

D^C Set of loads of competitive consumers.

G Set of generating units.

K Set of wind farms.

Ψ_n Set of system buses adjacent to bus n.

Sets D^S, D^C, G and K include subscript n if referring to the set of loads/units/farms located at bus n.

2.3.1.3 *Constants*

ϕ_ω Probability of scenario ω.

O_g Price offer by generating unit $g \in G$ equal to its marginal cost.

U_l^C Price bid by competitive load $l \in D^C$ [$MWh], equal to its marginal utility.

U_q^S Marginal utility of load of the strategic consumer $q \in D^S$ [$/MWh].

B^{Cap} Price cap for bids of the strategic consumer [$/MWh].

$\overline{P}^G$ Capacity of generating unit $g \in G$ [MW].

$\overline{P}_q^S$ Maximum demand of load $q \in D^S$ of the strategic consumer [MW].

$\overline{P}_l^C$ Maximum demand of competitive load $l \in D^C$ [MW].

$\overline{R}_g^{G^U}$ Maximum up reserve to be provided by generating unit $g \in G$ [MW].

$\overline{R}_g^{G^D}$ Maximum down reserve to be provided by generating unit $g \in G$ [MW].

$\overline{R}_g^{S^U}$ Maximum up reserve to be provided by load $q \in D^S$ of the strategic consumer [MW].

$\overline{R}_g^{S^D}$ Maximum down reserve to be provided by load $q \in D^S$ of the strategic consumer [MW].

$\overline{R}_l^{C^U}$ Maximum up reserve to be provided by competitive load $l \in D^C$ [MW].

$\overline{R}_l^{C^D}$ Maximum down reserve to be provided by competitive load $l \in D^C$ [MW].

V_l Value of lost load for competitive load $l \in D^C$ [$/MWh].

$W_{k\omega}^{act}$ Actual realization of wind power production of farm $k \in K$ under scenario ω [MW].

$\overline{W}_k$ Maximum power production of wind farm $k \in K$ to be scheduled in the DAM [MW].

S_{nm} Susceptance of transmission line (n, m) [S].

F_{nm} Capacity of transmission line (n, m) [MW].

2.3.1.4 *Variables*

P_g^G Scheduled production of generating unit $g \in G$ in the DAM [MW].

P_q^S Cleared power to be consumed by load $q \in D^S$ of the strategic consumer in the DAM [MW].

P_l^C Cleared power to be consumed by competitive load $l \in D^C$ in the DAM [MW].

W_k Scheduled wind production of farm $k \in K$ in the DAM [MW].

$r_{g\omega}^G$ Deployed reserve by generating unit $g \in G$ in the balancing stage under scenario ω [MW].

$r_{q\omega}^S$ Deployed reserve by load $q \in D^S$ of the strategic consumer in the balancing stage under scenario ω [MW].

$r_{l\omega}^C$ Deployed reserve by competitive load $l \in D^C$ in the balancing stage under scenario ω [MW].

$p_{l\omega}^{Shed}$ Involuntarily load shed of competitive load $l \in D^C$ in the balancing stage under scenario ω [MW].

$w_{k\omega}^{Spill}$ Wind power production spillage of farm $k \in K$ in the balancing stage under scenario ω [MW].

B_q^S Price bid by load $q \in D^S$ of the strategic consumer [$/MWh].

θ_n^{DA} Voltage angle of bus n in the DAM [rad].

$\theta_{n\omega}^{B}$ Voltage angle of bus n in the balancing stage under scenario ω [rad].

α_n^{DA} Day-ahead locational marginal price at bus n [$/MWh].

$\alpha_{n\omega}^{B}$ Probability-weighted balancing locational marginal price at bus n under scenario ω [$/MWh].

2.3.2 Bilevel Model

The optimal bidding strategy of a strategic consumer is designed using the following bilevel optimization model formulated in (1)–(2). Equations (1) and (2) represent the UL and LL problems, respectively.

$\Xi_{\mathrm{Primal}}^{\mathrm{LL}} = \left\{P_{\mathrm{g}}^{\mathrm{G}}, P_{\mathrm{q}}^{\mathrm{S}}, P_{\mathrm{l}}^{\mathrm{C}}, W_{\mathrm{k}}, r_{\mathrm{g\omega}}^{\mathrm{S}}, r_{\mathrm{l\omega}}^{\mathrm{c}}, p_{\mathrm{l\omega}}^{\mathrm{Shed}}, w_{\mathrm{k\omega}}^{\mathrm{Spill}}, \theta_n^{DA}, \theta_{n\omega}^{B}\right\}$ represents the primal set of variables of the LL problem, and $\Xi_{\mathrm{Dual}}^{\mathrm{LL}}$ indicates the LL problem's set of dual variables.

The corresponding dual variable of each constraint is after the constraint following a colon. Also, $\Xi^{\mathrm{UL}} = \{\Xi_{\mathrm{Primal}}^{\mathrm{LL}}, \Xi_{\mathrm{Dual}}^{\mathrm{LL}}, \mathrm{B}_{\mathrm{q}}^{\mathrm{S}}\}$ represents the primal set of the UL problem's variables. Note that B_q^S (bid price of the strategic consumer) is a decision variable within the UL problem and a parameter in the LL problem so that they are fixed bidding decisions in the LL problem. Therefore, the LL problem is linear and thus convex.

$$\underset{\Xi^{UL}}{\text{Maximize}} \sum_{q\in D^S}\left\{P_q^S\left(U_q^S-\alpha_{n:q\in D_n^S}^{DA}\right)+\sum_{\omega}\emptyset_\omega r_{q\omega}^S\left(\frac{\alpha_{(n:q\in D_n^S)\omega}^{DA}}{\emptyset_\omega}-U_q^S\right)\right\} \tag{1a}$$

subject to:

$$0\le B_q^S\le B^{cap} \qquad \forall q\in D^S \tag{1b}$$

$$\alpha_n^{DA},\alpha_{n\omega}^{B},P_q^S,r_{q\omega}^S \in \arg \underset{\Xi^{LL}_{\text{Primal}}}{\text{Maximize}}\left\{\sum_{\omega}\emptyset_\omega\left\{\begin{matrix}\sum_{g\in G}\left[O_g\left(P_g^G+r_{g\omega}^S\right)\right]-\sum_{q\in D^S}\left[B_q^SP_q^S-U_q^Sr_{g\omega}^S\right]\\ -\sum_{l\in D^C}\left[U_l^C\left(P_l^C-r_{l\omega}^C\right)-V_lp_{l\omega}^{\text{Shed}}\right]\end{matrix}\right\}\right\} \tag{2a}$$

subject to:

$$\sum_{q\in D_n^S}P_q^S+\sum_{l\in D_n^C}P_l^C+\sum_{m\in\Psi_n}S_{nm}\left(\theta_n^{DA}-\theta_m^{DA}\right)-\sum_{g\in G_n}P_g^G-\sum_{k\in K_n}W_k=0 \qquad : \alpha_n^{DA} \qquad \forall n \tag{2b}$$

$$\sum_{m\in\Psi_n}S_{nm}\left(\theta_{n\omega}^B-\theta_{m\omega}^B-\theta_n^{DA}+\theta_m^{DA}\right)$$

$$-\sum_{g\in G_n}r_{g\omega}^G-\sum_{q\in D_n^S}r_{q\omega}^S-\sum_{l\in D_n^C}\left(r_{l\omega}^C+p_{l\omega}^{\text{Shed}}\right) \tag{2c}$$

$$-\sum_{k\in K_n}\left(W_{k\omega}^{act}-W_k-w_{k\omega}^{\text{Spill}}\right)=0 \quad : \alpha_{n\omega}^B \quad \forall n,\forall\omega$$

$$0\le P_g^G\le \overline{P}_g^G \qquad : \underline{\mu}_g^G,\overline{\mu}_g^G \quad \forall g\in G \tag{2d}$$

$$0 \le W_k \le \overline{W}_k \quad : \underline{\mu}_k^W, \overline{\mu}_k^W \quad \forall k \in k \tag{2e}$$

$$0 \le P_q^S \le \overline{P}_q^S \quad : \underline{\mu}_q^S, \overline{\mu}_q^S \quad \forall q \in D^S \tag{2f}$$

$$0 \le P_l^C \le \overline{P}_l^C \quad : \underline{\mu}_l^C, \overline{\mu}_l^C \quad \forall l \in D^C \tag{2g}$$

$$S_{nm}(\theta_n^{DA} - \theta_m^{DA}) \le F_{nm} \quad : \zeta_{nm}^{DA} \;\; \forall n, \forall m \in \Psi_n \tag{2h}$$

$$-\pi \le \theta_n^{DA} \le \pi \quad : \underline{\delta}_n^{DA}, \overline{\delta}_n^{DA} \quad \forall n \tag{2i}$$

$$\theta_{n=1}^{DA} = 0 \quad : \delta^{DA(n=1)} \tag{2j}$$

$$-P_g^G \le r_{g\omega}^G \le \left(\overline{P}_g^G - P_g^G\right) : \underline{v}_{g\omega}^G, \overline{v}_{g\omega}^G \quad \forall g \in G, \forall \omega \tag{2k}$$

$$-\overline{R}_g^{G^D} \le r_{g\omega}^G \le \overline{R}_g^{G^U} \quad : \underline{\eta}_{g\omega}^G, \overline{\eta}_{g\omega}^G \quad \forall g \in G, \forall \omega \tag{2l}$$

$$\left(P_q^S - \overline{P}_q^S\right) \le r_{q\omega}^S \le P_q^S \quad : \underline{v}_{q\omega}^S, \overline{v}_{q\omega}^S \quad \forall q \in D^S, \forall \omega \tag{2m}$$

$$-\overline{R}_q^{S^D} \le r_{q\omega}^S \le \overline{R}_q^{S^U} \quad : \underline{\eta}_{q\omega}^S, \overline{\eta}_{q\omega}^S \quad \forall q \in D^S, \forall \omega \tag{2n}$$

$$\left(P_l^C - \overline{P}_l^C\right) \le r_{l\omega}^C \le P_l^C \quad : \underline{v}_{l\omega}^C, \overline{v}_{l\omega}^C \quad \forall l \in D^C, \forall \omega \tag{2o}$$

$$-\overline{R}_l^{C^D} \le r_{l\omega}^C \le \overline{R}_l^{C^U} \quad : \underline{\eta}_{l\omega}^C, \overline{\eta}_{l\omega}^C \quad \forall l \in D^C, \forall \omega \tag{2p}$$

$$0 \le p_{l\omega}^{\text{Shed}} \le \left(P_l^C - r_{l\omega}^C\right) : \underline{\eta}_{l\omega}^{\text{Shed}}, \overline{\eta}_{l\omega}^{\text{Shed}} \quad \forall l \in D^C, \forall \omega \tag{2q}$$

$$0 \le w_{k\omega}^{\text{Spill}} \le W_{k\omega}^{\text{act}} \quad : \underline{\eta}_{k\omega}^{\text{W}}, \overline{\eta}_{k\omega}^{\text{W}} \quad \forall k \in K, \forall \omega \tag{2r}$$

$$S_{nm}(\theta_{n\omega}^B - \theta_{m\omega}^B) \le F_{nm} \quad : \zeta_{nm\omega}^B \;\; \forall n, \forall m \in \Omega_n, \forall \omega \tag{2s}$$

$$-\pi \le \theta_{n\omega}^B \le \pi \quad : \underline{\delta}_{n\omega}^B, \overline{\delta}_{n\omega}^B \quad \forall n, \forall \omega \tag{2t}$$

$$-\pi \le \theta_{n\omega}^B \le \pi \quad : \underline{\delta}_{n\omega}^B, \overline{\delta}_{n\omega}^B \quad \forall n, \forall \omega \tag{2t}$$

$$\theta^{B}_{(n=1)\omega} = 0 \qquad : \delta^{B(n=1)}_{\omega} \quad \Big\}. \tag{2u}$$

In the UL problem, objective function (1a) represents the total expected utility of the strategic consumer for a single time period that consists of two terms: the first term corresponds to the strategic consumer's utility in the DAM and the second term models the strategic consumer's expected utility in the balancing stage over the set of scenarios. The consumer's utility in the DAM is calculated by multiplying the consumption quantities scheduled in the DAM for the consumer $\left(P^{S}_{q}\right)$ by the difference between the consumer's bid (U^{S}_{q}), the price it is willing to pay), and the day-ahead LMPs (α^{DA}_{n}). Likewise, the balancing LMPs ($\alpha^{B}_{n\omega}/\phi_{\omega}$) and deployed reserves $\left(r^{S}_{qw}\right)$ are used to determine the strategic consumer's utility under each scenario, and the expected utility over the set of scenarios. Note that $\alpha^{B}_{n\omega}/\emptyset_{\omega}$ is the probability-removed balancing LMP at bus n for scenario ω where $\emptyset_{\omega}$ is the probability of that scenario. Constraint (1b) ensures non-negativity of the strategic consumer's bid price and enforces that to be less than the price cap of the pool. The LL problem, which models the clearing of the pool, is presented in (2a)–(2u). Equation (2a) represents the objective function, which minimizes the minus of declared expected social welfare. Constraints (2b) to (2u) represent the constraints of the pool clearing model. Note that scenario-independent constraints (2b) and (2d)–(2j) correspond to the first stage (i.e., DAM clearing), while scenario-dependent constraints (2c) and (2k)–(2u) pertain to the balancing stage. Constraints (2b) and (2c) represent the balance constraints in the DAM and balancing stage for every bus n, respectively. Dual variables of these constraints for the specific bus n, i.e., α_n^{DA} and $\alpha_{n\omega}^{B}$, are the day-ahead and balancing LMPs of bus n, respectively. Constraints (2d) and (2e) bound the scheduled production for conventional and wind power generating units in the DAM to their minimum and maximum limits. The maximum production that can be scheduled in the DAM for a conventional unit is limited to its installed capacity, though the maximum production that is scheduled for a wind farm is limited to its expected production. Constraints (2f) and (2g) bound the minimum and maximum scheduled consumption in the DAM, respectively, for strategic and competitive loads. Constraint (2h) enforces transmission constraints in the DAM. Constraint (2i) enforces the upper and lower bounds of the voltage angles in the DAM. Constraint (2j) identifies bus $n = 1$ as the voltage angle's reference in the DAM.

Constraints (2k)–(2u) are all scenario-dependent representing the balancing stage constraints under different scenarios. Constraints (2k) and (2l) bound the maximum up and down reserve that conventional generating units can deploy. Constraints (2m)–(2p) represent the maximum up and down reserve that strategic and competitive loads deploy, respectively. Constraints (2q) and (2r) enforce the amount of corrective actions, including involuntary load shedding and wind spillage, to be within specific limits. Load shedding from the competitive load l in scenario ω must be lower than its adjusted consumption under scenario ω. Constraint (2s) enforces transmission constraints in the balancing stage. Constraint (2t) enforces the upper and lower bounds of the voltage angles in the balancing stage. Constraint (2u) identifies bus n = 1as the voltage angle's reference in the balancing stage under scenario ω.

2.3.2 MPEC

The linearity of the LL problem (2) allows replacing it by its Karush-Kuhn-Tucker (KKT) optimality conditions. This transformation renders an MPEC as given by (3)–(4) below:

$$\underset{\Xi^{UL}}{\text{Maximize}} \quad (1a) \tag{3a}$$

subject to:

(1b), (2b), (2c), (2j), (2u) (3b)

$$O_g - \alpha^{DA}_{n:g\in G_n} - \underline{\mu}^G_g + \overline{\mu}^G_g - \sum_\omega \left(\underline{v}^G_{g\omega} + \overline{v}^G_{g\omega}\right) = 0 \quad \forall g \in G, \forall \omega \tag{3c}$$

$$\emptyset_\omega O_g - \alpha^{DA}_{(n:g\in G_n)\omega} - \underline{v}^G_{g\omega} + \overline{v}^G_{g\omega} - \underline{\eta}^G_{g\omega} + \overline{\eta}^G_{g\omega} = 0 \; \forall g \in G, \forall \omega \tag{3d}$$

$$-\alpha^{DA}_{n:k\in K_n} + \sum_\omega \alpha^B_{(n:k\in K_n)\omega} - \underline{\mu}^W_k + \overline{\mu}^W_k = 0 \; \forall k \in K \tag{3e}$$

$$\alpha^B_{(n:k\in K_n)\omega} - \underline{\mu}^W_{k\omega} + \overline{\mu}^W_{k\omega} = 0 \quad \forall k \in K, \forall \omega \tag{3f}$$

$$-B^S_q + \alpha^{DA}_{n:q\in D^S_n} - \underline{\mu}^S_q + \overline{\mu}^S_q + \sum_\omega \left(\underline{v}^S_{q\omega} + \overline{v}^S_{q\omega}\right) = 0 \quad \forall q \in D^S \tag{3g}$$

$$\emptyset_\omega U^S_q - \alpha^B_{(n:q\in D^S_n)\omega} - \underline{v}^S_{q\omega} + \overline{v}^S_{q\omega} - \underline{\eta}^S_{q\omega} + \overline{\eta}^S_{q\omega} = 0 \, \forall q \in D^S, \forall \omega \tag{3h}$$

$$-U^C_l + \alpha^{DA}_{n:l\in D^C_n} - \underline{\mu}^C_l + \overline{\mu}^C_l + \sum_\omega \left(\underline{v}^C_{l\omega} + \overline{v}^C_{l\omega} - \overline{\eta}^{\text{Shed}}_{l\omega}\right) = 0 \; \forall l \in D^C \tag{3i}$$

$$\emptyset_\omega U^C_l - \alpha^B_{(n:l\in D^S_n)\omega} - \underline{v}^C_{l\omega} + \overline{v}^C_{l\omega} - \underline{\eta}^C_{l\omega} + \overline{\eta}^C_{l\omega} + \overline{\eta}^{\text{Shed}}_{l\omega} = 0 \quad \forall l \in D^C, \forall \omega \tag{3j}$$

$$\emptyset_\omega V_l - \alpha^B_{(n:l\in D^C_n)\omega} - \underline{\eta}^{\text{Shed}}_{l\omega} + \overline{\eta}^{\text{Shed}}_{l\omega} = 0 \; \forall l \in D^C, \forall \omega \tag{3k}$$

$$\sum_{m\in\Psi_n} S_{nm}\left(\alpha_n^{DA}-\alpha_m^{DA}\right)-\sum_{(m\in\Psi_n)\omega} S_{nm}\left(\alpha_{n\omega}^{B}-\alpha_{m\omega}^{B}\right)+\sum_{m\in\Psi_n} S_{nm}\left(\zeta_{nm}^{DA}-\zeta_{mn}^{DA}\right)$$
$$+\overline{\delta}_n^{DA}-\underline{\delta}_n^{DA}+\left(\delta^{DA(\mathrm{n=1})}\right)_{n=1}=0 \qquad \forall n \tag{3l}$$

$$\sum_{m\in\Psi_n} S_{nm}\left(\alpha_{n\omega}^{B}-\alpha_{m\omega}^{B}\right)+\sum_{m\in\Psi_n} S_{nm}\left(\zeta_{nm\omega}^{B}-\zeta_{mn\omega}^{B}\right)$$
$$+\overline{\delta}_{n\omega}^{B}-\underline{\delta}_{n\omega}^{B}+\left(\delta_\omega^{B(\mathrm{n=1})}\right)_{n=1}=0 \qquad \forall n,\forall\omega \tag{3m}$$

$$0\le P_g^G \perp \underline{\mu}_g^G \ge 0 \qquad \forall g\in G \tag{3n}$$

$$0\le \left(\overline{P}_g^G-P_g^G\right)\perp \overline{\mu}_g^G \ge 0 \qquad \forall g\in \tag{3o}$$

$$0\le W_k \perp \underline{\mu}_k^W \ge 0 \qquad \forall k\in K \tag{3p}$$

$$0\le \left(\overline{W}_k-W_k\right)\perp \overline{\mu}_{kg}^W \ge 0 \qquad \forall k\in K \tag{3q}$$

$$0\le P_q^S \perp \underline{\mu}_q^S \ge 0 \qquad \forall q\in D^S \tag{3r}$$

$$0\le \left(\overline{P}_q^S-P_q^S\right)\perp \overline{\mu}_q^S \ge 0 \qquad \forall q\in D^S \tag{3s}$$

$$0\le P_l^C \perp \underline{\mu}_l^C \ge 0 \qquad \forall l\in D^C \tag{3t}$$

$$0\le \left(\overline{P}_l^C-P_l^C\right)\perp \overline{\mu}_l^C \ge 0 \qquad \forall l\in D^C \tag{3u}$$

$$0\le \left[F_{nm}-S_{nm}\left(\theta_n^{DA}-\theta_m^{DA}\right)\right]\perp \zeta_{nm}^{DA}\ge 0 \qquad \forall n,\forall m\in\Psi_n \tag{3v}$$

$$0\le \left(\theta_n^{DA}+\pi\right)\perp \underline{\delta}_n^{DA}\ge 0 \qquad \forall n \tag{3w}$$

$$0\le \left(\pi-\theta_n^{DA}\right)\perp \overline{\delta}_n^{DA}\ge 0 \qquad \forall n \tag{3x}$$

$$0\le \left(P_g^G+r_{g\omega}^G\right)\perp \underline{v}_{g\omega}^G\ge 0 \qquad \forall g\in G,\forall\omega \tag{3y}$$

$$0\le \left(\overline{P}_g^G-P_g^G+r_{g\omega}^G\right)\perp \overline{v}_{g\omega}^G\ge 0 \quad \forall g\in G,\forall\omega \tag{3z}$$

$$0 \le \left(r_{g\omega}^{G} + \overline{R}_{g}^{G^{D}} \right) \perp \underline{\eta}_{g\omega}^{G} \ge 0 \qquad \forall g \in G, \forall \omega \tag{4a}$$

$$0 \le \left(\overline{R}_{g}^{G^{U}} - r_{g\omega}^{G} \right) \perp \overline{\eta}_{g\omega}^{G} \ge 0 \qquad \forall g \in G, \forall \omega \tag{4b}$$

$$0 \le \left(r_{q\omega}^{S} - P_{q}^{S} + \overline{P}_{q}^{S} \right) \perp \underline{v}_{q\omega}^{S} \ge 0 \quad \forall q \in D^{S}, \forall \omega \tag{4c}$$

$$0 \le \left(P_{q}^{S} - r_{q\omega}^{S} \right) \perp \overline{v}_{q\omega}^{S} \ge 0 \qquad \forall q \in D^{S}, \forall \omega \tag{4d}$$

$$0 \le \left(r_{q\omega}^{S} + \overline{R}_{q}^{S^{D}} \right) \perp \underline{\eta}_{q\omega}^{S} \ge 0 \qquad \forall q \in D^{S}, \forall \omega \tag{4e}$$

$$0 \le \left(\overline{R}_{q}^{S^{U}} - r_{q\omega}^{S} \right) \perp \underline{\eta}_{q\omega}^{S} \ge 0 \qquad \forall q \in D^{S}, \forall \omega \tag{4f}$$

$$0 \le \left(r_{l\omega}^{C} - P_{l}^{C} + \overline{P}_{l}^{C} \right) \perp \underline{v}_{l\omega}^{C} \ge 0 \quad \forall l \in D^{C}, \forall \omega \tag{4g}$$

$$0 \le \left(P_{l}^{C} - r_{l\omega}^{C} \right) \perp \overline{v}_{l\omega}^{C} \ge 0 \qquad \forall l \in D^{C}, \forall \omega \tag{4h}$$

$$0 \le \left(r_{l\omega}^{C} + \overline{R}_{l}^{C^{D}} \right) \perp \underline{\eta}_{l\omega}^{C} \ge 0 \qquad \forall l \in D^{C}, \forall \omega \tag{4i}$$

$$0 \le \left(\overline{R}_{l}^{C^{U}} - r_{l\omega}^{C} \right) \perp \overline{\eta}_{l\omega}^{C} \ge 0 \qquad \forall l \in D^{C}, \forall \omega \tag{4j}$$

$$0 \le p_{l\omega}^{\text{Shed}} \perp \underline{\eta}_{l\omega}^{\text{Shed}} \ge 0 \qquad \forall l \in D^{C}, \forall \omega \tag{4k}$$

$$0 \le \left(P_{l}^{C} - r_{l\omega}^{C} - p_{l\omega}^{\text{Shed}} \right) \perp \overline{\eta}_{l\omega}^{\text{Shed}} \ge 0 \quad \forall l \in D^{C}, \forall \omega \tag{4l}$$

$$0 \le w_{k\omega}^{\text{Spill}} \perp \underline{\eta}_{k\omega}^{\text{W}} \ge 0 \qquad \forall k \in K, \forall \omega \tag{4m}$$

$$0 \le \left(W_{k\omega}^{\text{act}} - w_{k\omega}^{\text{Spill}} \right) \perp \overline{\eta}_{k\omega}^{\text{Shed}} \ge 0 \qquad \forall k \in K, \forall \omega \tag{4n}$$

$$0 \le \left[F_{nm} - S_{nm} \left(\theta_{n\omega}^{B} - \theta_{m\omega}^{B} \right) \right] \perp \zeta_{nm\omega}^{B} \ge 0 \quad \forall n, \forall m \in \Psi_{n}, \forall \omega \tag{4o}$$

$$0 \le \left(\theta_{n\omega}^{B} + \pi \right) \perp \underline{\delta}_{n\omega}^{B} \ge 0 \qquad \forall n, \forall \omega \tag{4p}$$

$$0 \le \left(\pi - \theta_{n\omega}^{B} \right) \perp \overline{\delta}_{n\omega}^{B} \ge 0 \qquad \forall n, \forall \omega \tag{4q}$$

Constraint (3b) contains the only upper-level constraint and the equalities included in the LL problem (2). Equalities (3c)–(3m) and the complementarity conditions (3n)–(4q) are the KKT optimality conditions of the LL problem (2).

2.3.3 MPEC Linearization

The MPEC (3)–(4) above is nonlinear due to complementarity conditions (3n)–(4q) and the bilinear term $\sum_{q\in D^S}\left[P_q^S \alpha_{n:q\in D_n^S}^{DA} - \sum_\omega r_{q\omega}^S \alpha_{(n:q\in D_n^S)\omega}^B\right]$ in the objective function (1a), denoted below as Γ. The strong duality equality is utilized to substitute the bilinear term Γ by an exactly equivalent linear term by the following step-by-step approach [28]:

1) The strong duality equality corresponding to the LL problem (2) is obtained.
2) The complementarity conditions (3s) and (4c)–(4f) render the following equalities:

$$\sum_{q\in D^S} \overline{P}_q^S \overline{\mu}_q^S = \sum_{q\in D^S} P_q^S \overline{\mu}_q^S \tag{5a}$$

$$\sum_{(q\in D^S)\omega} \overline{P}_q^S \underline{v}_{q\omega}^S = \sum_{(q\in D^S)\omega} P_q^S \underline{v}_{q\omega}^S - \sum_{(q\in D^S)\omega} r_{q\omega}^S \underline{v}_{q\omega}^S \tag{5b}$$

$$\sum_{(q\in D^S)\omega} P_q^S \overline{v}_{q\omega}^S = \sum_{(q\in D^S)\omega} r_{q\omega}^S \overline{v}_{q\omega}^S \tag{5c}$$

$$\sum_{(q\in D^S)\omega} \overline{R}_q^{S^D} \underline{\eta}_{q\omega}^S = \sum_{(q\in D^S)\omega} r_{q\omega}^S \underline{\eta}_{q\omega}^S \tag{5d}$$

$$\sum_{(q\in D^S)\omega} \overline{R}_q^{S^U} \overline{\eta}_{q\omega}^S = \sum_{(q\in D^S)\omega} r_{q\omega}^S \overline{\eta}_{q\omega}^S \tag{5e}$$

3) The equalities (5) are substituted in the strong duality equality. Specifically, the left-hand side terms in (5) are substituted with the corresponding right-hand side terms.

4) KKT equalities (3g) and (3h) are multiplied by P_q^S and $r_{q\omega}^S$, respectively; then the resulting equalities are added up, which renders equality (6) below:

$$-\sum_{q\in D^S}\alpha^{DA}_{(n:q\in D_n^S)}P_q^S+\sum_{(q\in D^S)\omega}\alpha^{B}_{(n:q\in D_n^S)\omega}r_{q\omega}^S=-\sum_{q\in D^S}\left(B_q^S P_q^S+\underline{\mu}_q^S P_q^S-\overline{\mu}_q^S P_q^S\right) \tag{6}$$

$$+\sum_{(q\in D^S)\omega}\left(\underline{v}_{q\omega}^S P_q^S-\overline{v}_{q\omega}^S P_q^S+\emptyset_\omega U_q^S r_{q\omega}^S-\underline{v}_{q\omega}^S r_{q\omega}^S+\overline{v}_{q\omega}^S r_{q\omega}^S-\underline{\eta}_{q\omega}^S r_{q\omega}^S+\overline{\eta}_{q\omega}^S r_{q\omega}^S\right).$$

5) By substituting equality (6) in the strong duality equality obtained in step 3, the bilinear term can be replaced by the exact linear equivalent as follows:

$$\Gamma=-\sum_{\omega}\phi_\omega\left\{\sum_{g\in G}O_g\left(P_g^G+r_{g\omega}^G\right)\right\}-\sum_{g\in G}\overline{P}_g^G\overline{\mu}_g^G \tag{7}$$

$$-\sum_{(g\in G)\omega}\left(\overline{P}_g^G\overline{v}_{g\omega}^G+\overline{R}_g^{G^D}\underline{\eta}_{g\omega}^G+\overline{R}_g^{G^U}\overline{\eta}_{g\omega}^G\right)$$

$$+\sum_{\omega}\phi_\omega\left\{\sum_{l\in D^C}\left[U_l^C\left(P_l^C-r_{l\omega}^C\right)-V_l p_{l\omega}^{\text{Shed}}\right]\right\}-\sum_{l\in D^C}\overline{P}_l^G\overline{\mu}_l^G$$

$$-\sum_{(l\in D^C)\omega}\left(\overline{P}_l^C\underline{v}_{l\omega}^C+\overline{R}_l^{C^D}\underline{\eta}_{l\omega}^C+\overline{R}_l^{C^U}\overline{\eta}_{l\omega}^C\right)-\sum_{n(m\in\Psi_n)}F_{nm}\zeta_{nm}^{DA}-\sum_{n}\pi\left(\underline{\delta}_n^{DA}+\overline{\delta}_n^{DA}\right)-\sum_{k\in K}\overline{W}_k\overline{\mu}_k^W$$

$$-\sum_{(k\in K)\omega} W_{k\omega}^{act}\left[\overline{\eta}_{k\omega}^{W}+\alpha_{(n:k\in K_n)\omega}^{B}\right]-\sum_{n(m\in\Psi_n)\omega} F_{nm}\zeta_{nm\omega}^{B}-\sum_{n\omega}\pi\left(\underline{\delta}_{n\omega}^{B}+\overline{\delta}_{n\omega}^{B}\right).$$

For more on the principles of this approach see [28]. In addition, each complementarity condition (3n)–(4q) of the form $0 \leq a \perp b \geq 0$ is equivalent to the set of mixed-integer linear conditions $a \geq 0, b \geq 0, a \leq uM, b \leq (1-u)M$, where is an auxiliary binary variable, and M is a large enough positive constant [37].

2.4. Numerical Results

In this section, the one-area and the three-area IEEE reliability test systems (IEEE RTS-24 and RTS-72) [38] are used to illustrate different features and outcomes of the strategic consumer's bidding and the practical functioning and consistency of the proposed model.

2.4.1 Illustrative Case Study

2.4.1.1 Data

The data for the illustrative case study (single-area IEEE RTS) is presented in Table 1 and Table 2. Table 1 presents generating units' data and location. Maximum reserve capacities of base, intermediate and peak units are assumed 0%, 10% and 20% of their capacity, respectively.

Data for strategic and competitive loads including their type (responsive, non-responsive and semi-responsive), and location are given in Table 2. The case study has 17 loads; loads Q1 to Q7 and L1 to L10 are owned by the strategic and competitive

Table 1: Data for Generating Units (Single-Area Case Study)

Generating unit (g)	Type	Unit capacity (MW)	Marginal cost ($/MWh)	Maximum up and down reserve capacity (MW)	Location (bus)
G1	Base	40	15.00	0	1
G2	Base	152	12.46	0	1
G3	Base	40	15.00	0	2
G4, G5	Base	76	12.46	0	2
G6-G8	Base	100	16.00	0	7
G9-G11	Base	197	13.58	0	13
G12-G16	Peak	12	18.57	2.4	15
G17	intermediate	155	11.09	15.5	15
G18	Intermediate	155	11.09	15.5	16
G19	Base	400	12.00	0	18
G20	Base	400	12.00	0	21
G21-G26	Peak	50	0.00	10	22
G27, G28	Intermediate	155	11.09	15.5	23
G29	Intermediate	100	16.75	10	23
G30	Intermediate	100	17.25	10	23
G31	Intermediate	100	17.75	10	23
G32	Intermediate	50	18.10	5	23

consumers, respectively. Same as generating units, maximum reserve capacities of loads differ based on their type. Maximum reserve capacities for non-responsive, semi-responsive and responsive loads are assumed 0%, 7.5% and 15% of their maximum demand, respectively. Total maximum demand of the strategic consumer is 1,064.88 MW, which is 36.63% of total maximum demand of all loads (2,907 MW). Note that maximum demand of each load is identical to that in [38] raised by 2%. VOLL for competitive loads is assumed to be $10,000/MWh. Maximum energy bid price to be submitted by the strategic consumer is $180/MWh. For simplicity and to make the

Table 2: Data for Loads of the Strategic and Competitive Consumers

Load	Type	Maximum demand (MW)	Marginal utility ($/MWh)	Maximum up and down reserve capacity (MW)	Location (bus)
Strategic Consumer's loads					
Q1	Semi-responsive	110.16	23.5	8.26	1
Q2	Responsive	98.94	20.0	14.84	2
Q3	Non-responsive	183.60	26.5	0.00	3
Q4	Non-responsive	75.48	27.3	0.00	4
Q5	Responsive	72.42	19.0	10.86	5
Q6	Responsive	339.66	21.3	50.95	18
Q7	Semi-responsive	184.62	22.3	13.85	19
Competitive Consumers' loads					
L1	Non-responsive	138.72	27.3	0.00	6
L2	Non-responsive	127.50	29.0	0.00	7
L3	Semi-responsive	174.42	25.0	13.08	8
L4	Non-responsive	178.50	27.5	0.00	9
L5	Responsive	198.90	19.0	29.84	10
L6	Responsive	270.30	20.0	40.55	13
L7	Responsive	197.88	21.0	29.68	14
L8	Non-responsive	323.34	28.5	0.00	15
L9	Non-responsive	102.00	27.0	0.00	16
L10	Responsive	130.56	22.0	19.58	20

findings more intuitive, the capacity of all the transmission lines are increased to 600 MW, so transmission constraints are non-binding. However, the impact of transmission constraints on bidding strategy of the strategic consumer is studied later through a congested case.

Table 3 presents data for the two wind farms K1 and K2 of the single-area case study, including their production under different scenarios and probability of such scenarios. Wind farms K1 and K2 are located at buses 3 and 14, and their installed capacities are assumed to be 228 MW and 264 MW, respectively. Expected value and expected standard deviation of wind power production of farm K1 are 124.8 MW and 41.62 MW. For wind farm K2, expected value and expected standard deviation are 111.54 MW and 50.03 MW, respectively. Accordingly, the wind power production of farm K2 has higher volatility than that of farm K1. The case corresponding to Table 1to Table 3 is referred as “Base Case”.

The difference between the four cases considered are presented in Table 4. The cases differ in the participation of loads in reserve provision, their reserve deployment capacity, and characteristics of the wind farms.

2.4.1.2 Competitive Versus Strategic Bidding

In this section, Case 1 (which is our Base Case) is studied to compare the outcomes of the strategic consumer's competitive and strategic behavior. The result are presented in Table 5. Rows two and three of Table 5 give the values of dispatched wind in the DAM and the expected wind power spillage, respectively. The fourth row presents the strategic consumer's energy bid price for the DAM. Day-ahead LMPs and expected balancing LMPs are also given in rows five and six. The expected value of the strategic consumer's not-supplied energy is presented in the seventh row. Total expected utility of the strategic consumer is given in the eighth row. Rows ninth and tenth give expected utility of the strategic consumer in the DAM and the balancing stage, respectively. The eleventh and twelfth rows present the total expected utility of competitive consumers and the total expected profit of generating units, respectively.

Table 3: Wind Power Production Scenarios

Scenario #	$\emptyset_\omega$	$W^{act}_{(k=1)\omega}$	$W^{act}_{(k=2)\omega}$
1	0.015	200	170.00
2	0.030	162	137.00
3	0.040	153	130.05
4	0.040	144	122.40
5	0.050	135	114.75
6	0.050	126	107.10
7	0.030	108	91.80
8	0.030	90	76.50
9	0.030	81	68.50
10	0.015	54	45.90
11	0.020	184	120.00
12	0.020	165.6	108.00
13	0.040	147.2	96.00
14	0.040	138	90.00
15	0.050	128.8	84.00
1	0.015	200	170.00
16	0.050	119.6	78.0
17	0.035	110.4	72.0
18	0.030	92.0	60.0
19	0.025	55.2	36.0
20	0.020	46.0	30.0
21	0.015	228.0	264.0
22	0.030	209.0	242.0
23	0.040	180.5	209.0
24	0.040	152.0	176.0
25	0.050	133.0	154.0
26	0.050	114.0	132.0
27	0.030	95.0	110.0
28	0.030	76.0	88.0
29	0.030	57.0	66.0
30	0.025	38.0	44.0

The last row shows total expected social welfare of the market. In this case, the strategic consumer has the opportunity to supply a fraction of its demand deploying down

Table 4: Characteristics of Case Studies

Cases	Reserve provision by the demand-side	Reserve capacity of loads as % of minimum demand			Expected standard deviation of production of wind farms (MW)		Expected production of wind farms (MW)	
		NR*	SR*	R*	K1	K2	K1	K2
Case 1	√	0.0	7.5	15				
Case 2	–	0.0	0.0	0.0	41.62	50.03	124.80	111.54
Case 3	√	0.0	5.5	13				
Case 4	√	0.0	7.5	15	27.92	32.53		

* NR: Non-responsive, SR: Semi-responsive, R: Responsive

reserve in the balancing stage depending on the deployment capability of its loads.

Results for Case 1 given in Table 5 show that:

a) LMPs are lower under the strategic demand-side (equal to $13.58/MWh) as the strategic consumer underbids its demand in the DAM. Although by underbidding the demand the strategic consumer reduces its utility from supplying energy (i.e., expected unsupplied energy increases) this cost is more than offset by the increase in utility from lower DAM's LMPs. The net effect is that the expected utility of the strategic consumer in the DAM is $1,128 higher when it behaves strategically (row 9).

b) A fraction of the strategic consumer's demand is not scheduled in the DAM under strategic bidding. However, part of the unscheduled demand is supplied in the balancing stage through down-reserve deployment so it is expected the consumer will only have 46.14 MWh of expected energy not supplied.

c) The strategic behavior of the large consumer reduces the scheduled wind production in the DAM and hence increases both the availability of free wind energy and the required down reserves in the balancing stage necessary in order to maximize the supply to meet its demand. As a result, its expected utility in the balancing stage increases by $140 (row 10).

d) The total expected utility of the competitive consumers is higher in the strategic case. Indeed, although the competitive consumers behave as price-takers, they free-ride on the strategic consumer's behavior fully supplying their load at lower LMPs relative to prices in the competitive case. Neither in the strategic nor in the competitive cases the competitive consumers have any unserved load, but in the strategic case LMPs are lower.

e) The strategic behavior of the large consumer has detrimental impacts on other

Table 5: Strategic and Competitive Bidding Results for Case 1

Result	Strategic demand-side	Competitive demand-side
Scheduled wind power production in the DAM (MW)	25.51	44.01
Expected wind power spillage (MW)	1.56	0.68
Energy bid price by the strategic consumer ($/MWH)	13.58	Marginal utility
Day-ahead LMPs ($/MWh) (Buses 1 to 24)	13.58	15.00
Expected balancing LMPs ($/MWh) (Buses 1 to 24)	13.58	15.00
Expected energy not supplied of the strategic consumer (MWh)	46.1	0.00
Total EU* of the strategic consumer ($)	9517	8249
Utility of the strategic consumer in the DAM ($)	8766	7638
EU of the strategic consumer in the balancing state ($)	751	611
Total EU of all competitive consumers ($)	19920	17305
Total expected profit of all generating units ($)	7391	11064
Expected social welfare ($)	30818	39771

* Expected utility

market outcomes relative to the competitive case, including the total expected profit of generating units ($3673 lower) and expected social welfare of the market ($8953 lower).

2.4.1.3 Strategic Bidding Outcomes in Different Cases

This section highlights factors impacting the strategic consumer's behavior and its outcomes by comparing Case 2, Case 3, and Case 4 to Case 1, all presented in Table 6. Comparison of the results for the first three cases (Case 1, Case 2, and Case 3) highlights the effects of increased capability of reserve provision. Note that Case 3 is intermediate between Case 1 (maximum reserve provision capability) and Case 2 (no reserve provision capability). Furthermore, comparison of Case 1 and Case 4 explores the effects of increased wind power production variability, under similar reserve provision capability.

Table 6: Strategic Bidding Results for All Cases

Result	Case 1	Case 2	Case 3	Case 4
Scheduled wind power production in the DAM (MW)	24.51	190	111.258	95.67
Expected wind power spillage (MW)	1.56	10.70	0.55	0.97
Day-ahead LMPs ($/MWh) (Buses 1 to 24)	13.58	13.58	13.58	13.58
Expected energy not supplied of the strategic consumer (MWh)	46.1	112.0	51.3	48.8
EU* of the strategic consumer in the balancing state ($)	751	0	623.44	746
Total EU of strategic consumer ($)	9517	9120	9487	9500
Expected social welfare ($)	30818	29994	30721	30958

* Expected utility

Rows 2 and 3 present the scheduled wind production in the DAM and expected wind spillage, respectively. Day-ahead LMPs are also given in row 4. Row 5 presents the expected value of the strategic consumer's not-supplied energy. Rows 6 and 7 present the expected utility of the strategic consumer in the balancing stage and in total, respectively. The last row shows the expected value of the total social welfare of the market.

The following conclusions can be drawn from comparing the results of Case 2, where DAM is the strategic consumer's sole option for supplying its demand, to Case 1:

a) As the strategic consumer is banned from reserve provision in Case 2, a larger amount of wind energy is scheduled in the DAM.

b) In Case 2, the only available tool to the strategic consumer for gaming is cutting a part of its demand in the DAM. As a result, the expected value of the strategic consumer's not-supplied energy increases by 65.9 MWh (112–46.1) in Case 2 so that its total utility is reduced by $397 (i.e., $9517-$9120).

c) Reserve deployment significantly contributes to the large consumer's market power and its influence on market outcomes.

Another factor affecting the strategic consumer's strategic behaviour (investigated using Case 3) is its reserve deployment capacity. Comparing the results of this case with Case 1 reveals that the reduction in the strategic consumer's reserve deployment capacity increases the scheduled wind production in the DAM. This reduces the demand for down-reserve deployment in the balancing stage, and forces the strategic consumer to accept a higher expected value of energy not supplied in order to achieve the same LMPs as in Case 1. Therefore, its expected total utility is lower in Case 3. Similar results are obtained in Case 4. In Case 4, production of the wind farms have lower expected standard deviation (as a measure of variability) than Case 1, while the expected production values are the same. The lower variability reduces demand for reserve deployment so that a smaller fraction of reserve's demand is supplied by the strategic consumer, and hence its expected utility decreases with respect to Case 1.

2.4.1.4 Strategic Bidding Outcomes in Different Cases

In this section, Case 1 (the Base Case) is modified to investigate the reactions of the strategic consumer to congestion in the network and its impacts on market outcomes. To create congestion in Case 1, the test case (IEEE RTS-24) is divided into two subareas, North and South, where the North subarea includes buses 14–24, and the South subarea buses 1–13. The two subareas are interconnected through four branches: 1) from bus 24 to bus 3, 2) from bus 14 to bus 11, 3) from bus 23 to bus 12, and 4) from bus 23 to bus 13. The available transmission capacity (ATC) of the interconnection between the subareas is 500 MW. To better highlight the impact of congestion on the bidding behavior of the strategic consumer and its market outcomes, the strategic bidding results in congested conditions are compared to results obtained under strategic bidding when there is no congestion (i.e., Case 1) in Table 7. Note that the order of reported results in rows of Table 7 are identical to the

Table 7: Strategic Bidding Results in Congested and Normal Conditions for Case 1

Result	Normal condition	Congested condition
Scheduled wind power production in the DAM (MW)	24.51	72.17
Expected wind power spillage (MW)	1.56	0.53
Energy bid price by the strategic consumer ($/MWH) (South, North)	13.58, 13.58	13.58, 12.00
Day-ahead LMPs ($/MWh) (South, North)	13.58, 13.58	13.58, 12.00
Expected balancing LMPs ($/MWh) (South, North)	13.58, 13.58	13.58, 12.00
Expected energy not supplied of the strategic consumer (MWh)	46.1	105.9
Total EU* of the strategic consumer ($)	9517	9991
Utility of the strategic consumer in the DAM ($)	8766	9198
EU of the strategic consumer in the balancing state ($)	751	793
Total EU of all competitive consumers ($)	19920	21101
Total expected profit of all generating units ($)	7391	4646
Expected social welfare ($)	30818	29943

order of reported results in Table 5. The following observations can be made from the results presented in Table 7:

a) Due to transmission congestion the LMPs are different in the two subareas, with the LMP in the North being lower than in the South. Moreover, the LMP of the North in the congested case is lower than that in the uncongested case. Consequently, under transmission congestion, the expected utility of the strategic consumer is higher than under no congestion, though the expected value of its not-supplied energy is higher than in the uncongested case.

b) All the expected not-supplied energy in the congested case corresponds to strategic loads located in the South subarea where the majority of strategic loads are Located. This is because having not supplied load in the north subarea further exacerbates the congestion and increases the need for generation from more expensive units in the South to alleviate congestion, which would further increase the LMPs.

c) The general conclusion to be made is that the bidding behavior of the strategic consumer in a congested network and its market outcomes significantly depend on the topology of the grid (location of generating units and loads), and the subareas resulting from congestion.

d) In some cases, it may happen that the strategic consumer forces congestion to increase its expected utility.

2.4.2 Large-Scale Case Study

In this section, the strategic bidding model is examined on the three-area test system (IEEE RTS-72) [38] for a 24-hour time period (running the model individually for each hour). Assumptions on conventional generating units, loads (strategic and nonstrategic) and intra-area transmission lines of the three areas are identical and equal to those in the previous subsection. Transmission constraints of the lines interconnecting the three areas are chosen to be non-binding. Three wind farms K1, K2, and K3 are assumed to be located at bus 3 of areas 1, 2, and 3, respectively. The uncertainty on wind generation is represented with a total of 30 scenarios of hourly wind power production from each farm. Note that instead of discretizing the uncertainty set through scenarios in order to reduce the infinite-dimensional problem to a finite dimensional one, it would be possible to choose a set of functions that serve as a basis for the uncertainty set. The scenarios used for in-sample simulations are constructed based on the data for the first 500 days of the available 1000 data points, on aggregated hourly power production from wind farms in Belgium [39] and Ireland [40] (so there are 500 data points for the production of each wind farm in each hour). From the data, for each of the 24 hours (including off-peak hours t1 to t11, shoulder hours t12 to t17 and t22 to t24, and peak hours t18 to t21), we divided the range of observed values into 5 equal-length intervals corresponding to five different possible states of wind power generation: very low, low, medium, high and very high. The probabilities of each of the 5 states were calculated as the frequency of each state observed in the sample. Because wind power production from the three farms is assumed to be independent of each other, for each hour there are $5^3 = 125$ possible scenarios of aggregated wind power production. In order to maintain computational tractability the set of 125 possible scenarios is reduced to a set of 30 chosen using the method presented in [41].

Although reducing the set of scenarios to 30 may fail to represent all the possible conditions of wind power generation, any misrepresentation of the uncertainty does not have an impact in the in-sample analysis we conduct or its results. This is because the same 30 scenarios represent the information used by the strategic consumer to design its bid (and by the market operator to clear the DAM) are also assumed to be representative of the wind production observed in real time and the corresponding clearing of the balancing stage. However, this use of scenarios implicitly assumes that the strategic consumer has a very good idea of what future wind power production may be. In order to explore the robustness of strategic consumer's bids to its imperfect characterization of the uncertainty on wind power production we conduct an “out-of-sample” simulation. That is, we look at a case where the strategic consumer has a less accurate characterization of the uncertainty and rather than constructing scenarios from the same 500 days of available historical data (i.e., days 1 to 500), has information about only the second half of the data (i.e., days 501 to 1000). Hence, for the out-of-sample results, the expected outcomes are calculated over a different set of scenarios than those used as input to the model. In other words, for the in-sample results, it is assumed that the strategic consumer has complete information about the distribution function of wind power production identical to the operator of the market, when generating the set of scenarios. However, for the out-of-sample results, the strategic consumer has incomplete information and the utilized distribution function is constructed using a different subset of the data available to the market operator. In a sense, out-of-sample simulation evaluates the quality of the generated scenarios for production of the wind farms and whether or not they appropriately capture the uncertainty of wind power production from the strategic consumer's perspective.

Figure 1 and Figure 2 illustrate in-sample results for the strategic and competitive bidding of the strategic consumer. Note that the maximum system demand depicted in Figure 1 refers to the possible maximum electricity demand in the system, which is equal to the sum of the demand from all strategic and competitive loads when the price is zero (i.e., the demand curve's intercept with the vertical axis). Wind spillage ratio in Figure 2 refers to the ratio of expected wind spillage to the expected wind power production over the set of scenarios. As seen, the strategic consumer's strategic bidding lowers the LMPs during off-peak hours (t1, t3, t6, and t8), shoulder hours (t12) and peak hours (t19 and t20). As a result, expected total daily utility of the strategic consumer increases by 15,009 (2.65%) with strategic bidding. However, 938 MWh, equivalent to 4.68% of its maximum daily demand, are unsupplied.

Figure 3 shows the out-of-sample results of the strategic and competitive bidding. Wind spillage ratio in Figure 3 refers to the ratio of the expected wind spillage to the expected wind power production over the set of unseen wind power production

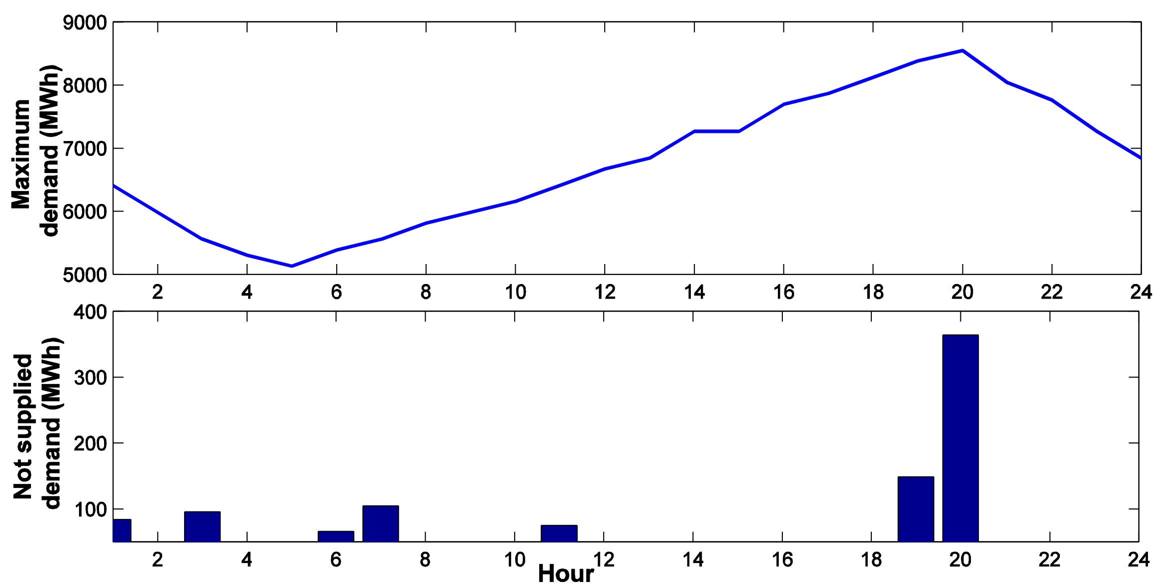

Figure 1: Maximum System Demand And Hourly Not-Supplied Demand Of The Strategic Consumer For The Three Area System Obtained In-Sample

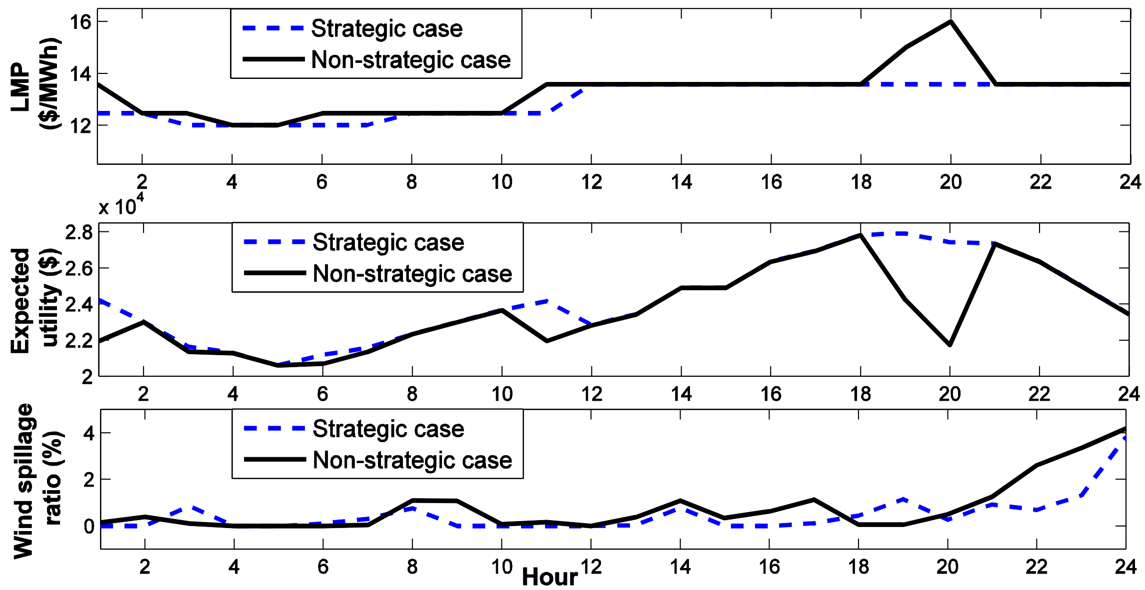

Figure 2: LMPs, Expected Utility of The Strategic Consumer And Wind Spillage ratio for the three area system obtained in-sample

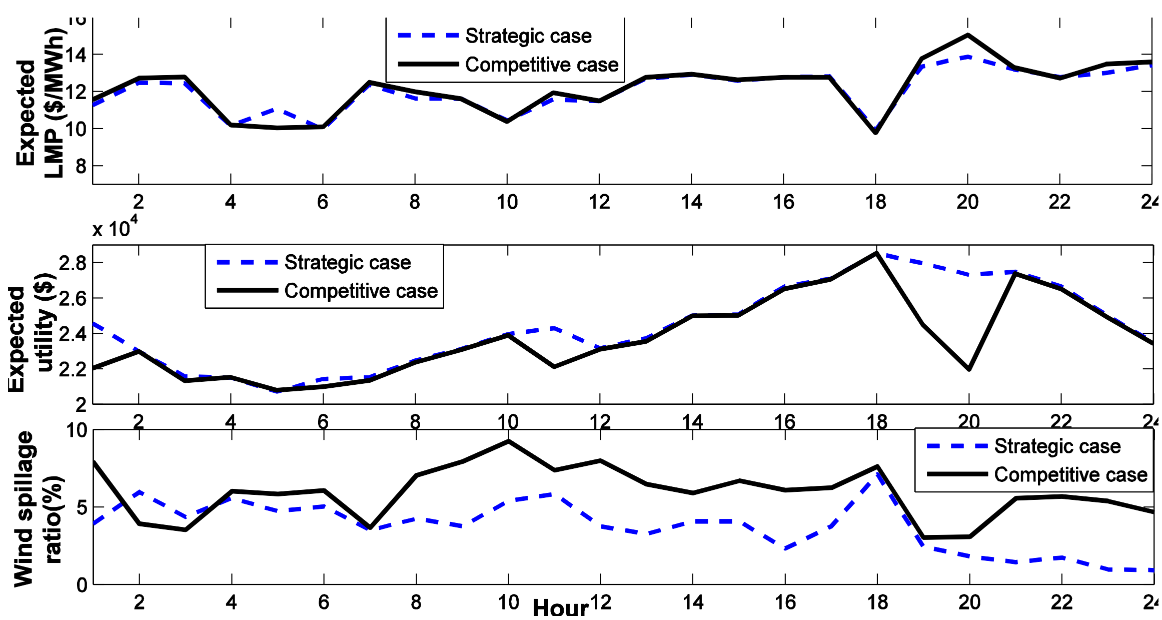

Figure 3: Expected Balancing LMP, Expected Utility Of The Strategic Consumer, And Wind Spillage Ratio Of The Three Area System Obtained Out-of-Sample

samples. As seen, the calculated out-of-sample results for competitive and strategic biding cases follow the patterns similar to the in-sample results. For instance, total expected utility of the strategic consumer from strategic bidding is $15,499 higher (%2.72) than that obtained in the competitive case. This increase in the out-of-sample expected utility from strategic bidding is due to a higher realization of wind power production than what was expected by the strategic consumer from its uncertainty characterization. Additionally, under the strategic case, the expected LMPs in the balancing stage are lower than those obtained in the competitive case except during time periods t5, t10, t12, and t17. These and other differences (such as those on the wind-spillage ratio) between the in-sample and out-of-sample results, stem from different characteristics of the in-sample and out-of-sample wind power production data sets. For instance, hourly average expected wind production for the in-sample data is 487 MW, which is 41 MW lower than the hourly average out-of-sample wind power production. Higher amounts of down-reserve scheduled in the strategic case, with respect to those in the competitive case, contribute to the wind-spillage ratio differences as the strategic consumer's behavior tends to increase the demand for down-reserve deployment in the balancing stage.

2.4.3 Computational Considerations

The computational burden of the proposed model is characterized in Table 8 for the single-area (IEEE RTS-24) and the three-area (IEEE RTS-72) test cases. As shown, the CPU time for solving the illustrative case study (IEEE RTS-24) for a single time period is

73 seconds, and for the large-scale case study (IEEE RTS-72) for a 24-hour time horizon is 11,880 seconds. It is worth noting that increasing the number of wind farms further increases the computational complexity of both the stochastic market clearing problem and the derivation of the strategic day-ahead bidding curves for the large consumer. This is due to the fact that adding wind farms exponentially increases the size of the set of scenarios required to characterize the uncertainty on the wind power production. This increase in the number of scenarios is matched with an increase in the number of continuous and binary decision variables. Nevertheless, there are multiple alternatives available for resolving this problem including utilizing a supercomputer, implementing decomposition and/or parallel computing techniques [42], [43] applying appropriate techniques to simplify the network [44] and reducing the number of scenarios through existing scenario-reduction techniques [41]. For all case studies, CPLEX 12.3 under GAMS [45] is used to solve the resulting MILP problem on a PC with two processors clocking at 3.3 GHz and 4 GB of RAM.

Table 8: Results Related to the Computational Complexity of the Strategic Bidding Model

Test Case	Number of variables		Number of constraints	CPU time (Second)
	Continuous	Binary		
IEEE RTS-24	22586	8688	24019	73
IEEE RTS-72	60065	22702	76262	11880

2.5 Conclusions and Future Research

The numerical results reveal that a large, price-responsive strategic consumer providing operating reserves can increase total expected utility and decrease the expected value of its energy not-supplied. The market power of this strategic consumer is enhanced in proportion of its capacity to provide operating reserves, and can significantly impact the scheduling of wind power production in the DAM, and increase the required down reserve in the balancing stage. Since this paper considers a single-hour auction, the introduced model underestimates market power of the strategic consumer as its load-shifting capability is ignored. Also, it is worth noting that the outcomes of this study are obtained assuming the large consumer has full information about the network, demand bids, supply offers, and distribution function for production of the wind farms. Therefore, the calculated outcomes represent an upper bound on the extent that the strategic consumer can exercise market power. Future work will study the strategic behavior of a large consumer that benefits from energy storage and load shifting capabilities and the interaction of strategic consumers and producers.

3. Economic and Environmental Implications of Different Approaches to Hedge Against Wind Production Uncertainty in Electricity Markets

The Supporting Information (SI) of this chapter is available in Appendix B of this dissertation.

3.1 Abstract

This paper compares the economic, and environmental outcomes of two alternative electricity market clearing designs for cost-effective integration of wind power production. The first alternative introduces new products called "DA ramp-capability requirements" into the conventional deterministic market-clearing algorithm in order to lower the expected cost of real-time deviations from day-ahead point estimates of wind generation. The second alternative uses stochastic optimization to directly account for wind production uncertainty in setting day-ahead market clearing schedules and prices.

The alternative mechanisms are assessed by simulating the electricity market operations of a test system and comparing results in terms of operating costs, prices, revenues to producers, welfare, integration of wind power, and air emissions.

The test system consists of a 12% scaled version of PJM's fossil-fired power generation fleet and uses data on coincident demand and wind production from the Bonneville Power Administration (BPA) system in years 2010-2014. The simulations are performed hourly for a whole year. Results show that the stochastic market clearing design is superior to the one with ramp-capability requirements. It reduces power

plant's operating costs by 0.9% under a scenario of 12% of wind penetration by energy, when compared to the conventional design. The stochastic market clearing also cuts the spread between the day-ahead and real-time prices by more than 40%, reduces out-of-market short-term revenue sufficiency payments by 58%, reduces CO_2 emissions by 3.52%, and decreases power plants' cycling. It also reduces the revenues of coal producers and rises those of wind energy and fast-start producers.

3.2 Introduction

Increased use of wind energy in electricity systems can help reduce green house gas emissions and enhance energy security. However, wind's low marginal cost, variability, and uncertainty may challenge the efficient and reliable operation of systems with high shares of wind production capacity. Wind production uncertainty and variability may cause inefficient scheduling and dispatch of the conventional generation fleet [46], [47] rising the balancing costs [48], distorting prices [2], increasing revenue sufficiency guarantee payments [49], and increasing wind curtailment during low-load periods and transmission bottlenecks [50]. To solve this problem regulators [51], independent system operators (ISO) [7], [52], [53], and researchers [14], [54]–[57] are constantly exploring adjustments to the market structure.

The current structure of most electricity markets is based on a two-settlement process, henceforth referred to as "*deterministic market clearing*" (DMC) mechanism. Under this mechanism, the first market is run a day ahead of the real-time (RT) operation to schedule the commitment of slow- and medium-start supply resources, e.g.

coal and combined cycle natural gas units. The second market is cleared between minutes to an hour ahead of real time to reconcile the mismatch between the real-time supply and demand. The real-time market is cleared based on the market participants' offers for deviating from their day-ahead (DA) schedules. In effect, the DA and RT markets are cleared separately such that the DA energy and ancillary services schedules are not affected by the RT operation outcomes and the associated costs.

In the DA market, the participants submit their offers/bids for energy and ancillary services, i.e., regulation and contingency reserves. Then deterministic models co-optimize the energy and operating reserves schedules based on demand bids and supply offers and a number of system's reliability and power generator's technical constraints. Reserve requirements ensure the DA committed capacity is adequate to ensure the reliable supply of electricity despite load's forecast errors and unexpected failures of generation or transmission infrastructure. These reserve requirements are set well ahead of time, based on static rules and in general, are not frequently revised to reflect updated information on the variability or uncertainty of next-period's wind power production[3].

The uncertainty on next-day electricity demand or generation/transmission outages is in general lower and/or better characterized than that of wind production. Wind production can be predicted with some degree of accuracy only a few hours ahead of real-time operation [5], and hence, DA market schedules, which are based on its expected production, frequently require sizable real-time adjustments. This is also a consequence of the fact that, deterministic models, do not commonly account for DA updates on uncertainty around production of wind energy resources. This incomplete characterization of wind production uncertainty at the DA scheduling stage causes an information gap that degrades the efficiency, reliability, affordability, and environmental sustainability of the systems' operations. DA schedules that turn out to be incompatible with real-time wind power production, force the system operator to redispatch its resources in RT, e.g., bring online more expensive fast-start generators, curtail wind power, and/or to deploy demand-response resources. These adjustments increase the system balancing costs, the frequency and magnitude of scarcity pricing events, exacerbate DA and RT price divergence, and increase the need for out-of-market revenue sufficiency guarantee payments (or uplift payments) [7], [52], [58].

Strategies to deal with wind production uncertainty and variability include: a) adding a multi-interval look-ahead real-time unit commitment (RTUC) stage, to adjust the commitment of fast-start generators and revise production schedules as the updated forecasts become available; b) introducing a new ancillary service product to the conventional deterministic market mechanisms to ensure sufficient and ramp-feasible capacity in real time operations; and c) modifying the unit commitment and dispatch processes entirely to directly include DA updated uncertainty of key inputs. Among the markets that have adopted the look-ahead RTUC with extended optimization horizons are California ISO (CAISO) and Mid-Continent ISO (MISO) [59]. Likewise, PJM uses the Intermediate-Term Security-Constrained Economic Dispatch Tool (IT SCED), which commits fast-starting resources commitment over a two-hour look-ahead period [60]. With the look-ahead commitment process, the RT operation evolves from an auction to offset the RT deviations, to a market that continuously revises the DA commitment decisions based on the most accurate information available. This mitigates the volatility of real-time prices and the opportunities for exploiting market power.

CAISO and MISO have also introduced *flexible ramp* products into real-time and/or DA markets [6], [7], [52], [61]. These flexible ramp products are analog to *following reserve requirement* or *flexibility reserve* requirements, as referred to in renewable integration studies [2], [62]. They share the same principles for determining the ramping capacity necessary to follow net load variations, but differ in their deployment during the RT operation [2], [52], [62].

Other potential market modifications that have been extensively researched consist of directly considering the wind's uncertainty into the core daily market processes of commitment [12], [53], [54], [63], scheduling, and pricing [13]–[15], [19], [64]. Such models, built upon principles of stochastic programming, optimize the DA commitment decisions by accounting for the characterization of wind uncertainty in RT to assure least-cost sufficient and flexible capacity for managing plausible realizations of wind. The Inclusion of the inputs' uncertainty through a stochastic unit commitment [12], [65]–[69] and its computational challenges [11], [63], [70] have been extensively addressed. However, stochastic commitment models merely focus on committing the best set of producers to meet demand under uncertainty but keep the other market clearing processes for the allocation of energy and ancillary services, determination of associated prices, and settlement of energy transactions, identical to the current deterministic practice.

In contrast, *"stochastic market clearing"* (SMC) refers to the incorporation of uncertainties into all market clearing processes, including commitment, dispatch, and pricing [13]–[15]. SMC enables the scheduling of ramp-capability/following-reserves based on the probability distribution of uncertain inputs and the expected cost of RT deviations from DA decisions. In fact, SMC positions the generation fleet in the DA market to optimally deal with a range of demand and intermittent power generation scenarios at the minimum expected cost, rather than centering the DA scheduling on a single DA forecast scenario equal to expected values (of wind production and other uncertain variables). Accounting for the expected operation costs enables SMC to internalize the hidden real-time costs of uncertainty in the DA energy prices.

Implementing the SMC requires certain adjustments to the market mechanisms. In the SMC framework, market participants simultaneously submit two sets of offers in the day ahead, one for energy and another for deviating from DA energy schedules. Then a stochastic auction, which is based on two two-stage linear stochastic programming models, is used to simultaneously clear the DA energy and ramp capability schedules (which are the maximum possible deviations from DA schedules). In both models, the first stage corresponds to the DA market while the second stage corresponds to the anticipation of RT operations and its associated outcomes. A mixed-integer linear version (i.e., the Unit Commitment model, UC) determines the commitment of generating units, while a linear version (i.e., the Economic Dispatch, ED) determines their dispatch. This linear version also delivers two sets of prices, which are the dual variables of the first-stage (DA) and second-stage (RT) nodal balance constraints that guarantee the equality of electricity supply and demand at each bus/node in the system. The DA price at a node represents the incremental cost of serving an additional MW of electricity in the DA and is equivalent to the expected cost of serving the next MW of electricity across all balancing-stage scenarios. There is a balancing price for each individual scenario considered in the SMC, which is the incremental cost of serving a MW of electricity if that balancing stage scenario occurs.

In a two-settlement SMC, in order to settle the DA and RT energy transactions, the market operator combines the DA schedules and prices generated by the SMC with the RT dispatch prices generated in the RT spot market. Note that, although the SMC anticipates the outcomes and prices of the RT, a RT spot market is still needed to optimize the dispatch of resources and to accommodate the realized wind production in RT and determine the corresponding prices. Nonetheless, the RT balancing offers must be locked in the DA to ensure the SMC accounts for the true expectation of RT operation costs.

The recent literature on SMC has focused on its modeling, pricing, and settlement aspects. Pritchard et al., 2010 proposed a two-stage stochastic market clearing and developed a single-settlement scheme based on first-stage and second-stage dual variables. The proposed pricing scheme is also proved to ensure revenue adequacy of the system operator in expectation, in a loss-less network. Morales et al., 2012 applied the stochastic market clearing design proposed by [13] to a pool highly dominated by wind producers, and proved it ensures the ISO's revenue adequacy and producers' cost recovery in expectation considering operations of an IEEE RTS24 test system during a single time period. Zavala et al., 2016 extended the work done in Morales et al., 2012; and Pritchard et al., 2010 to address price consistency. They concluded that under SMC, DA prices converge to RT prices in expectation. They also show that uplift payments converge to zero, (with uplift payments referring to out-of-market payments to generators that occur due to imperfect information and inefficient dispatch instructions, not to those caused by unit commitment price non-convexities such as generators' start-up and no-load costs). These conclusions are also examined on the IEEE reliability test system for a single time period. Khazaei et al., 2014 also conducted a comparison of DMC and SMC in terms of plants' operation costs in the New Zealand's electricity market. New Zealand does not have a DA market and instead is based on a pre-dispatch scheduling mechanism running two hours ahead of RT when wind can be predicted with a fair degree of accuracy. Also, its generation capacity includes 58% from hydropower which enhances its ability to respond to wind uncertainty and variability. Some recent studies have also examined the implications of SMC for renewables integration. Daraeepour et al., 2016 investigated the impact of demand-side participation in the provisioning of reserves in an SMC electricity market with high penetration of wind. Similarly, Martin et al., 2015 assumed a SMC setting to study the operational and economic effects of feed-in-tariffs. Recently, Abbaspourtorbati et al., 2016 have proposed a three-stage stochastic market clearing and have compared its performance to the two-stage SMC.

Also, there have been studies that assess the efficiency gains of considering uncertainty in the DA unit commitment process only. Hargreaves and Hobbs, 2012 propose a stochastic dynamic programming approach to DA unit commitment and compare its dispatch outcomes with those of the deterministic approach. Papavasiliou et al., 2011b compare the expected dispatch cost of using deterministic and stochastic models in the residual unit commitment process, identifying the commitment of slow-start generators. The comparison is conducted for a scaled version of CAISO for eight representative days to estimate the potential for plants' fuel and variable cost savings. Price, 2015 follows Papavasiliou et al., 2011a's procedure to conduct a similar analysis for CAISO, but with further simplifications such as a characterization of wind's uncertainty with only two scenarios and assuming constant following reserve requirements. Unlike [53], [54] which address DA hourly operations [56], [74] address the impacts of deterministic and stochastic models in intra-hour real-time operations. [56], [74] investigate the effects of introducing real-time ramp capability products in comparison to a stochastic dispatch assuming the committed units are known and highlighting the sensitivity of benefits to the RT flexibility ramp requirements.

Although the existing literature has probed the general implications of using stochastic models for accounting for wind uncertainty in market clearing and commitment processes, its analysis has been limited in scope, method, and questions. The existing studies do not comprehensively investigate the relative advantages of SMC with respect to other adjustments that can enhance DMC's performance. Most studies focus on somewhat narrow applications of stochastic programming models to electricity markets failing to examine the market design and welfare implications of their use in the entire market clearing process in a more realistic setting. For instance, a number of studies investigating SMC [13]–[15], [75], ignore the impacts that generators' commitment costs and constraints have on day-ahead market outcomes, and hence may have failed to identify the system's flexibility limitations for reacting to wind and demand variations. Conversely, the studies exploring the implications of including uncertainty in the unit commitment processes [53], [54], [73], have mainly focused on fuel and variable production costs without addressing net impacts on market clearing, price formation, settlement, or other market design outcomes.

Another shortcoming of previous studies is that they test the implications of SMC on small systems and only for a few hours [13]–[15]; or for relatively larger systems for a few representative days[9], [53], [73]. This approach does not allow a proper assessment of impacts of recognizing uncertainty in the commitment or the entire market clearing process. Also, those studies that look at the RT dispatch outcomes of DA commitments are based on a simplified representation of the sequential operation of DA and RT electricity market operations which may distort the assessment of impacts [12], [53], [54], [73].

Finally, previous studies comparing the deterministic and stochastic approaches may not be entirely fair to the deterministic framework [9], [53]. A fair comparative analysis requires the DA hourly ramp capability requirements, for following wind ramps and fluctuations, to be updated based on the same characterization of wind production uncertainty used for the stochastic framework.

The objective of this paper is to fill this gap and assess the performance of SMC when compared to an augmented DMC (ADMC) that has access and uses the same daily-updated information on wind-power generation uncertainty to set maximum system-wide ramp capability requirements. We investigate the economic efficiency of these alternative designs by comparing their impacts on production costs and welfare. We also compare their impacts on market efficiency in terms of price convergence between DA and RT markets and out-of-market payments made to guarantee the sufficiency of producers' short-run revenues. Given the importance of producers' flexibility/ramping capability in managing the variation of intermittent producers, we study how the alternative designs remunerate the provision of flexibility by producers and how both designs change the system's costs and the revenues of all producers. The environmental implications, in terms of wind power integrated, CO_2, SO_2, and NO_X emissions, and the cycling of power plants are also analyzed. We also explore the sensitivity of our conclusions to assumptions about some structural conditions and the behavior of market participants.   To do so, we consider scenarios with higher wind penetration levels and producers with strategic behavior in bidding RT balancing energy.

Our approach for assessing SMC's advantages consists of simulating the operation of a scaled version of PJM's system under the conventional deterministic framework DMC, the deterministic updated with flexibility ramp requirements ADMC, and the SMC design for one year. To do so, we use an Electricity Market Simulation Tool (EMST), illustrated in Figure 4, that represents three-stages of the market clearing: a DA market that commits conventional units (nuclear, fast and slow start units) and wind; an hourly two-hour look-ahead commitment process that adjusts the on/off status of fast-start producers; and a real-time balancing market that adjusts the dispatch of conventional units according to the realization of wind power production and settles the RT deviations. The simulation of market operations is carried out with hourly resolution and hence, intra-hour fluctuations on wind power and demand are not represented.

Because there is a tradeoff between economic and reliability outcomes, we set up our experiment so that both models achieve the same reliability levels at the least possible cost and hence compare them only based on economic and environmental outcomes. Ensuring both models achieve the same reliability outcomes requires finding an equivalence between the Value of Lost Load (VOLL) used to penalize imbalances between demand and supply in the SMC, and the ramp capability requirements set for the DMC and ADMC.

To focus on the wind-power production uncertainty only, we assume electricity demand to be certain, and assume the probability of generator outages is zero.

The rest of the chapter is organized as follows: the method, including the designed modeling framework for a fair comparison of the DMC and SMC and the market assumptions is presented in Section 3.3. The formulation for DA and RT market clearing are provided in Section 3.4, followed by a description of the case studies and data in Section 3.5. Results for alternative market clearing approaches are presented in Section 3.6, followed by further insights into the comparative analysis in Section 3.7. Additional information is provided in the supplementary information document (SI).

3.3 Method

In order to conduct a fair comparison between the three market clearing mechanisms in a setting replicating real electricity market situations, we follow four steps illustrated in Figure 4 and listed below:

1. Generation of hourly wind-power production scenarios and their associated probabilities to be used as inputs each day of the year for which the market clearing is simulated. In the SMC, these scenarios are used directly. In the DMC and ADMC, the expected value of wind power production across the set of generated scenarios is selected as the DA system-wide aggregated wind power production forecast. The forecast error, represented in the scenarios set - in combination with a ramp requirement-setting rule determined in step 2- is used to estimate the up and down ramp capability requirements considered in the ADMC (see Section 3.3.1).

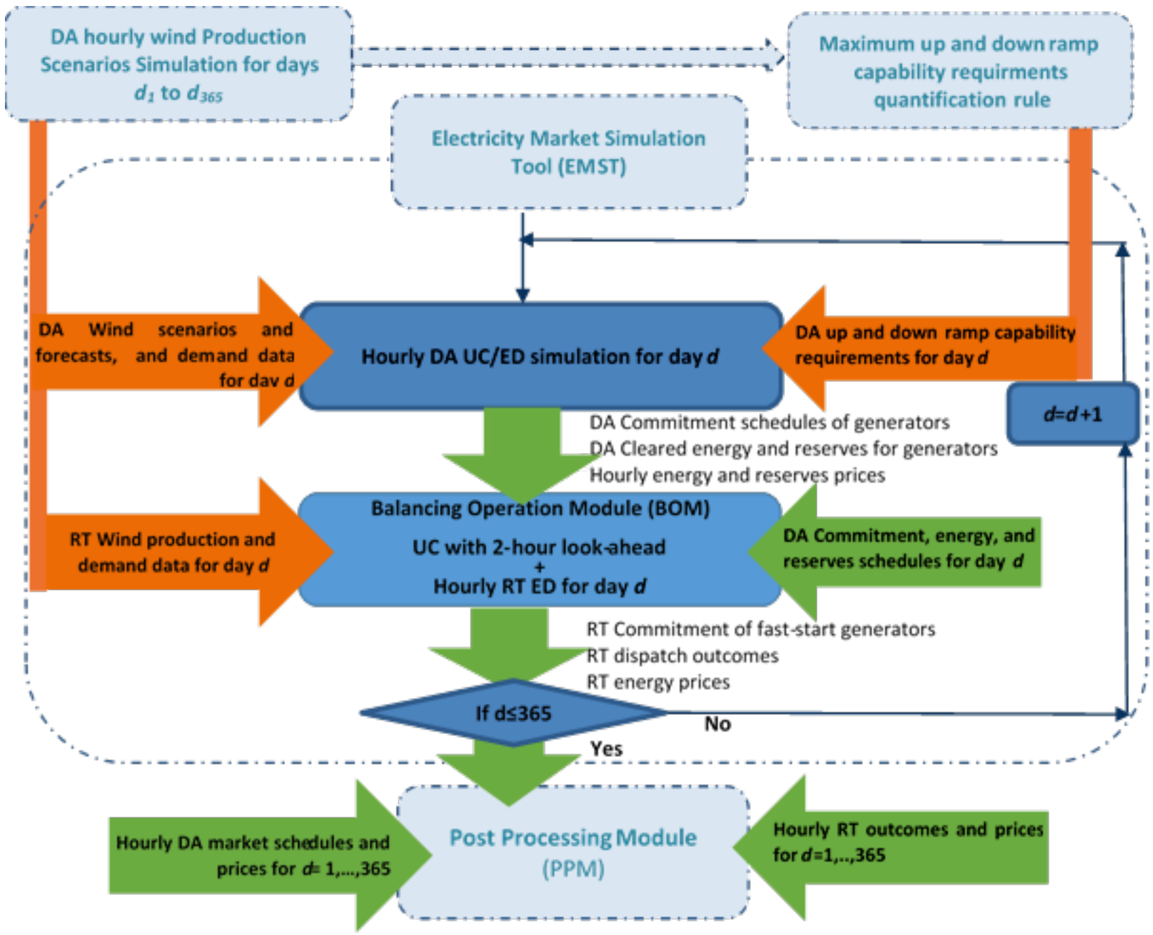

Figure 4: Flowchart of the Framework for Replicating the PJM Market Operation sand Comparing the Augmented Deterministic and Stochastic Market Clearing Designs

2. Determination of the adequate rule for setting market-wide up and down ramp capability requirement considered in the DA deterministic market clearing.

3. Simulation of one year of operations under each of the three market clearing mechanisms using the Electricity Market Simulation Tool (EMST) (see Section 3.3.4).

4. Simulation of the market settlement process and estimation of annual market outcomes (See Section 3.3.5).

Steps 1-4 are repeated for case studies with different wind penetration levels and sensitivity analyses.

3.3.1 Generation of Day-ahead Wind Power Production Scenarios

We characterize the uncertainty on next-day hourly wind power by generating a set of scenarios and their corresponding probabilities of occurrence. The discrepancy between a day-ahead scenario of hourly wind production and its realization corresponds to a forecast error. In this step a set of DA forecast errors is generated and then applied to historical DA wind power production to obtain a set of day-ahead forecast scenarios that represent the same uncertainty observed in a historical data-set.

To simulate the electricity market operation for year Y, we take four-years of five-minute resolution historical data on DA forecasts and realizations of wind power production. Using this data we generate wind production scenarios for each day of year Y. We first generate 200 scenarios of forecast errors, then reduce this set to only 30 scenarios, and finally, use these to generate scenarios of wind power production.

In the first step, we use the SynTiSe [76] a Markov-chain Monte Carlo simulation tool. SynTiSe takes the historical five-minute time-series data of DA wind forecast errors observed during years Y-4 to Y-1, and generates a set of 200 independent and identically distributed (i.i.d) time series of DA forecast error scenarios for all days of year Y. SynTiSe fits multi-regime, multi-stage Markov Chain Monte Carlo (MCMC) models of up to order 5 to the historical DA error time series and uses them to generate synthetic time series that replicate the probability distribution function (PDF), auto-correlation function (ACF), and step changes (or ramp), of the original time series.

In the second step, for each day d of year Y, 30 forecast-error scenarios are selected from the original set of 200 scenarios generated with SynTiSE. This is accomplished using a scenario reduction method, proposed in [77], [78]. This scenario reduction process runs individually for each day and selects a representative set of scenarios that retains the properties of the original set. The process is carried over iteratively using a forward selection method where a scenario is chosen to minimize a probabilistic distance metric (Kantorovich distance) between the original set and the representative set. The Kantorovich distance sums the deviation in probabilities of the two random variables for all possibilities of the variables (See Section 1 in Appendix B for details on the scenario reduction method).

We then generate day-ahead five-minute production scenarios, taking the reduced set of error scenarios for year Y and adding them to the data on observed wind power production for year Y. Finally, since the scenarios have five-minute resolution, hourly averages are calculated to obtain a set of scenarios with hourly granularity. Section 2 in Appendix B illustrates the implementation of the scenario generation process and how its outputs are used in simulating market operations.

3.3.2 Determination of Rules for Dynamically Updating Hourly Up and Down Ramp Capability Requirements for the ADMC Mechanism. Determination of VOLL for the SMC Mechanism

The targets for hourly ramp capability requirements are set daily based on the same day-ahead wind generation scenarios that characterize the uncertainty in the stochastic model. These up and down ramp capability requirements to be considered in the day-ahead dispatch are updated every day and for every hour based on a) the probability distribution of the differences between wind power production and DA forecast –estimated as an expected value considering all the possible DA scenarios-, and b) a rule on how much uncertainty must be covered by the up and down ramp capability requirements $\overline{RR_t}^{\mathrm{Up}}$ and $\overline{RR_t}^{\mathrm{Dn}}$. After the hourly cumulative probability distributions of deviations are derived, $\overline{RR_t}^{\mathrm{Up}}$ and $\overline{RR_t}^{\mathrm{Dn}}$ are set such according to a rule characterized by probability bounds α^{Up} and α^{Dn}. According to the rule $\overline{RR_t}^{\mathrm{Up}}$ must be such that the probability of a negative deviation from the DA forecast being larger (more negative) than $\overline{RR_t}^{\mathrm{Up}}$ is α^{Up}. Similarly, $\overline{RR_t}^{\mathrm{Dn}}$ is set up such that the probability of a positive deviation being larger than $\overline{RR_t}^{\mathrm{Dn}}$is 1-$\alpha^{Dn}$. that the probability bounds α^{Up} and α^{Dn} are the same for all hours of the year, but the probability distribution of production deviations form DA forecasts are updated hourly (see section 5 in Appendix B for a full description of the rule and its implementation).

The optimal probability bounds α^{Up} and α^{Dn} that characterize the rule, are found by running the Electricity Market Simulation Tool (EMST) iteratively with different values of α^{Up} and α^{Dn} seeking to minimize system's operating costs, while meeting a reliability standard of zero MWh of not supplied energy over a year. The costs include those of having to procure ramp capability in real-time by dispatching expensive fast-start generators due to a poor scheduling of slow-start generators, and the opportunity costs of not being able to integrate all the wind production due to insufficient down ramp capability. The Value of Lost Load (VOLL) used in ADMC is found iteratively by running the EMST with stochastic market clearing, such that it represents the minimum value that guarantees no load shedding in one year. Finally, given the pre-specified reliability standard and VOLL, the optimal dynamic ramp capability requirement policies that comply with the reliability standard at the least cost are identified and applied to ADMC. Note that, the main focus of the determination of the rule for setting ramp capability requirements is on minimizing operation costs (see Section 5.2 in Appendix B for a full description of the iterative approach used for identifying the ramp capability requirement rules).

3.3.3 Simulation of One Year of Hourly System Operations

The EMST simulates the sequence of DA and RT market clearing processes. It assumes the typical setting of an organized electricity market, where an Independent System Operator (ISO) ensures the balance of supply and demand at the minimum cost (expected value of cost, in the case of SMC) while abiding technical constraints of the generators and reliability ensuring constraints.

3.3.3.1 Market assumptions

The EMST assumes a perfectly competitive market where all generators (both fast-start, and slow-start) offer their true start-up, and marginal costs to the market operators. Balancing energy offers are assumed to be equal or marginally more expensive than the DA energy offers due to possible extra-costs incurred to provide a timely response to deviations from the DA schedule. These extra-costs are significant when the deviations make it necessary to start in the real time generators that were scheduled to be offline. Section 3.6 explores the sensitivity of market outcomes to different assumptions on generators' offers for balancing energy.

Given we only consider wind power generation uncertainty, neither the SMC, DMC or ADMC include requirements for contingency or frequency-regulation reserves. Both ADMC and SMC markets however, co-optimize energy and ramp capability requirements. In ADMC, a demand curve set by the ISO determines the price producers are paid for maintaining up and down ramp capability requirements when the associated constraints are binding. As in MISO, under ADMC, producers are assumed to accept to provide any combination of energy and flexible ramp requirements when submitting their energy offers and do not submit a separate offer of their ramp capability. SMC, uses an energy-only pricing scheme and hence producers are not paid for maintaining ramp capability reserves (or any other service). To ensure a fair comparison and highlight the impact of ramp capability payments, the ADMC results are presented without these payments (see Section 3 in Appendix B for the full description of both settlement schemes).

The maximum up- and down-ward ramp capability a generator can provide, is limited to the capacity that can be fully deployed within a 10-minute timeframe. The system-wide demand curves for ramp capability requirements are updated daily for every hour based on DA uncertainty. Similar to MISO's DA ramp products [6], [7] the demand curves imply a price of zero when the system's available ramp capabilities are greater than the pre-specified ramp capability requirements and a price of up to $5/MW when the ramp capability available is lower than the specified maximum requirement.

The market clears in two stages –DA and RT (Section 4 in Appendix B discusses the differences between the EMST and the PJM market structure and operations). The first stage runs the DA unit commitment and economic dispatch algorithms to determine the set of units scheduled to operate, and their levels of electricity generation, ramp capability requirements, and corresponding prices. The second stage, illustrated by BOM in Figure 4, runs a real-time unit commitment and dispatch to commit fast-starting units, and to determine the hourly-average electricity generation level of all units, and hourly-average real time prices. Because, for computational efficiency its resolution is hourly, intra-hour commitment and trades are not considered. This real-time unit commitment looks two hours ahead to account for the most accurate wind production forecasts and commit fast-start producers (those with combustion turbine frames) in order to ensure ramp feasible online capacity for following wind production. The hourly real-time production schedules and energy prices are determined in the real-time economic dispatch used to settle the deviations from DA schedules.

The timing of the offers that generators present to system operators differs between the deterministic designs and the SMC. In the deterministic mechanisms, two sets of offers are made by generators: one before the DA auction, for energy and the other before each balancing auction, for deviating from the DA schedule, hereafter referred to as balancing energy. The two auctions are cleared separately. The DA ramp capability requirements are quantified exogenously as discussed in section 3.3.2. These DA ramp capability requirements are met by DA committed generators.

Instead, under SMC, the generators simultaneously offer DA and balancing energy prior to the DA market clearing stage. DA energy and ramp capability reserve schedules are determined accounting for the likely next-day wind energy production and the expected balancing energy costs. No new offer is made in the real-time stage, and hence, the real-time stage is not an auction but a balancing mechanism that determines the optimal dispatch of resources (generation of conventional and wind producers), and optimal load shedding, based on the locked-in balancing energy offers of generators and the VOLL.

One of the main differences between the SMC and the ADMC is in their determination of ramp capability requirements. While in the SMC the DA ramp capability requirements/schedules are determined endogenously, in the ADMC are determined exogenously based on the ramp capability requirement rules determined ex-ante and applied to that day's uncertainty on wind power output. The other main difference is in the optimization models representing the market clearing mechanisms. The SMC runs a DA stochastic unit commitment and stochastic economic dispatch represented in the form of *two-stage stochastic optimization* models (see Section 3.4.3) that consider the wind-power production scenarios and their probabilities. In contrast, the DMC is composed of deterministic unit commitment and deterministic economic dispatch models that consider the DA forecast of wind production –set as the expected value of the wind power scenarios— and up and down ramp capability deemed necessary to cover the uncertainty around DA wind production.

3.3.3.2 Electricity market simulation tool (EMST)

As illustrated in Figure 1 the EMST runs a *DA Operations Module* (DOM) and a *Balancing Operations Module* (BOM) for a year-long period. The DOM is run daily –for each hour of the day-, and the BOM is run hourly.

The models are run sequentially such that the outputs of one serve as the inputs for the next so they can be solved in chronological order. First, the DA unit commitment is fed with the DA wind production forecasts, hourly demand, and the producers' offers. It then determines the commitment schedule of generating units that is an input to the economic dispatch model. The economic dispatch model solves for energy and ramp capability requirements (maximum deviation from DA schedules) provided by committed generating units, and calculates the DA hourly prices to settle energy transactions.

The BOM runs every hour to adjust the commitment of fast-start generators and determine the optimal dispatch of all generators for the given latest wind and demand data of the look-ahead period (see Section 3 in Appendix B). At the end of each daily cycle, all DA and BOM transactions are settled based on the DA and BOM schedules and prices, and the BOM operation's outcomes are used to initialize the Next day's DA operations.

The EMST simulates the system operation in either DMC, ADMC or SMC mode.

3.3.4 Simulation of Market Settlement Process and Calculation of the Market Outcome

After system operations are simulated for a whole year the Post-Processing Module (PPM) runs to calculate the generators' hourly and daily revenues and up-lift payments for the whole year, as well as other annual system operation indicators. PPM takes the DA and BOM production schedules and prices to estimate the outcomes of the settlement processes. Both DA and RT energy transactions are settled on an hourly basis. Out-of-market adjustment payments (uplift or revenue-sufficiency guarantee payments) are also calculated daily for each individual generator to ensure the generators that follow the ISO's instructions do not run at a loss (see Section 3.3 in Appendix B).

The market operation and settlement results are used to estimate other annual indicators such as total annual electricity produced and revenue collected by different generation technologies, uplift payments, price spread, wind energy curtailment, atmospheric emissions (CO_2, SO_2, and NO_x), total number of startups and shutdowns, and total amount of load shed during the year.

3.4 Models

The EMST contains eight optimization models that reflect both the unit commitment and economic dispatch in the DA and RT, for the different market mechanisms simulated DMC, SMC, ADMC. The DA economic dispatch models (ED) are almost identical to the DA unit commitment models (UC) with the only difference being that the UC's binary decision variables representing whether a unit is on or off at a particular time are fixed inputs into the ED. The RT ED is also similar to the RT UC with the only difference being that the real-time dispatch is a single-period optimization while the RT commitment is a multi-interval two-hour look-ahead model. The three UC models of the EMST are: 1) Deterministic DA unit-commitment (D-DA-UC), 2) Augmented Deterministic DA unit commitment (AD-DA-UC) which represents the day-ahead deterministic commitment model with ramp-flexibility requirements (see Section 3.4.2); 3) Stochastic DA unit commitment (S-DA-UC) (see Section 3.4.3), and 4) the real-time unit commitment (RT-UC) (see Section 3.4.4). Given the similarities between the DA UC and DA ED models and the fact that the D-DA-UC is a special form of AD-DA-UC in which the set of ramp capability requirements are not considered. We only present the DA UC models for ADMC and SMC, together with the RT-UC employed by the three market clearing mechanisms. Transmission constraints are assumed to be non-binding and are not presented in the formulation.

Section 3.4.1 describes the nomenclature used in the formulation of the models. The superscripts DA or RT refer to the day-ahead or real-time decision variables, while the subscript ω is applied to the scenario dependent decision variables used in the second-stage of the stochastic UC models. In all models, power generators are partitioned into two sets: slow-starting and fast-starting. Slow-starting generators cannot be started in real time, while fast-starting can be committed or de-committed in real time to manage deviations from DA forecasts. To reflect this difference, some of the constraints apply only to one of the sets. The commitment of each generator is modeled through a set of three binary variables representing generator's on/off status, startup, and shutdown.

3.4.1 Notation

3.4.1.1 Sets

Ψ^G Set of all generators, $g \in \Psi^G$ running from 1 to N_G.

Ψ^S Set of slow generators, $s \in \Psi^S$ running from 1 to N_s.

Ψ^F Set of fast generators, $f \in \Psi^F$ running from 1 to N_F.

Ψ^T Set of time periods, $t \in \Psi^T$ running from 1 to N_T.

Ψ^C Set of wind production scenarios, $\omega \in \Psi^C$ running from 1 to Ω.

Ψ^O Set of feasible solutions.

3.4.1.2 Parameters

L Length of interval (t) in minutes.

Δ Ramp response time in minutes.

$C_g^{SU*}(t)$: Startup cost of generator g in period t (\$/st).

O_{gt}^{DA} DA energy offer price, O_{gt}^{B*}: balancing energy offers of generator g in period t

ρ_g^{SU} Startup ramp-rate, ρ_g^{SD*}: Shutdown ramp-rate, ρ_g^{o} operating ramp-rate of

v^{LOL} Value of lost load (\$/MWh).

π_ω Probability of scenario ω.

$\overline{P_g}$ Maximum power output of generator g (MW).

$\underline{P_g}$ Minimum power output of generator g (MW).

D_t Electricity demand in period t (MWh).

$\overline{RR_t}^{\mathrm{Up}}$ Market-wide up-ramp capability requirement in period t (MW).

$\overline{RR_t}^{\mathrm{Dn}}$ Market-wide down-ramp capability requirement in period t (MW).

RCP_t^{UP} Market-wide up ramp capability demand curve price in period t (\$/MW).

RCP_t^{Dn} Market-wide down ramp capability demand curve price in period t (\$/MW).

D_t Electricity demand in period t (MWh).

W_t^{Av} Available wind production realized in RT in period t (MWh).

$\overline{W_t}^{DA}$ Wind production expected in the DA (MWh).

$w_{t\omega}^{DA}$ Wind production forecast for period t under scenario ω (MWh).

2.4.1.3 Continuous Decision Variables

P_{gt}^{DA} DA scheduled production for generator g in period t (MWh).

W_t^{DA} Total DA scheduled wind production for period t (MWh).

UR_{gt}^{DA} DA scheduled up-ramp capability reserve for generator g in period t (MW).

DR_{gt}^{DA} DA scheduled down-ramp capability reserve for generator g for period t (MW).

$\underline{\underline{RR}}_t^{\mathrm{Up}}$ DA procured up-ramp capability requirement for period t

$\underline{\underline{RR}}_t^{\mathrm{Dn}}$ DA procured down-ramp capability requirement for period t

$p_{gt\omega}$ Balancing-stage production of generator g in period t under scenario ω (MWh).

$b_{gt\omega}^{Up}$ Balancing energy deployed by spinning generator g in period t under scenario ω (MWh).

$b_{gt\omega}^{Dn}$ Balancing energy deployed by spinning generator g in period t under scenario ω (MWh).

$b_{ft\omega}^{NsU}$ Balancing energy supplied by non-spinning fast generator *f* in period *t* under scenario ω (MWh).

$d_{t\omega}^{Sh}$ Load shedding during period *t* under scenario ω (MWh).

$s_{t\omega}$ Total wind power curtailment in period *t* under scenario ω (MWh).

P_{gt}^{RT} Real-time dispatched production of slow-starting generator *g* during period *t* in the RTUC (MWh).

W_{t}^{RT} Real-time dispatched wind production during period *t* in the RTUC (MWh).

S_{t}^{RT} Real-time Wind production curtailment during period *t* in the RTUC (MWh).

$D_{t}^{Sh^{RT}}$ Load shedding during period *t* in the RTUC (MWh).

3.4.1.4 Binary Decision Variables

U_{gt}^{DA}: on/off status, V_{gt}^{DA} : startup, Y_{gt}^{DA}: shutdown schedule of generator *g* in period *t* in

u_{ft}: on/off status, v_{ft} : startup, y_{ft}: shutdown schedule of fast generator *f* in period *t*

U_{ft}^{RT}: on/off status, V_{ft}^{RT} : startup, Y_{ft}^{RT} : shutdown schedule of fast generator *f* in period *t* in

U^{DA}: Vector of all U_{gt}^{DA}, V^{DA}: vector of all V_{gt}^{DA}, Y^{DA}: vector of all Y_{gt}^{DA}.

u: Vector of all u_{ft}, v: vector of all v_{ft}, y: vector of all y_{ft}.

U^{RT}: Vector of all U_{gt}^{RT}, V^{RT}: vector of all V_{gt}^{RT}, Y^{RT}: vector of all Y_{gt}^{RT} .

3.4.2 Augmented deterministic day-ahead unit commitment (AD-DA-UC)

Equations (1 a)-(1 j) represent the deterministic UC formulation. The model minimizes the total cost of satisfying net electricity demand (demand – scheduled wind production) and ramp capability requirements while abiding generators', ramp capability requirements', and market clearing constraints.

The objective function, expressed in (1 a), consists of minimizing generators' operation costs, including the startup, and variable generation costs based on their DA three-part offers, minus the benefits of procuring up and down ramp reserve capability products. Constraints (1 b)-(1 c) limit the scheduled production and ramp capability reserves for each generator to its minimum and maximum generation limits. Constraints (1 d)-(1 g) ensure ramp-feasibility of DA ramp capability reserves and energy schedules. (1 d)-(1 e) cap the ramp capability reserves schedules of each generator to the maximum production to be ramped up and down within a 10-minute timeframe. (1 f)-(1 g) guarantee the inter-hour variations of generators' energy production and the procured up and down ramp reserves are ramp-feasible. (1 h) relates the on/off generators' status transition with their corresponding startup and shutdown indicators (1 i) sets the maximum DA wind production schedule to the DA forecast, which is equal to the expected wind production (1 j) enforces the balance of total electricity demand and supply. (1 k)-(1 l) states that available up and down ramp reserves cannot exceed the ramp reserves provided by the producers. (1 m)-(1 n) limit the procurement of ramp capability reserves to the maximum level required by the market operator. These maximum ramp capability requirements $\overline{RR_t}^{\mathrm{Up}}$ and $\overline{RR_t}^{\mathrm{Dn}}$ are an input to the UC model, while procured reserves $\underline{\underline{RR}}_t^{\mathrm{Up}}$ and $\underline{\underline{RR}}_t^{\mathrm{Dn}}$ are decision variables. $\overline{RR_t}^{\mathrm{Up}}$ and $\overline{RR_t}^{\mathrm{Dn}}$ are quantified as explained in Section 3.3.2. by applying a dynamic ramp requirement-rule determined in prior for the whole year, to each DA hourly uncertainty. (1 o) corresponds to a number of other constraints that are included in the model, but not presented here to keep this description brief. These constraints ensure that the min-up-time and min-down-time limits of generators are upheld, and that the commitment variables (on/off status, startup, and shutdown) are binary. The resulting problem is a Mixed Integer Linear Programming (MILP) problem that can be solved with a commercial optimization package.

The model used to represent the economic dispatch (ED) is nearly identical to the one presented above for the UC with the only difference being that the commitment, startup, and shutdown variables are no longer decision variables, but taken as parameters. This converts the MILP into a linear programming (LP) problem that allows estimating the shadow prices of constraint (1 j) -representing the DA price for energy- and the shadow price of constraints (1 k)-(1 l), representing the prices of the up and down ramp capability reserves. As stated before, the price of up ramp capability reserves is capped at RCP_t^{UP} which is determined by the system operator to be the benefit of this resource. When the available up ramp capability is greater than the maximum set requirement ($\overline{RR_t}^{\mathrm{Up}}$), the reserve price is set to zero. The same applies to down ramp capability reserve prices.

$$\min TC = \sum_{t=1}^{N^T}\left[\sum_{g=1}^{N_G}\left(C_{gt}^{SU}\ V_{gt}^{DA} + P_{gt}^{DA} O_{gt}^{DA}\right)\right] - \sum_{t=1}^{N^T}\left[\underline{\underline{RR}}_t^{\mathrm{Up}}\ RCP_t^{UP} + \underline{\underline{RR}}_t^{\mathrm{Dn}}\ RCP_t^{Dn}\right] \tag{1 a}$$

S.t.

$$P_{gt}^{DA} + UR_{gt}^{DA} \le \overline{P}_g U_{gt}^{DA} \quad \forall g, \forall t \tag{1 b}$$

$$\underline{P}_g U_{gt}^{DA} \le P_{gt}^{DA} - DR_{gt}^{DA} \ \forall g, \forall t \tag{1 c}$$

$$0 \le UR_{gt}^{DA} \le \rho_g^o \left(\frac{\Delta}{L}\right) U_{it}^{DA}\ \forall g, \forall t \tag{1 d}$$

$$0 \le DR_{gt}^{DA} \le \rho_g^o \left(\frac{\Delta}{L}\right) U_{it}^{DA}\ \forall g, \forall t \tag{1 e}$$

$$\frac{P_{gt}^{DA}}{L} - \frac{P_{g,t-1}^{DA}}{L} + \frac{UR_{gt}^{DA}}{\Delta} \le \frac{\rho_g^o}{L} U_{g,t-1}^{DA} + \frac{\rho_g^{SU}}{L} V_{gt}^{DA} \quad \forall g, \forall t \tag{1 f}$$

$$\frac{P_{gt-1}^{DA}}{L} - \frac{P_{gt}^{DA}}{6L} - \frac{DR_{gt}^{DA}}{\Delta} \le \frac{\rho_g^o}{L} U_{gt}^{DA} + \frac{\rho_g^{SD}}{L} Y_{gt}^{DA} \quad \forall g, \forall t \tag{1 g}$$

$$U_{g,t-1}^{DA} - U_{gt}^{DA} + V_{gt}^{DA} - Y_{gt}^{DA} = 0 \quad \forall g, \forall t \tag{1 h}$$

$$0 \le W_t^{DA} \le \overline{W_t}^{DA} \quad \forall t \tag{1 i}$$

$$\sum_{g=1}^{NG} P_{gt}^{DA} + W_t^{DA} - D_t = 0 \quad \forall n, \forall t \tag{1 j}$$

$$\sum_{g=1}^{N_G} UR_{gt}^{DA} \ge \underline{RR_t}^{\mathrm{Up}} \quad \forall t \tag{1 k}$$

$$\sum_{g=1}^{N_G} DR_{gt}^{DA} \ge \underline{RR}_t^{\mathrm{Dn}} \quad \forall t \tag{1 l}$$

$$\underline{RR}_t^{\mathrm{Up}} \leq \overline{RR}_t^{\mathrm{Up}} \tag{1 m}$$

$$\underline{RR}_t^{\mathrm{Dn}} \leq \overline{RR}_t^{\mathrm{Dn}} \tag{1 n}$$

$$(U^{DA}, V^{DA}, Y^{DA}) \in \Psi^{O} \tag{1 o}$$

3.4.3 Stochastic day-ahead unit commitment (SDAUC)

The stochastic unit commitment model, presented in (2 a)-(2 p), is a two-stage stochastic programming model. The first stage represents the DA market decisions and constraints, and the second-stage the anticipation of the balancing operations that would be required to accommodate different wind production scenarios. Based on the generators' offers for DA and balancing energy, the model minimizes the expected cost of supplying net load, which include both the DA energy costs plus the expected costs of energy in the balancing stage. The generator-related and market-clearing constraints are enforced in both stages. Other constraints enable endogenous determination of DA up and down reserve schedules and ensure the feasibility of all DA schedules under the set of wind scenarios considered.

The stochastic model's objective function is presented in (2 a). The first line in (2 a) constitutes the DA costs of supplying net load and ramp reserves. The second and third lines represent the expected cost of deviating from DA schedules, including the startup and energy production costs. Finally, the last line adds up the cost of expected unsupplied energy, which is penalized at the VOLL. The first stage constraints are identical to (1 b)-(1 h), (1 j), and (1 o) which include the DA generators' and market clearing constraints. Note that, the DA wind producers are not constrained to the expected production in the stochastic model.

(2 c)-(2 j) correspond to the second-stage constraints, and hence, are scenario dependent. (2 c) specifies the minimum and maximum production of slow-starting and fast-starting generators under each scenario. (2 d) and (2 e) respectively represent constraints on the up and down ramping capability of slow and fast generators. (2 f) represents the on/off transition of fast generators in the balancing stage. (2 g) limits the wind curtailment under a scenario to the realized wind production, and (2 h) limits the load shedding in each scenario to the demand. (2 i) ensures the balance of supply and demand under each scenario. (2 j) represents all other balancing-stage constraints, such as min-up-time and min-down-time limits of fast generators and the binary nature of fast generators' commitment variables.

(2 k)-(2 o) represent the set of linking constraints that enable the endogenous determination of the reserve schedules. (2 k)-(2 l) link the DA and balancing stage decisions and decompose the deployed balancing energy to up- and down-ward balancing energy by spinning producers and upward energy by non-spinning producers. (2 m) ensures deployed down-ward balancing energy does not exceed DA scheduled energy. (2 n) sets the DA up reserve schedule of producer g to its maximum upward deviation from its DA energy schedule across the scenarios. (2 o) sets the DA down reserve schedules to the maximum downward deviations.

Finally, (2 p) represents the set of non-anticipativity constraints for slow-start producers whose DA commitment, startup, and shutdown status must be preserved in the balancing stage.

$$\min TEC = \sum_{t=1}^{T} EC_t = \sum_{t=1}^{N^T} \left[\sum_{g=1}^{N_G} (C_{gt}^{SU} \; V_{gt}^{DA} + C_{gt}^{NL} U_{gt}^{DA} + P_{gt}^{DA} O_{gt}^{DA}) \right]$$

$$+ \sum_{\omega=1}^{\Omega} \pi_\omega \sum_{t=1}^{N^T} \left[\begin{array}{c} \sum_{f=1}^{N_F} \left[C_f^{SU} \left(v_{ft\omega} - V_{ft}^{DA} \right) \right] \\ + \sum_{g=1}^{N_G} (b_{gt\omega}^{S}) O_{gt}^{B} + \sum_{f=1}^{N_F} (b_{ft\omega}^{NS}) O_{ft}^{B} \\ + d_{t\omega}^{Sh} v^{LOL} \end{array} \right] \quad (2\text{ a})$$

S.t.

(1 b)-(1 h), (1 j) and (1o) (2 b)

$$\underline{P}_g u_{gt\omega} \le p_{gt\omega} \le \bar{P}_g u_{gt\omega} \quad \forall g, \forall t, \forall \omega \quad (2\text{ c})$$

$$p_{gt\omega} - p_{g,t-1,\omega} \le \rho_g^{O} u_{g,t-1,\omega} + \rho_g^{SU} v_{gt\omega} \quad \forall g, \forall t, \forall \omega \quad (2\text{ d})$$

$$p_{g,t-1,\omega} - p_{gt\omega} \le \rho_g^{o} u_{gt\omega}^{B} + \rho_g^{SD} y_{gt\omega} \quad \forall g, \forall t, \forall \omega \quad (2\text{ e})$$

$$u_{g,t-1,\omega} - u_{gt\omega} + v_{gt\omega} - y_{gt\omega} = 0 \quad \forall g, \forall t, \forall \omega \quad (2\text{ f})$$

$$0 \le s_{t\omega} \le w_{t\omega}^{DA} \quad \forall k, \forall t, \forall \omega \quad (2\text{ g})$$

$$0 \le d_{t\omega}^{Sh} \le D_t \quad \forall t, \forall \omega \quad (2\text{ h})$$

$$\sum_{g=1}^{NG} p_{gt\omega} + (w_{t\omega} - s_{t\omega}) \text{-} (D_t - d_t^{Sh}) = 0 \quad \forall t, \forall \omega \quad (2\text{ i})$$

$$(u, v, y) \in \Psi^{O} \quad (2\text{ j})$$

$$p_{st\omega} = P_{st}^{DA} + b_{st\omega}^{Up} - b_{st\omega}^{Dn} \quad \forall s, \forall t, \forall \omega \quad (2\text{ k})$$

$$p_{ft\omega} = P_{ft}^{DA} + b_{ft\omega}^{Up} - b_{ft\omega}^{Dn} + b_{ft\omega}^{NsU} \ \forall f, \forall t, \forall \omega \quad (2\ l)$$

$$p_{gt\omega} \geq -P_{gt}^{DA} \forall g, \forall t, \forall \omega \quad (2\ m)$$

$$0 \leq b_{gt\omega}^{Up} \leq UR_{gt}^{DA}\ U_{gt}^{DA} \quad \forall g, \forall t, \forall \omega \quad (2\ n)$$

$$0 \leq b_{gt\omega}^{Dn} \leq DR_{gt}^{DA}\ U_{gt}^{DA} \quad \forall g, \forall t, \forall \omega \quad (2\ o)$$

$$u_{st\omega} = U_{st}^{DA}, v_{st\omega} = V_{st}^{DA}, y_{st\omega} = Y_{st}^{DA} \ \forall s, \forall t, \forall \omega \quad (2\ p)$$

3.4.4 Real-time unit commitment (RTUC) model

RTUC runs at the beginning of each hour *h* to find the hour-ahead commitment of fast-start generators that minimizes the costs of meeting balancing energy requirements during the next two hours (*h*+1, *h*+2). RTUC commits and de-commits fast-start generators in response to variations in real-time wind production and based on the generator's balancing energy offers. The real-time commitments for hour *h* are then fixed and input as parameters into the real-time economic dispatch (RTED). The RTED determines the least-cost real-time dispatch of all committed generators and the hour *h* hourly-average real-time at which all real-time energy transactions are settled. The RTED formulation is similar to that of the RTUC except the optimization is executed over *h*. Nonetheless, all the inter-temporal constraints of generators, such as ramping, min-up-time, and min-down-time constraints are also enforced.

In the RTUC's formulation, DA market decisions (on/off status, and generation level) - denoted by superscript DA- are treated as parameters in the RTUC. Real-time decisions from the previous time periods, denoted by superscript RT and subscript t-1, are also taken as parameters in period t.

The RTUC's formulation is presented in (3 a)-(3 k). The objective function, represented in (3 a), is the total cost of offsetting deviations from DA schedules, estimated for the period between the beginning of period h and the beginning of period h+2. Because the RTUC runs sequentially, it considers the adjustments from real-time runs for previous hours. The first line of (3 a) gives the total startup costs of fast generators started in the look-ahead period and the second line corresponds to the sum of generators' balancing energy production cost and load shedding costs. (3 b)-(3 k) correspond to the set of RTUC's constraints. Equations (3 b) sets the minimum and maximum limits for real-time production of slow and fast starting generators. Constraints (3 c)-(3 d)ensure the ramp-feasibility of real-time production of all generators. (3 e) represents the real time on/off transitions of fast-start generators considering their DA status. Constraint (3 f) limits the hourly real-time load shedding to the total hourly demand. Constraints (3 g) and (3 h) confine the real-time wind curtailment and wind energy production to the realized wind power. (3 i) ensures that total real-time production equals total demand. The shadow price (i.e., dual variable) of (3 i) in the RTED is taken as the real-time price for settling real-time imbalance energy transactions. (3 j) sets the commitment transition trajectory of slow-start generators to their DA scheduled status. Min-up-time and min-down-time constraints of fast generators and integrality of commitment variables (on/off status, start-up and shutdown) are all represented by (3 k).

$$\min C = \sum_{t=h}^{h+2} \left[\begin{array}{c} \sum_{f=1}^{N_F} \left[C_{ft}^{SU} \, V_{ft}^{RT} \right] \\ + \sum_{g=1}^{N_G} (P_{gt}^{RT} - P_{gt}^{DA})\, O_{gt}^{B} + v^{LOL} D_t^{Sh^{RT}} \end{array} \right] \tag{3 a}$$

S.t.

$$\underline{P}_g U_{gt}^{RT} \leq \; P_{gt}^{\mathrm{RT}} \leq \; \bar{P}_g \; U_{gt}^{RT} \quad \forall g, \; \forall t \in \{h, \dots, h+2\} \tag{3 b}$$

$$P_{gt}^{RT} - P_{g,t-1}^{RT} \leq \; \rho_g^o U_{g,t-1}^{RT} + \rho_g^{SU} V_{st}^{RT} \quad \forall g, \forall t \in \{h, \dots, h+2\} \tag{3 c}$$

$$P_{g,t-1}^{RT} - P_{gt}^{RT} \leq \; \rho_g^o U_{gt}^{RT} + \rho_g^{SD} Y_{gt}^{RT} \quad \forall g, \forall t \in \{h, \dots, h+2\} \tag{3 d}$$

$$U_{ft}^{RT} - U_{ft-1}^{RT} - U_{ft}^{DA} + U_{ft-1}^{DA} - V_{ft}^{RT} + Y_{ft}^{RT} = 0 \;\; \forall f, \;\; \forall t \in \{h, h+1, h+2\} \tag{3 e}$$

$$D_t^{Sh^{RT}} \leq D_t, \forall t \in \{h, h+1, h+2\} \tag{3 f}$$

$$S_t^{RT} \leq W_t^{Av}, \forall t \in \{h, h+1, h+2\} \tag{3 g}$$

$$W_t^{RT} + S_t^{RT} = W_t^{Av}, \forall t \in \{h, h+1, h+2\} \tag{3 h}$$

$$\sum_{g=1}^{N_G} P_{gt}^{RT} + W_t^{RT} - \; (D_t - D_t^{Sh^{RT}}) = 0 \;\; \forall n, \forall t \in \{h, h+1, h+2\} \tag{3 i}$$

$$U_{st}^{RT} \; = \; U_{gt}^{DA}, V_{st}^{RT} \; = \; V_{st}^{DA}, Y_{st}^{RT} \; = \; Y_{st}^{DA} \;\; \forall s, \forall t \in \{h, h+1, h+2\} \tag{3 j}$$

$$(U^{RT}, V^{RT}, Y^{RT}) \in \Psi^{O} \tag{3 k}$$

3.5 Test System and Data

The market outcomes and environmental implications of adopting a stochastic framework are investigated on a 12% capacity-scaled version of PJM[1]'s power generation resources as reported in the National Electric Energy Data System (NEEDS v.5.13) (US EPA, 2016) compiled by EPA(US EPA, 2015). The system is assumed to have a peak load of 17241 MW, and 67 fossil-fired generators with a total of 20000 MW of installed capacity. Wind power generation capacity is 4641 MW in the base case and 7300 MW in the high wind penetration case. Assuming the same demand and wind-farm capacity factor, the base-case has 12% of wind energy penetration while the high wind penetration case has 21%. Given its installed capacity and peak load, the system has a 16% long-term reserve margin under the base-case wind assumptions which is consistent with PJM's long-term reserve margin policy [81].

3.5.1 Data on conventional power generators

Table 9 summarizes information on the technology, fuel-type installed capacity, quick-start and ramp capability of the 67 conventional generators included in the test system. Following PJM's rules, all combustion turbines with 2-hour or shorter start-up time are classified as fast-starting, and others as slow-starting units. All technology types except nuclear are capable of providing ramp capability reserves and can be treated as

[1] PJM Interconnection is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia.

load-following generators. Nuclear generators are as assumed to operate at a constant capacity [82]. (See section 6 in Appendix B for full description of the conventional generators data).

The marginal operating costs of fossil-fired generators assumed to be equal to the DA and balancing energy offers, are calculated from the heat-rates of the generators and the cost of fuel. The prices of fuel delivered to power plants are assumed to be \$2.1/MBTU for coal, \$2.9/MBTU for natural gas, and \$10/MMBTU for oil as reported by the EIA's Electricity Dta Browser for the PJM region in year 2016; and \$2770/kg or \$0.85/mmbtu for uranium[83], [84].

Table 9: Installed Capacity and Number of Units by Fuel Technology for the Fossil-Fired Generating Units in the Scaled Test Grid

Technology	# of units	Capacity (MW) & share (%)	Ramp capability	Quick start
Nuclear ST[(i)]	4	4616 (23%)	No	No
Coal ST	19	8727 (44%)	Yes	No
NGCC [(ii)]	14	2996 (15%)	Yes	No
Oil CT [(iii)]	8	631 (3%)	Yes	No
NGCT	22	3030 (15%)	Yes	Yes

(i) Steam Turbine; (ii) Combined Cycle; (iii) Combustion Turbine.

3.5.2 Data on electricity demand and wind power production

Data on electricity demand, wind power DA forecasts, and wind power production is taken from a time-coincident 5-minute resolution dataset from the Bonneville Power Administration (BPA) [85]. Demand data is aggregated hourly and then scaled up by 63% so that it reaches a peak of 17241MW. Wind data is taken as is to represent a 12% wind-penetration case, and scaled to represent the 21% wind penetration case.

3.6 Results

Results from the comparison of the outcomes of DMC, ADMC and SMC under a base case of 12% wind penetration show SMC's superiority. While both ADMC and SMC represent an improvement from DMC, SMC is superior. As presented in detail below, SMC reduces the use of coal, integrates slightly more wind power, reduces fuel costs, and start-up costs lowers air emissions, develops prices reflective of marginal system operation costs, and increases convergence of DA and RT markets, ultimately increasing the social welfare.

3.6.1 Dispatch and Economic outcomes

Table 10 shows that ADMC and SMC reduce the annual operating costs of conventional power plants (fuel, start-up, and no-load costs) by 0.36% and 0.9% relative to DMC. SMC's total cost reduction is the result of lower start-up and no-load costs, and lower fuel costs due to the integration of 27761 MWh of additional wind power. The main difference between ADMC and SMC is in the way they affect DA and RT schedules and costs. As discussed in Section 3.6.3 below, SMC schedules more wind in the DA market than ADMC and hence causes a 12 fold reduction in DA costs with respect to ADMC. Deploying reserves in the RT market to offset deviations in the wind schedules increases the RT plant's costs, but this increase is more than offset by the reduction in DA costs.

Table 10: Market Settlement And Cost Implications Of DMC and SMC Mechanisms (M$)

Outcomes	DMC	ADMC	SMC
Economic outcomes			
Total plants Cost	Base (1,125 M$)	-0.36%	-0.90%
DA plants' cost	Base (1,124 M$)	-0.29%	-3.38%
RT plants' costs	Base (0.5 M$)	-152.31%	5536.93%
Start-up costs	Base (27.5 M$)	-17.00%	-27.40%
Producers' revenue	Base (1,809 M$)	3.40%	1.73%
Producers' surplus	Base (684 M$)	9.59%	6.36%
Consumers' surplus	Base (258,205 M$)	-0.024%	-0.012%
Social Surplus	Base (258,888 M$)	0.002%	0.005%
UP1	Base (21 M$)	-47.27%	-58.25%
UP2	Base (3 M$)	-55.17%	-55.20%
Average DA price	Base (20.44 $/MWh)	3.95%	2.11%
Average RT price	Base (20.78 $/MWh)	0.09%	1.55%
Dispatch generation outcomes by technology (MWh)			
Coal	Base (27489)	-2.42%	-3.74
NGCC	Base (9467)	7.43%	9.92%
NGCT	Base (166)	-26.25%	32.85%
Wind	Base (10442)	0.06%	0.32%

Both ADMC and SMC increase the producers' revenues and surplus, and by increasing DA prices, they both reduce the consumer's surplus. The payments for providing ramp capability reserve under ADMC account for 0.08% of the additional producers' revenues and profits observed in ADMC relative to DMC (see Section 7.2 in Appendix B). The increased producers' surplus under ADMC and SMC suggests that both designs would offer sufficient incentives for producers to offer their ramp capability reserves to the grid.

While ADMC would be more appealing to producers given the expected increase in their surplus, it would be far-less attractive than SMC to consumers. The consumer welfare reductions caused by SMC ($31 million) are half those observed under ADMC ($62 million). This reduction in consumers' welfare is the result of increased DA prices to hedge against wind power uncertainty.

In terms of the social welfare, SMC outperforms ADMC. Although both ADMC and SMC improve the social welfare, the increase caused by SMC ($12 million) is three times greater than that of ADMC ($4 million).

SMC is more effective than ADMC in reducing total uplift payments to producers. These uplift payments have been decomposed into two components presented in the last two rows of Table 10. *Uplift Payment 1* (*UP1*), is equal to the uplift payments made to cover the startup costs of power plants. *Uplift Payments 2* (*UP2*) is equal to the payments made to cover the other pricing non-convexities not covered by the DA and RT energy prices (see equations in Section 3.3 in Appendix B). ADMC and SMC respectively cut the total uplift payments by respectively 46% and 58%. The significant reduction in *UP1* payments observed under SMC is due to its more efficient commitment of conventional producers, also reflected in the reduction of start-up costs. Although, the absolute reduction in *UP2* caused by ADMC and SMC is very similar, it is a much higher component of the revenue under SMC and hence proves SMCs effectiveness minimizing the prominence of uplift payments. Uplift payments are deemed undesirable because they reduce the transparency of the market and hence fail to send the right signals for enticing participation or investment in the right resources.

Departing from the dispatch prescribed by DMC rises the total producers' surplus, but not all generators benefit from this. As shown in Table 11 both ADMC and SMC shift revenue from coal producers, which generally have lower ramping capability, to more flexible NGCC producers and wind producers. The shifts in allocation are greater under SMC. A notable difference between the two market designs is their impact on the revenue share of NGCT producers which are the most flexible and most expensive producers. The revenue share of NGCT producers increases under SMC and decreases under ADMC. Overall, SMC demonstrates a more consistent behavior in remunerating more flexible producers while making the market friendlier to wind producers. As seen in the SI, when ramp flexibility reserves are not compensated, there is a slight reduction in the revenue share of coal and gas generators and an increase in the share of revenue received by nuclear plants.

Table 11: Shift in Distribution of Revenues Among Different Production Technologies (%)

Share of revenues (%)	DMC	ADMC	SMC
Coal	Base (33.45%)	-1.13%	-1.83%
NGCC	Base (10.95%)	0.95%	1.28%
Nuclear	Base (44.22%)	0.21%	0.22%
Oil	Base (0.00%)	0.00%	0.00%
NGCT	Base (0.29%)	-0.08%	0.05%
Wind	Base (11.09%)	0.05%	0.28%

3.6.2 DA and RT prices and convergence

Convergence between the DA and RT prices and main dispatch features is deemed desirable because it reduces the risk-hedging needs of market participants [86], and is correlated with a reduction on uplift payments.

As shown by Figure 5, ADMC and SMC average, DA prices are very close to each other, and significantly higher than under DMC. Discrepancies between ADMC and SMC DA prices are only observed during the late night and early morning hours, when the expectation of higher wind production allows SMC to schedule more of this resource and further reduce prices.

Panel (b) in Figure 5 shows that average RT prices are higher under SMC except for the late night and early morning hours when wind power production tends to be larger. Panel (c) shows that the difference between average hourly prices for the DA and RT (i.e. the spread) tends to be smaller for SMC than for ADMC and DMC. In fact, for SMC, the absolute value of average hourly spread is always lower than 0.5 $/MWh. In contrast, for ADMC, the absolute spread can be higher than 1 $/MWh. The average of the absolute value of spreads between DA and RT prices for 24 hours is 0.55 under DMC, 14.5% lower under ADMC (Absolute spread = 0.47), and 40% lower under SMC (Absolute spread=0.33). The greater convergence between DA and RT prices under SMC is not surprising, given that by design, this scheme accounts for the expected cost of

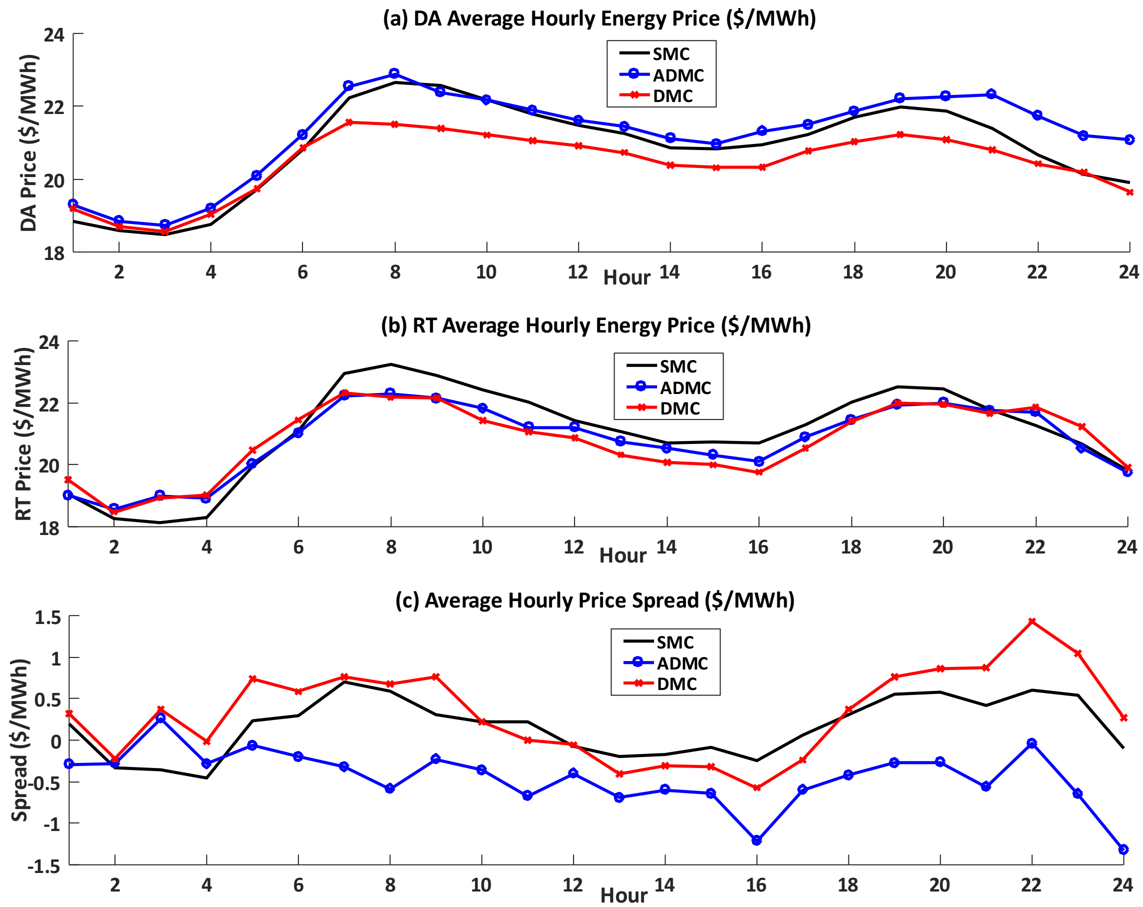

Figure 5: Annual Average of Hourly DA and RT Energy Prices and Price Spread between DA and RT Prices (Spread = RT Price – DA Price)

wind production uncertainty in the DA and hence these DA prices are consistent with the RT.

Figure 6 shows that the enhanced price convergence between DA and RT markets observed under SMC is due to higher consistency between the scheduling and dispatch. Panels a-d show for each hour the proportion of time during the year, when each fuel-type sets the DA and RT price. As seen, there is more consistency between the DA and RT marginal fuel under SMC relative to ADMC.

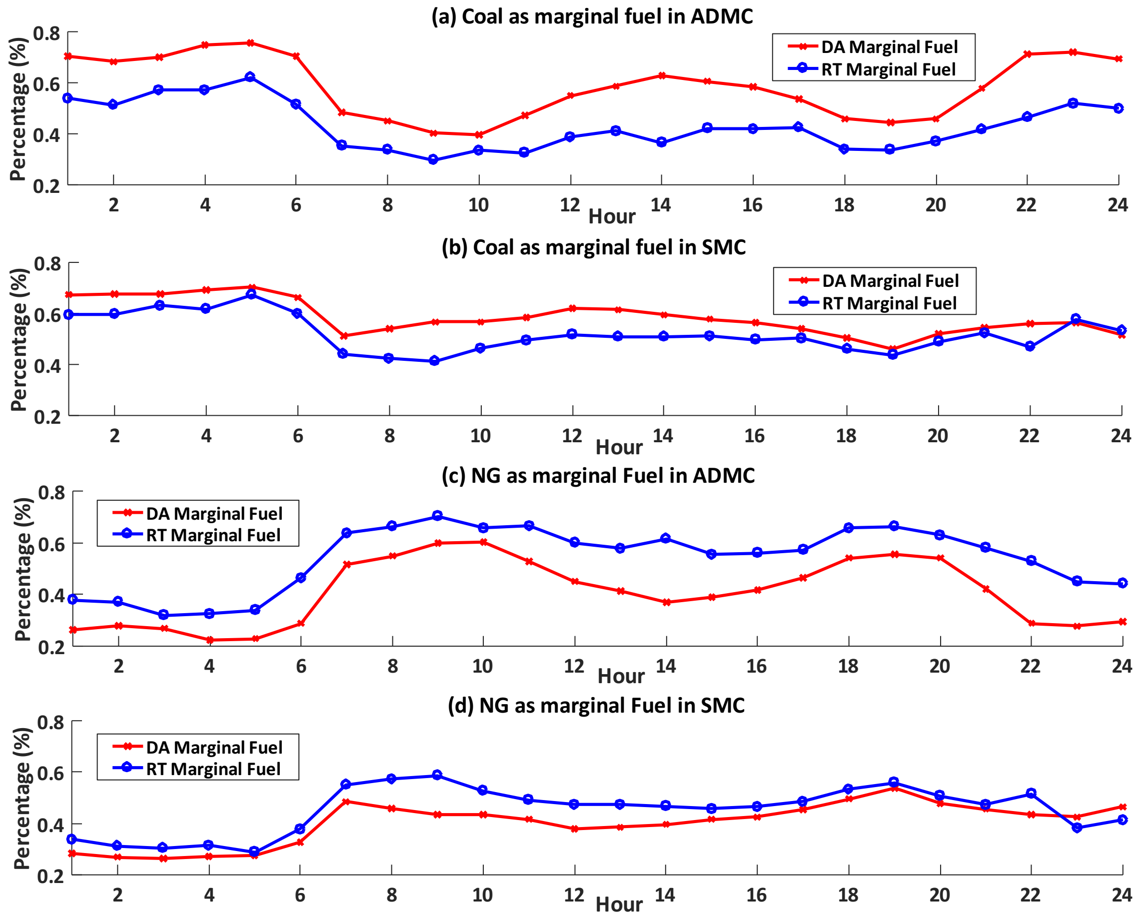

Figure 6: Proportion of Time During the Year When Coal and NG Are Marginal Fuels in The DA and RT Markets

3.6.3 Impacts on scheduling and dispatch

The dispatch outcomes, presented in Table 12, show that both ADMC and SMC replace the production of coal-fired with electricity from NG plants. While SMC increases the production of both NGCC and NGCT to replace coal-fired electricity, ADMC reduces the production of coal and NGCT plants and replaces it with production from NGCCs. These effects are driven by scheduling in DA energy and reserves as described in the next subsection.

Another important benefit of ADMC and SMC relative to DMC is the increased integration of wind power production. ADMC and SMC replace about 5.9 and 33.7 GWh of fossil-fired electricity with wind power. Although a small percentage from the total, increased wind-power integration causes important cost-savings under both models, but especially so under SMC.

The dispatch outcomes of ADMC and SMC are a direct consequence of changes in the scheduling of energy and reserves in the DA market, and in particular, of changes in wind energy scheduling. As shown in

Table 13 SMC schedules significantly more wind power than ADMC and DMC, while reducing the amount of electricity from coal and NGCTs. The magnitude of wind-power scheduling in the DA is the fundamental difference and advantage of SMC. Figure 7 illustrates this in more detail. While DMC and ADMC by design will always schedule in the DA an amount of wind-power equal to its expected value (unless there is not enough demand), the SMC will schedule an amount that is closely related to the ratio of expected wind-production to electricity demand. Sometimes, SMC will schedule

Table 12: Percentage Variation of Annual Dispatch Outcomes in Alternative Designs (%)

Generation (GWh)	DMC	ADMC	SMC
Coal	27,489	-2.42%	-3.74%
NGCC	9,467	7.43%	9.92%
Nuclear	39,107	0.00%	0.00%
Oil	0	0.00%	0.00%
NGCT	166	-26.25%	32.85%
Wind	10,442	0.06%	0.32%

Table 13: Percentage Variation of Annual DA Energy Schedules in Alternative Designs (%)

Generation MWh	DMC	ADMC	SMC
Coal	Base (27,532)	-2.75%	-7.36%
NGCC	Base (9,521)	8.13%	5.83%
Nuclear	Base (39,107)	0.00%	0.00%
Oil	Base (0)	0.00%	0.00%
NGCT	Base (103)	-17.33%	-40.77%
Wind	Base (10,408)	0.02%	14.53%

the maximum possible amount of wind power if it is much less than the expected electricity demand. Figure 7 shows the number of hours in a year of simulation, when SMC schedules an amount of wind power that is less than its expected value (*low wind scheduling* –blue bars), more than its expected value but less than the possible (*medium wind scheduling* –red bars), or exactly the maximum amount (*max wind scheduling* – green bars), for three categories of DA wind-power forecast as given by its ratio to electricity demand. The figure shows the results of two simulations; the bottom panel corresponds to the case when wind-power installed capacity is such, that it could cover about 12% of the annual demand (i.e., 12% wind –energy penetration), while the second case (top panel) corresponds to a 21% wind power penetration. The figure shows that, under 12% wind power penetration, during the vast majority of the 8760 hours of the year, the DA expected-value of wind-power production is less than 35% of the electricity demand. Under those cases, SMC schedules the maximum amount of wind-power. During the few hours when the expected value of wind power is more than 45% of the demand, SMC will schedule a wind power amount that is lower than its DA expected value. Under the 21% wind-power penetration, the number of hours during which the ratio of DA's expected wind production exceeds 45% of the electricity demand, increases. For the most part, under those circumstances, SMC will schedule an amount of wind-power production that is lower than its expected value. This correlation between DA wind-

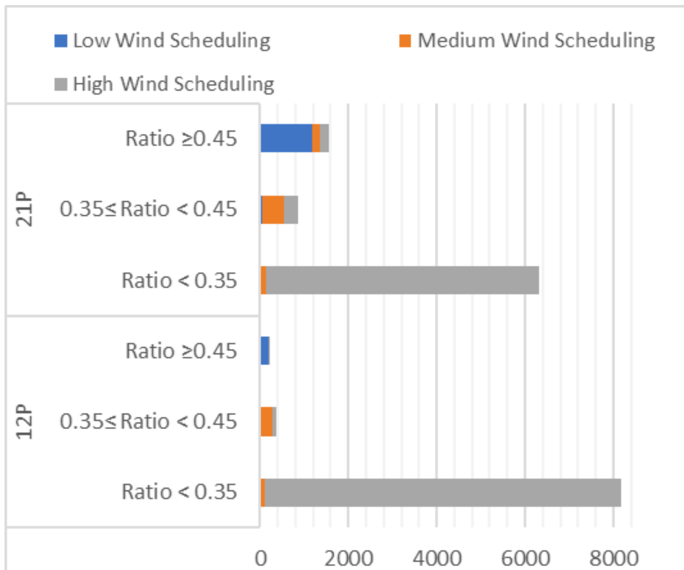

Figure 7: Variations of DA Wind Schedules for Three Categories According to the Ratio of Expected Wind Production to Demand, under 12% and 21% Wind Penetration Levels

Table 14: Schedules of Ramp Capability Reserves under Alternative Market Designs (GW)

Capacity (GW)	DMC	ADMC	SMC
Scheduled up-reserve	0.00	1741	2670
Scheduled down-reserve	0.00	1331	1936
Ratio of up-reserve to wind	0.00	0.17	0.22
ratio of down-reserve to wind	0.00	0.13	0.16

power schedules and the ratio of demand to expected value of wind is explained by the availability of ramping capability. When the ratio is lower than 0.35, the scheduled conventional generators provide abundant reserves for compensating any real-time shortages or excesses of wind power production. As the ratio increases beyond 0.45, the DA wind power schedules are often lower than the expected wind production because the limited up ramp capability of the system, makes the cost of scheduling more wind lower than its benefits. This is because under the expectation of large wind-power production, the amount of scheduled fossil-fired generation is low, and consequently, up and down ramp capability is also low.

Although SMC frequently schedules much more wind than ADMC or SMC, it also results in more conservative schedules of up and down reserves to hedge against the uncertainty on wind production. As shown in Table 14 SMC schedules more up and down reserves compared to ADMC and the ratio of DA-scheduled reserves to DA-scheduled wind is also greater under SMC. Up and down reserves respectively refer to the total up and down ramp-feasible capacity on committed generating units.

3.6.4 Startups and cycling effects

The number of times when fossil-fired generators start-up and shut-down in a year, is a good indicator of the efficiency in which market algorithms dispatch the fleet. This is because in general, start-ups imply increased fuel consumption and higher associated costs and air-emissions. As Table 15 shows, ADMC and SMC have a similar impact on the startups of slow producers and differ in their impacts on fast-start producers. Both of them reduce the number of startups by coal producers and increase those of NGCC producers. The reduction in coal startups with respect to DMC is almost two times greater for SMC. In contrast, the number of NGCT startups is 10% higher under SMC (72 more startups) and 20% lower under ADMC (162 fewer startups). The number of NGCT plants scheduled to startup in the DA decreases for ADMC and later some of the NGCT producers that are scheduled to startup are decommitted and hence do not startup either. By reducing the number of startups of coal-fired generators SMC results in reduces their cycling costs. Finally, the startup results highlight the fact that ADMC incurs in an unnecessary scheduling of fast-start generators in the DA market that need to be later de-committed during the RT operation. Instead SMC schedules fewer DA fast startups compared to DMC and waits for more accurate wind info to commit a greater number of fast startups during the RT. The inefficient overscheduling and de-commitment that occurs under ADMC results in an additional cost for consumers because the RT market is settled at RT prices that are lower than the

Table 15: Relative Change in the Annual Number of Startups Distinguished by Startup Technology. There is a Roughly Equal Amount of Shut-Downs Which are Assumed to Be Cost Free

	DMC	ADMC	SMC
Total startups	Base (3400)	+151	+150
Coal Startups	Base (1359)	-204	-479
NGCC Startups	Base (1240)	+517	+557
DA NGCT Startups	Base (366)	-68	-149
RT NGCT commitment changes	Base (431)	-94	+221
Total NGCT starts	Base (797)	-162	72

associated DA prices and hence the generators keep a portion of the DA payment and collect some revenue without producing energy.

3.6.5 Environmental outcomes

As shown in Table 16, SMC accomplishes a remarkable reduction in CO_2, NOx, and SO_2 emissions when compared to both DMC and ADMC. The substitution of coal for natural gas and the integration of additional wind power causes air emissions under ADMC and SMC to be lower than under the DMC case. Nonetheless, the emissions mitigation is 2 to 4 times higher under SMC than ADMC. As shown in Table 16, SMC is much more effective in substituting the generation of coal- fired power plants which have an average CO_2 emissions rate of 0.11 ton/mmbtu, with electricity from NGCC and

Table 16: Annual Air Emissions of Alternative Market Clearing Mechanisms from Startup and Power Generation

Emission ($\times 10^3$ ton)	DMC	ADMC	SMC
Percentage variation of emission (%)			
Total CO_2	Base (37326.95)	-1.60%	-3.52%
Start-up CO_2	Base (1057.00)	-18.91%	-30.64%
Generation CO_2	Base (36269.96)	-1.10%	-2.72%
Total NOx	Base (21.41)	-2.09%	-7.51%
Start-up NOx	Base (0.76)	-14.91%	-31.44%
Generation NOx	Base (20.65)	-1.62%	-6.64%
Total SO_2	Base (354.35)	-2.13%	-4.74%
Start-up SO_2	Base (9.55)	-17.63%	-28.93%
Generation SO_2	Base (344.80)	-1.70%	-4.07%
Dispatch generation outcomes by technology (MWh)			
Coal	Base (27489)	-2.42%	-3.74
NGCC	Base (9467)	7.43%	9.92%
NGCT	Base (166)	-26.25%	32.85%
Wind	Base (10442)	0.06%	0.32%

Table 17: Annual Air Emissions by Fuel/Turbine Technology

	DMC	ADMC	SMC
CO_2 emissions by production technology ($\times 10^3$ ton)			
Coal	Base (32273.49)	-2.89%	-5.56%
NGCC	Base (4930.32)	7.47%	8.96%
NGCT	Base (123.14)	-26.60%	32.71%
NOx emissions by production technology ($\times 10^3$ ton)			
Coal	Base (20.69)	-2.34%	-8.38%
NGCC	Base (0.61)	10.09%	14.96%
NGCT	Base (0.10)	-25.19%	34.64%
SO_2 emissions by production technology ($\times 10^3$ ton)			
Coal	Base (354.35)	-2.13%	-4.74%
NGCC	Base (0.00)	0.00%	0.00%
NGCT	Base (0.00)	0.00%	0.00%

NGCT units which have a much lower average emissions rate of 0.069 and 0.064 ton/mmbtu. Also, SMC has a lower number of start-ups from slow-starting generators than ADMC and this accounts for 25%, 15% and 16% reduction in CO_2, NO_x and SO_2 emissions. As seen in Table 17 both ADMC and SMC cause a significant reduction in air-emissions from coal-fired power plants. This tremendous reduction, more than offsets the increase in CO2 and NOx emissions from NGCC plants observed under both ADMC and SMC, and the increase in emissions from NGCT plants caused by SMC.

3.6.6 Sensitivity analyses

Here we investigate the sensitivity of results to changes in two types of assumptions regarding a) the price that producers charge for balancing energy and b) the amount of wind- power generation capacity. Table 18 summarizes the cases explored. Case 1 is the base case that has been discussed in the previous sections. Case 2 assumes producers offer their balancing energy at prices higher than their marginal costs and their downward balancing energy at prices lower than the marginal costs, in an attempt to rise RT prices and their corresponding revenue. Case 3 looks at a higher wind power installed capacity expected to produce an amount of energy corresponding to 21% of expected demand.

The results of Case 2 shows that the assumption that producer's offers for balancing energy become more expensive (increase by 20% for up reserve deployment and decrease by 20% for down reserve deployment) has a negative impact on the outcomes of ADMC and even more strongly on those of SMC. Although assuming these changes in the balancing energy offers of the SMC results in producers having the highest revenues and surplus of all cases, still the total social surplus is higher than under ADMC. Despite the apparent incentives for producers to rise their balancing offers, this scenario is unlikely to result in a stable equilibrium because it rewards coal producers at the loss of NGCC producers, and hence the latter, are not incentivized to engage in this behavior. In turn, if NGCC's refrain from increasing their balancing offers, other producers will have to follow them, in order to remain competitive.

Table 18: Cases Explored in The Sensitivity Analysis

	Strategic balancing energy offering	penetration of wind energy
Case 1	----	12 %
Case 2	✓	12%
Case 3	----	21%

Table 19: Impacts of Balancing Energy Bidding Behavior and Wind Penetration on Alternative Market Clearing Mechanisms Outcomes

	Case 1		Case 2		Case 3	
	ADMC	SMC	ADMC	SMC	ADMC	SMC
Market outcomes						
DA scheduled wind (GWh)	10410	11921	10408	11137	16988	19111
Integrated wind (GWh)	10448	10476	10446	10476	16842	16906
Number of startups	3,551	3,555	3,553	3,553	4,601	4,516
Economic outcomes						
Total fuel cost (M$)	1,121	1,115	1,127	1,123	997	991
DA cost (M$)	1,121	1,086	1,121	1,121	993	944
RT cost (M$)	- 0	28	5	5	4	50
Producers' revenue (M$)	1,870	1,840	1,868	1,868	1,654	1,642
Producers' surplus (M$)	749	727	741	746	657	652
Social surplus (B$)	258.892	258.901	258.887	258.892	259.016	259.023
Total uplift payment (M$)	13	10	14	14	22	19
Producers' revenues (M$)						
Coal revenues	604.38	581.28	605.82	588.06	504.70	484.56
NGCC revenues	222.69	224.99	224.85	222.81	189.63	186.31
NGCT revenues	3.86	6.19	4.88	7.16	7.93	12.37
Wind revenues	208.34	209.01	202.67	203.17	220.90	230.42
Air emissions ($\times 10^3$ ton)						
CO_2 emissions	35,856	34,236	35,848	35,848	29,399	27,508
NOx emissions	20.3	18.7	20.1	20.1	16.6	15.3
SO_2 emissions	339	322	338	338	274	257

Finally, the results of Case 3 show that increased wind-power generation capacity results in ever better environmental and economic benefits of ADMC and even more so, of SMC. The plant operation cost reduction in SMC is by 1.42% greater than ADMC-UP, which is around two times the cost reduction in Case 1 with 12% wind penetration. The lower costs under SMC are explained by a better prepositioning and dispatch of fossil-fired resources. SMC’s wind integration, which is by 0.64 % greater than ADMC’s wind integration, plays a significant role in its greater cost reduction. The distribution of DA and RT costs also imply that under SMC, a larger amount of trade is shifted to the RT market. The uplift payments also display an interesting pattern.

3.7 Discussion and Conclusions

Comparing the outcomes of SMC with DMC and ADMC reveals that implementing SMC offers great benefits and positive impacts on market design outcomes. Implementing SMC provides a more efficient dispatch of fast and slow resources, cuts fuel, startup costs, enhances wind integration, and lowers the cost of wind production uncertainty. Such impacts result in sizable benefits for implementing SMC in the PJM interconnection. The results indicate implementing SMC achieves 0.9% reduction in the annual plant operation costs incurred in the base DMC with 12% wind penetration case. The reported reduction is around half of the cost-savings achieved by stochastic unit commitment, reported in [54] as the only work comparable to this study. [54] compares stochastic and deterministic unit commitments on a scaled version of CAISO with 14% wind energy penetration for eight representative days whose results may not truly represent the market outcomes for the entire year. Our findings also indicate SMC's plant operation cost saving are 0.54% higher than that in ADMC, compared to 1.1% reported in [54]. The cost saving differences can be explained by the fact that [54] ran the comparison for only 8 days on a different generation mix, modeled following reserve requirements differently, and quantified the reserve requirements by a less efficient heuristic rule-of-thumb criteria, and considered demand uncertainty in its analysis. The approximations made in replicating the power system operation could be also another reason. Nonetheless, 0.9% and 0.54% reductions in PJM operation costs with M$ 30,753 energy markets annual billing [87] still counts as sizable savings.

Cost reductions attained by SMC have two drivers: 1) maintaining additional ramp capability reserves; and 2) accounting for the RT operation costs in allocation of energy and reserves. It is the second driver that makes SMC achieve greater benefits. In fact, ADMC can ensure those reductions gained by maintaining reserves if quantified efficiently; however, it cannot take advantage of full characterization of wind production uncertainty and account for the expected balancing costs. This difference enables SMC to deliver a more efficient dispatch of energy and reserves that positions the system a day ahead of the system operation to effectively hedge against wind uncertainty. Uncertainty-adjusted allocations under SMC shifts the production towards producers with greater flexibility and prepares the system for integrating maximum cost-effective level of wind power production.

Besides cost effective operation of resources, SMC is clearly more efficient in pricing resources. SMC internalizes the expected cost of DA schedules and wind uncertainty in DA prices, which causes average lower DA prices in early morning hours when most wind curtailments occur and higher DA prices in other hours. The internalization also creates a closer convergence between the DA and RT prices and lessens the average price spread by 30% compared to the best outcome observed in deterministic designs. The price convergence encourages participants to view the two-period markets as one market and be less concerned about the RT price volatilities. It also alleviates the demand for convergence bidding (virtual arbitraging) to enforce the convergence and the inefficiencies they create. The efficient dispatch price convergence also significantly cuts the out-of-market adjustments.

SMC's cost-effective dispatch of resources and its efficient pricing scheme lead to a more profitable situation for both consumers and producers of electricity compared to ADMC. The prices are good enough to incentivize producers provide reserves and follow the ISO's dispatch instructions in both designs, yet the overall producers' surplus is greater under ADMC. Despite that, the consumers' surplus realized by SMC overshadows ADMC's consumer welfare, indicating the electricity is more affordable to consumers under SMC, and the SMC's social welfare exceeds ADMC's welfare as well.

SMC and ADMC designs also offer substantial non-monetized benefits in terms of CO_2, SO_2, and NO_X emission reductions and cycling effects. Similar to monetized benefits, yet to a greater extent, SMC outperforms ADMC in terms of air emissions mitigation. The SMC's CO_2 emissions mitigation are particularly so large that ADMC can achieve them by taxing CO_2 emissions at 4.5 $/ton. In other words, SMC's CO_2 emission results without any CO_2 pricing policies are roughly equal to the CO2 emissions in a scenario that ADMC design is used to clear the markets and CO_2 emissions are priced at 4.5 $/ton. A roughly similar reduction in emissions could be achieved by the startup patterns also indicate SMC lessens the cycling effects of fossil-fired producers. However, the monetary value of such effects have not been assessed in this study. Likewise, they have not been included the startup costs of producers. The cycling effect and emission mitigations see a significant reduction in higher wind energy penetration levels.

The reported results show that the SMC outcomes will be negatively affected if producers submit balancing energy offers that differ from their marginal costs. At the same time, the outcomes of SMC are expected to improve with higher market penetration of wind producers.

4. Interaction of Renewable Supporting Policies and Market Clearing Design

4.1 Abstract

This study investigates the economic and environmental implications of three approaches for integrating the DA wind uncertainty into the market clearing designs and evaluate their sensitivities to the alterations made to the supply curve's merit order when the CO_2 emissions are priced. The merit order changes shift the less flexible coal producers to the middle of supply curve where they are more prone to fast net demand ramps and more susceptible to the wind uncertainty. The investigated approaches include DA ramp products, Stochastic Residual Unit Commitment (SRUC), and Stochastic Market Clearing (SMC). This study quantifies the economic and environmental inefficiencies caused by not integrating wind production uncertainty to market clearing mechanisms and assesses the benefits that can be achieved by directly or indirectly integrating the uncertainty characterization through different designs. This comparative analysis is conducted on a scaled version of PJM with 12% wind energy penetration under two CO_2 pricing scenarios: 0 and 10 $/ton. The results indicate that SMC can lower the production costs by 0.91% in the business as usual where ramp products and SRUC combined can fulfill only 0.45% of that reduction. In another scenario that CO2 emissions are priced, SMC maintains its superior performance, but ramp products and SRUC become less effective as the CO_2 price shifts the coal suppliers to the middle of supply curve between NGCC and NGCT suppliers.

4.2 Introduction

4.2.1 Scope and Overview

Renewable portfolio standards (RPS) and emission pricing policies, i.e. the carbon tax and the cap-and-trade system, play a pivotal role in transition to low-carbon electricity grids in the U.S. The political, engineering, and market design challenges associated with these policies aside, they complicate the electricity markets scheduling and dispatch processes which distort the market and grid operation outcomes, and cause economic and environmental inefficiencies. Variable renewable energy resources (VER) are inherently intermittent and highly unpredictable, whereas the traditional structure for least-cost operation of short-run electricity markets is not designed to deal with those characteristics. Thus, ever-increasing market penetration of VER distorts the allocation of energy among producers [9], [12], [14], increases the operation costs [9], [88], as well as causes the price of electricity to shift away from its desirable levels [15], [89] impairing the fair distribution of revenues among individual market players [49], [89] and suboptimal settlement of energy transactions among producers and consumers of electricity [89] , and engenders environmental inefficiencies [89], [90]. On the other hand, CO2 pricing policies alter the priority dispatch order of generators in the supply curve which has positive and negative ramifications on the overall grid flexibility for following the fluctuations of VER and managing their uncertain behavior. Such problems have directed the focus of the research studies during the last decade toward designing and implementing adjustments to traditional electricity market clearing design that integrate the intermittency and uncertainty of VER and ultimately overcome the inefficiencies brought about by their uncertainty and intermittency [6]–[9], [14], [56], [91], [92]. However, no attention has been given to the consequences of wind uncertainty in a carbon-constrained system and whether market- clearing adjustments can effectively overcome these challenges in such systems.

4.2.2 Background

The traditional design of daily energy markets in the U.S. consists of sequential day-ahead (DA) and real-time (RT) markets which are administered by Independent System Operators (ISO) or a Regional Transmission Operators (RTO) that ensure the least-cost and reliable supply of electricity based on participant demand bids and supply offers. The DA market occurs a day prior to the physical generation/consumption based on DA predictions for demand and VER to determine the optimal schedules and prices for the generation and consumption of energy, so slow-start resources have sufficient time to fulfil the binding commitments they take on. The DA market clearing occurs in two stages; first a unit commitment model is used to optimize the on/off status trajectory of generators and then an economic dispatch model is used to determine the optimal hourly schedules for the winning generators and the associated prices. The real-time market occurs a few minutes prior to the real-time operation based on the RT values of demand and VER to ensure maintaining the instantaneous balance of demand and supply at the least cost by optimizing the corrective actions (e.g.

commitment/decommitment of fast-start producers, producers' redispatch, load shedding, wind curtailment, and etc.) [59], [60].

In the U.S. electricity markets, the standard DA and RT market process are respectively amended by the Residual Unit Commitment (RUC) and Look-ahead RT commitment/dispatch processes. RUC is a process that maintains the DA schedules and runs based on the ISO's point estimates of demand and VER after the DA market clearing ends to minimize the commitment costs for supplying the residual demand and/or reliability requirements (e.g., voltage support and black start services) not supplied by the DA schedules. The RUC process is particularly essential for committing long-start generators that would be impossible to startup in a few hours to the physical generation [59], [93]. In addition to RUC, Some ISOs run look-ahead RT commitment with 2 two 4 hours look-ahead horizon in parallel with the RT market clearing to address shortcomings of single-period RT dispatch. The RT look-ahead models optimize the RT commitment and dispatch of fast-start producers at the first period of the look-ahead horizon by anticipating the ramping requirements and associated balancing costs in the upcoming periods [94], [95]. In fact, the ISOs typically consider the first interval outcomes as binding for settlement and the upcoming periods' outcomes advisory. Look-ahead processes with extended horizons of 4 to 5 hours can to a fair extent fulfill the benefits of an intraday commitment process.

The traditional market design has stood the test of time and proved economic efficiency in the past. However, the introduction of climate mitigation policies poses serious challenges to its economic efficiency. This study is focused particularly on the challenges posed by high penetration of wind energy resources and shifts in the priority dispatch order of conventional producers driven by CO2 pricing. Growing penetration of wind energy resources increases the uncertainty and intermittency beyond the level system operators used to deal with in the past. In the absence of flexible demands, the system operator relies on conventional generators' flexibility to manage the intermittency and fluctuations of wind production during RT operation. However, wind production uncertainty impairs the system operator's ability to utilize the generators' flexibility in an optimal and cost-effective manner (See section 3.6).

Since the DA wind predictions are currently highly inaccurate [5], the uncertainty around the DA wind energy offers distorts the DA market outcomes leading to suboptimal DA schedules that could be operationally infeasible and insufficient for correcting the RT deviations from DA schedules and ramping needs. As only a limited set of producers are nimble enough to respond to ISO's high speed redispatch and commitment adjustment instructions, the information gap between the DA and RT markets can increase the operation costs and divergence between DA and RT prices, diminishes the producers' revenues, increases the uplift payments, and motivates the market participants for strategically using virtual bids to access relatively higher/lower RT prices [89].

Pricing CO2 emissions alters the priority dispatch order of producers and their profit margins to spur on investment in cleaner energy resources in the long run. In the short run, it can affect the overall supply-side flexibility both positively and negatively, and the impacts escalate as the share of slow-start coal produces increases in the supply resource composition, e.g. PJM and ERCOT. Figure 8 further clarifies this matter by illustrating the supply curve priority dispatch for a scaled version of PJM's conventional technology/fuel mix based on the region's 2016 average fuel prices under two scenarios with and without CO2 pricing. Panel (a) of Figure 8 illustrates the supply curve in the business as usual (BAU) scenario with no CO_2 policy, and panel (b) demonstrates the supply curve under a CO_2 price of $10/ton. As expected, in the BAU case, the flexibility and marginal cost of production technologies increases from left to right, so the base load is supplied by nuclear- and coal-fired steam-turbine generators and the peak load by the open cycle combustion turbine (CT). However, in the CO_2 pricing scenario, natural gas combined cycle (NGCC) displaces coal in the priority dispatch order which means base load would be covered by nuclear and NGCC making the coal the intermediate merit technology. This switch increases the overall supply-side flexibility as NGCC producers' running time increases, yet makes the coal producers' commitment more vulnerable to wind uncertainty in the DA market due to their longer startup processes and inability to adjust their status in near RT commitment processes.

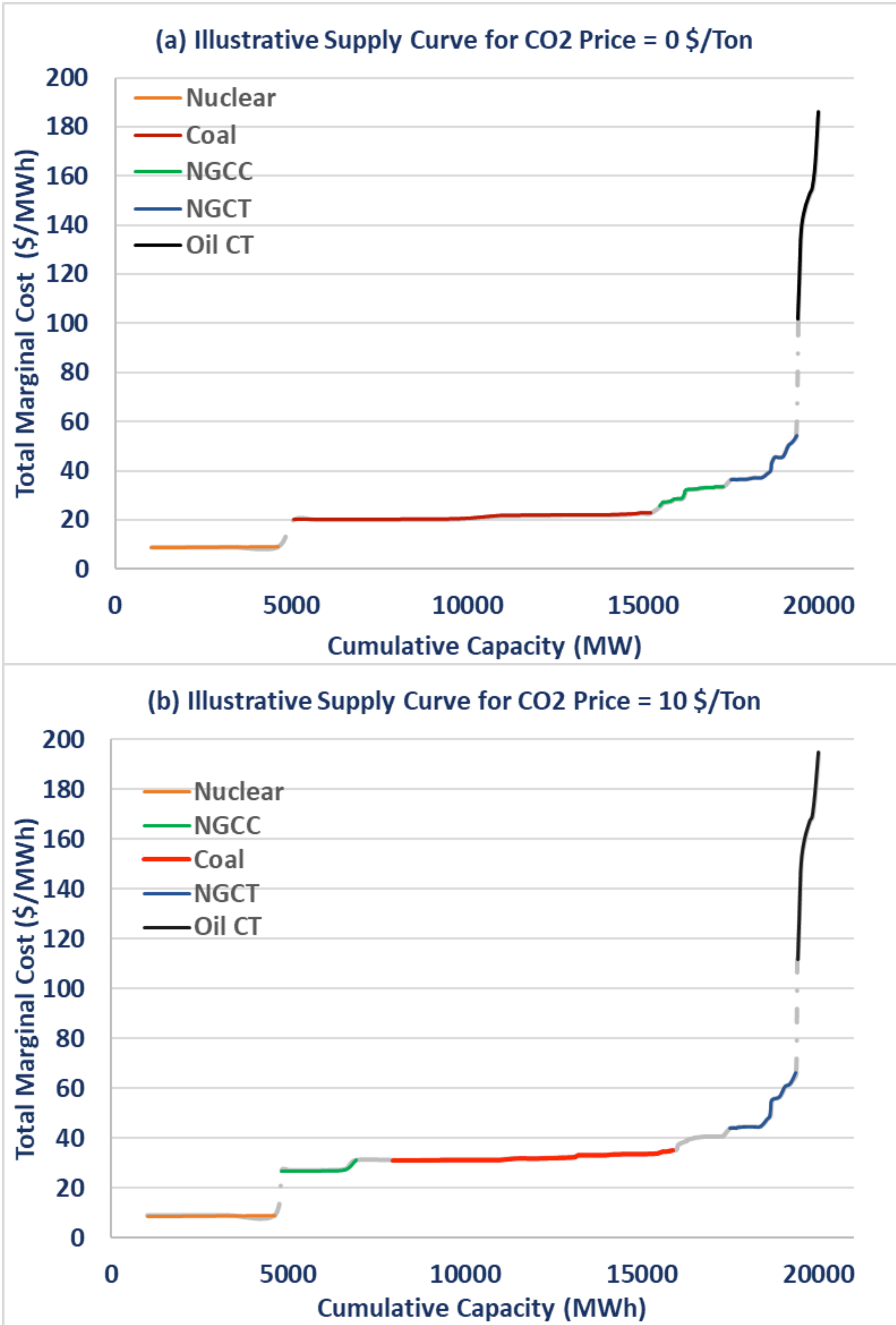

Figure 8: Illustrative Supply Curve for a Scaled Version of PJM's Conventional Generation Mix under two CO2 Pricing Scenarios

4.2.3 Literature Review

Various approaches have been proposed to integrate the DA wind uncertainty and variability into the market clearing design, including the ramp capability requirements [6]–[8], [56], [96], stochastic unit commitment (SUC) [12], [54], [67], [97], [98], and stochastic market clearing [13]–[15], [18], [99]. These approaches are designed to: a) supplement DA and RT energy schedules with additional up and down headroom capacity to follow the RT deviations from DA schedules and minimize the associated costs and b) reflect the cost of wind uncertainty in energy prices to incentivize the provision of flexibility for following wind fluctuations. Despite their common goals, they differ in their approach for integrating wind uncertainty into the market clearing design. Ramp products directly include the wind uncertainty into DA market clearing. In fact, the wind uncertainty is used to calculate the ramp capability requirements exogenous to the DA market clearing formulation. SUC employs two-stage stochastic optimization to directly include the uncertainty in the RUC phase after the DA market clearing, where the uncertainty is characterized through a set of scenarios. Finally, SMC directly includes the wind uncertainty into the DA commitment and dispatch processes by adopting two-stage optimization models. SMC makes the most effective use of probabilistic information available about wind production, but its implementation requires dramatic changes from the existing deterministic design making the system operators and regulators reluctant about its implementation.

Another approach that is not addressed in this study is robust unit commitment. Robust unit commitment differs from other approaches in the sense that it positions the generators for the worst-case scenario of the uncertainty realization and is very conservative relative to the above approaches [100]–[102]. Robust unit commitment has recently received a lot of attention for implementation in the RT look-ahead commitment phase to deal with near RT uncertainties and variability [103], [104] which is out of the focus of this study.

There is a significant body of literature performing comparative analysis on the dispatch and operation cost outcomes of the above-referenced approaches with the conventional designs. [6], [56], [74] study the implications of introducing DA and/or RT ramp products. [105] proposes combinations of RT look-ahead dispatch pricing and RT ramp requirements and evaluate their added efficiency with conventional look-ahead and single-period dispatch models. [53], [54], [67], [73], [106], [107] study the operational and economic impacts of SUC in systems with high penetration of wind. They all determine the commitment of long-start generators using SUC and DUC and then simulate and compare the expected RT dispatch and operation costs under a large set of out-of-sample wind production realization scenarios. [15], [18], [108], [109] conducts comparisons between the stochastic and traditional deterministic market clearing outcomes under wind or net load uncertainty. [18] investigates the potential cost benefits of implementing SMC in New Zealand's two-hour ahead pre-dispatch mechanism for scheduling and pricing energy relative to the market's conventional deterministic pre-dispatch. Khazaei et al. develops a supply-function equilibrium model to compare the social surplus efficiency of single-settlement stochastic and two-settlement deterministic market clearing in New Zealand's pre-dispatch mechanism in imperfect competition settings [108]. Zavala et al. studies the price consistency of the stochastic market clearing mechanism and compared their resulting price spread and uplift payments with their deterministic market clearing counterparts [15]. Finally, Daraeepour et al. examine the economic and environmental benefits of stochastic market clearing and DA ramp products in a scaled model of PJM [89]. [89] shows DA ramp products marginally reduce the operation costs and improve other market efficiency indicator by maintaining additional up and down ramp requirements, while SMC takes the improvements to a far greater extent because not only it maintains ramp requirements, but also it optimizes the energy and ramp reserve schedules by accounting for the expected balancing stage costs.

Despite the recent efforts, the literature has yet to provide a valid, comprehensive, and conclusive picture of the relative benefits that could be achieved by integrating the wind uncertainty into the market clearing design. [53], [54], [67], [73], [106], [107], which all address the benefits of SUC, suffer from improper study design and limited scope. First, [53], [54], [67], [73], [106], [107] simulate the SUC in the DA market-clearing (commitment) stage (i.e. before the residual commitment stage), which lead to more efficient commitment and scheduling outcomes and hence overestimation of the benefits that can be achieved by SUC.

The improvements that are enforced by Stochastic Residual Unit Commitment (SRUC) are far more limited than those of the DA SUC because SRUC maintains the DA market clearing outcomes, determined by DA deterministic UC and ED models, while DA SUC does not have such constraints. Second, their design does not include either the DA market clearing, look-ahead commitment, and other processes that can help overcoming wind uncertainty, and hence their study design limit their results to operation costs and expected dispatch outcomes, so they don't address the impacts on prices, revenues, and welfare. Third, their study horizons are limited to a few representative days. [107] is the only exception that runs its analysis for two months.

Except [89], all other studies related to SMC [15], [18], [108], [109], have used analytical setting to compare its pricing properties with DMC, and have not examined its implications in a realistic setting on including all necessary market processes. [89] evaluates the upper bound on efficiency enhancements that would be achieved by moving into a stochastic design for market clearing, and it does not address the maximum enhancements that could be realized by integrating the wind uncertainty into a deterministic design through a combination of ramp products and Stochastic Residual Unit Commitment (SRUC).

The other major area that remains unexplored in the literature, which is the focus of this study, is how complexities raised by the wind characteristics are affected by a CO_2 price that alters the merit order of generators.

4.2.4 Objectives

This research evaluates the economic and environmental consequences of wind uncertainty in a carbon-constrained system with a significant share of coal-fired generators under various market clearing designs and CO2 price scenarios to: a) elucidate the distortions that not integrating wind uncertainty characterization to market clearing mechanisms inflicts on overall economic efficiency and environmental efficacy of the market, b) quantify to what extent adjusted deterministic and stochastic designs overcome the efficiencies, c) how schedule and dispatch changes posed by wind uncertainty and CO2 pricing drive such distortions, and d) how CO_2 pricing affects the inefficiencies and the enhancements made by the market clearing adjustments. The distortions and improvements are measured in terms of deviations from the economic and environmental outcomes that would be delivered by the conventional design (DMC). The economic performance is measured by assessing the operation costs, DA and RT prices, distribution of benefits through settlement of energy transactions, (i.e., surplus for producers and consumers and profits collected by individual technologies), and out-of-market uplift payments. The environmental performance is evaluated in terms of air emissions, i.e. CO_2, SO_2, and NO_X emissions.

To address the above-referenced questions, we simulate PJM's electricity market operations for a scaled representation of its generation fleet under combinations of wind energy penetration level (12%) and CO_2 price (0 and 10 $/Ton). For each case, the electricity market model, developed in [89], is extended and employed to simulate the annual market and grid operations with hourly granularity using four different electricity market clearing designs. The market simulation tool includes deterministic and stochastic unit commitment and economic dispatch formulation and their associated bidding designs to clear the DA market under various deterministic and stochastic designs, and stochastic residual unit commitment. It also includes RT unit commitment (RTUC) with two-hour look-ahead horizon and single-period RT economic dispatch (RTED) for RT market clearing. The variety of models included in the market simulation tool allows us to simulate and compare the market outcomes under four designs: a) Conventional Deterministic Market clearing (DMC), b) Augmented Deterministic Market Clearing (ADMC), c) Hybrid Deterministic Market Clearing (HDMC), and d) Stochastic Market Clearing (SMC). DMC is the market clearing design with no adjustment for integrating wind uncertainty, ADMC is DMC with DA ramp capability products, and HDMC is DMC with both ramp products and SRUC. In this study, we take the DMC outcomes as the base line and measure the performance of other methods by comparing their outcomes with respect to that baseline.

Since we assume consumer's demand bids and wind producers supply offers do not differ from ISO's forecasts of demand and VER, simulating a deterministic residual unit commitment would not change the market outcomes as its outcomes would be identical to those of the DAUC. However, simulating the SRUC shows the value of using wind uncertainty characterization in the RUC stage. Finally, demand is assumed fully certain in the DA, so the results only reflect the consequences of wind uncertainty.

The market simulation tool allows a fair comparison of the alternative market clearing designs in terms of economic and environmental outcomes. Since the grid reliability criteria affect the system operation costs, EMST establishes a trade-off between the system operation costs and reliability, so all the alternative designs meet the reliability requirement (annual loss of load = 0) at the minimum cost.

The remaining sections of this chapter are presented in the following order: Sections 3 and 4 describe the method and data. The results are presented in section 5 and discussed in section 6.

4.3 Method

Our method consists of simulating PJM's energy market operations under alternative market clearing designs for one year that allows an apple to apple comparison of their dispatch, economic, and environmental outcomes. In doing so, the software package, developed in Chapter 3, is extended to include and simulate various market clearing designs addressed in this study. The Package has a core, called Electricity Market Simulation Tool (EMST), that integrates different unit commitment and economic dispatch algorithms with proper bidding rules and key inputs (e.g., demand and VER) in different fashions, so each individual market design is represented and simulated appropriately. The package is also equipped with three auxiliary modules for: a) generating DA wind production scenarios to characterize wind uncertainty, b) calculating hourly up and down ramp capability requirements in the associated deterministic designs, and c) setting the adjustable parameters of the system operation such as the reliability criteria and ramp requirement rule in a manner that ensures all designs meet the same reliability criteria and at the least cost to allow a fair comparison of them. EMST and the auxiliary packages are combined to run the daily markets and grid operations for an entire year as depicted by Figure 4 presented in Chapter 3. In this study, the EMST and the auxiliary packages are used in the manner, presented in Section 3.3, to simulate one year of system operations and calculate the annual economic, dispatch, and environmental outcomes. However, EMST is extended in this study to include HDMC design. The next subsection summarizes the EMST and how the extension is implemented.

4.3.1 Extended Electricity Market Simulation Tool (EESMT)

EMST simulates the DA scheduling, RT dispatching, settlement of DA and RT energy and ramp capability reserves transactions, and calculation of revenue-sufficiency-guarantee payment in a manner that reflects the realistic sequence of market and grid operations in PJM Electricity Market to deliver a comprehensive set of daily market operations, including generation (scheduling and dispatch), economic (operation costs, revenues, prices), reliability (annual not-supplied energy), and environmental (CO_2, SO_2, NO_X emission) outcomes. EMST consists of a DA module, a RT module, and post-processing module. The DA module runs daily based on DA prediction of key inputs to determine DA commitments, schedules, and prices. RT module takes the DA schedules and runs hourly based on RT realization of hourly aggregated load and wind generation to determine the least cost dispatch of resources in RT and the associated prices for balancing energy. The post-processing module takes the DA schedules and prices along with RT dispatch and prices to settle the DA and RT energy and reserve schedules and calculate the uplift payments that make all producers, who followed the ISO's dispatch instructions, whole to their operation costs (i.e., no-load, startup, and variable operation costs).

4.3.1.1 Simulation of alternative market clearing designs in EEMST

Table 20 clarifies differences of alternative market clearing designs in terms of least-cost commitment and dispatch models and supplemental processes used in each certain designs. In DMC, ADMC, and HDMC designs, deterministic UC and ED models are used to clear the DA market and produce the schedules and prices based on the point estimates of demand and wind production. In HDMC, the DA schedules are complemented by additional commitments made by SRUC right after the DA market clearing results are revealed. In fact, SRUC is a part of the DA market clearing process, but the commitments made in this process are settled in the RT market, that is, producers committed by the SRUC submit their energy offers to the RT market. Conversely, SMC uses two-stage stochastic UC and ED models to clear the DA market based on a set of scenarios characterizing the uncertainty on offered wind production. In all four designs, the RT market is cleared by running deterministic two-hour look-ahead UC and deterministic single-period ED models, where only the first-hour commitment results are binding in the settlement process, and the remaining hours remain advisory. All DA and RT unit commitment models in deterministic and stochastic designs have a set of three binary variables to model the commitment trajectory of generators (on/off status, startup, and shutdown variables). Following the PJM's procedures, power producers are partitioned into two groups: those with startup times shorter than 2 hours are categorized as *fast-start* and are able to adjust their commitment in the RT market while the others are considered as *slow-start* whose RT commitment does not deviate from their DA's schedules [110].

Table 20: Characteristics of DA and RT Scheduling and Dispatching Processes Underlying Deterministic and Stochastic Market Clearing Designs

Market Clearing Design	DA Processes				RT Processes	
	Deterministic DA UC and ED	Stochastic UC and ED	DA ramp Requirements	SRUC	RT look-ahead UC	RT single-period dispatch
DMC	✓	---	---	---	✓	✓
ADMC	✓	---	✓		✓	✓
HMC	✓	---	✓	✓	✓	✓
SMC	---	✓	---	---	✓	✓

4.3.1.2 Information Flow in EEMST

To ensure a fair comparison of the market clearing designs, we use a framework, developed in [89], to deal with their inherent differences that affect their economic outcomes, such as utilizing the information about wind uncertainty and exogenous and endogenous calculation of up and down ramp capability requirements. The developed framework ensures all market clearing designs are fed by the same information about wind uncertainty and use the information wisely such that their differences in calculation of reserves are settled. Figure 9 demonstrates how the alternative designs

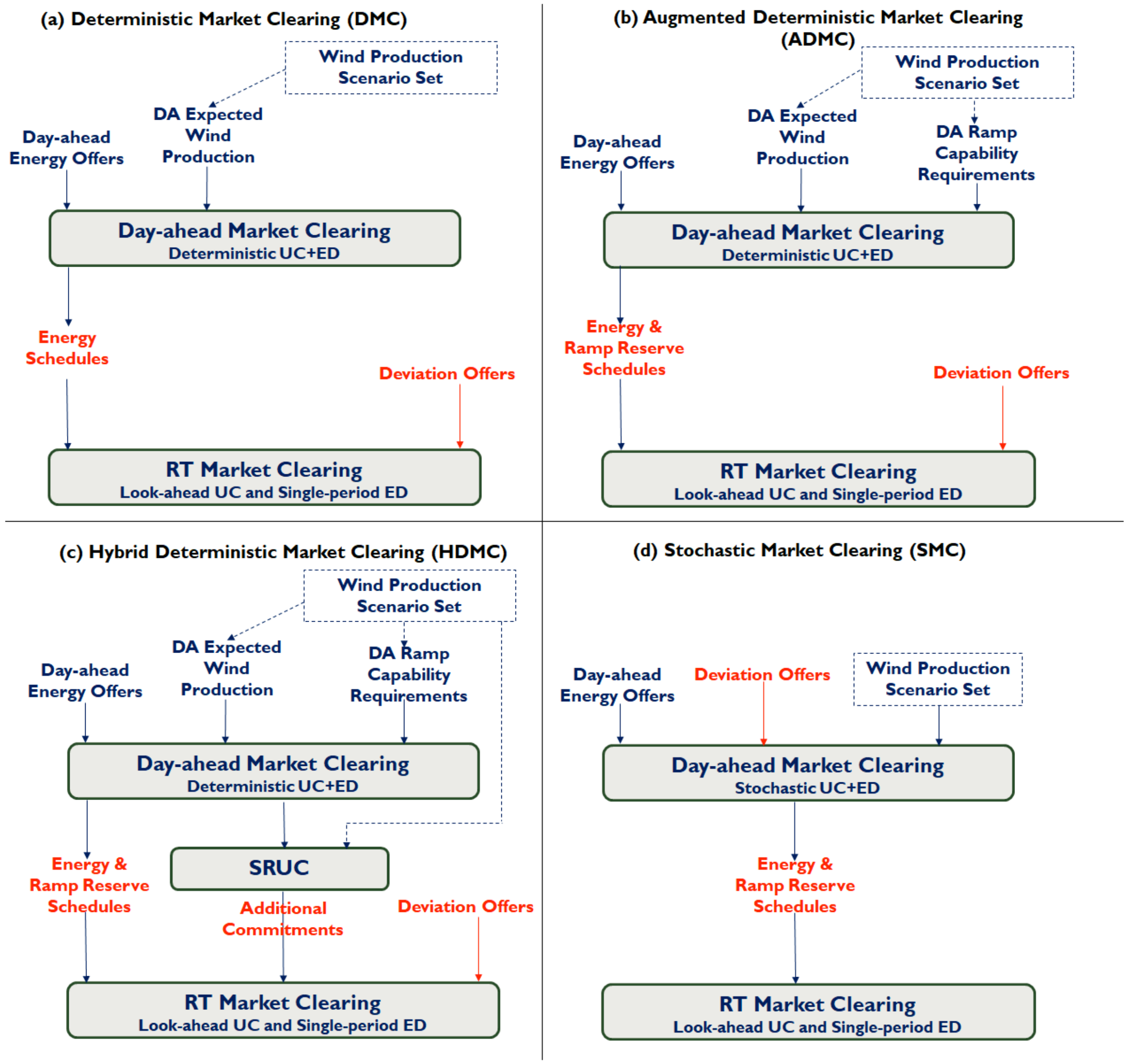

Figure 9: Bidding Structure and Information Flow in the Deterministic and Stochastic Market Clearing Designs

are informed by symmetrical information about wind uncertainty and highlights their differences in utilizing the information. We use a set of likely DA wind production scenarios to characterize a full specification of wind uncertainty, where each scenario represents a distinct wind generation time series for the next 24 hours with a probability of occurrence. In different designs, the scenario set is used in a different fashion to integrate the uncertainty into different designs. In all deterministic designs, the expectation of scenarios is used as the aggregated production offer of wind producers. In ADMC and HDMC, the set of scenarios are used to quantify the exogenous hourly ramping requirements. In HDMC, the set of scenarios is directly used in the SRUC process. Likewise, SMC directly uses the scenarios in the stochastic UC and ED models.

4.3.1.3 DA and Balancing Energy Bidding in EEMST

As observed in Figure 9, the deterministic and stochastic designs also differ in their time window for submitting the balancing energy offers. In the deterministic designs, the time window begins after the DA market clearing ends. However, in the stochastic design, they are submitted by the DA market clearing stage to allow the valid calculation of expected balancing costs that influence the DA energy and reserves schedules. The balancing energy supply offers are assumed to be equal to the DA offers as we assume the fuel price and marginal production costs do not change between DA and RT markets. Similar to the stochastic design, SRUC in the HDMC design, takes the DA energy supply offers to use in the anticipation of the balancing stage operation.

4.3.1.4 DA and RT Markets Settlements in EEMST

The settlement process, including the calculation of revenues, profits, and uplift payments, is identical to the model described in Section 3 of Appendix B for DMC, ADMC, and SMC designs. To make the model compatible with the HDMC design, we follow the PJM's procedure that settles the additional commitments made in the RUC stage in the RTM based on RT prices [110], [111].

4.3.1.5 SRUC Optimization Model

All the optimization models used in this study are presented in Section 3.4 except SRUC. SRUC is a two-stage stochastic unit commitment model with slight differences from the Stochastic DAUC presented in 3.4. In its first stage, SRUC only accounts for costs and technical constraints associated with commitment (on/off status) of generators, so the DA energy and reserves are not scheduled. The second stage optimizes the expected costs of energy production and adjustments made to commitment of fast-start producers such that the demand is fully supplied under all probabilistic wind scenarios. The optimization is also constrained to non-anticaptivity constraints that ensure the commitment of slow producers are not adjusted in second stage scenarios. SRUC's outputs that are transferred to the RTM are the additional slow producers that are committed at SRUC phase. These additional commitments include new units that were not committed in the DAM, or those unts that are already committed in the DAM whose commitment is prolonged by the SRUC beyond the DAM schedules.

4.4 Test System and Data

The market outcomes and environmental implications of alternative market clearing mechanisms are investigated on the PJM's representative test system presented in chapter 3. It is a 12% scaled version of PJM's supply resource mix as reported in the National Electric Energy Data System (NEEDS v.4.10) [112] compiled by EPA [113]. The system has 67 fossil-fired generators with a total of 20,000 MW of installed capacity, plus wind generation capacity with 12% energy penetration. The annual peak load is assumed to be 17,241 MW which given the assumed generation, results in a 16% long-term reserve margin, consistent with PJM's policies [81]. The prices of natural gas (NG), coal, oil, and uranium are equal to the average prices in PJM region for year 2016 as reported by the EIA's electricity browser data [114]. Detailed description of the representative generation fleet, including their heat rate, emission rates, and other technical characteristics are presented in section 7 of Appendix B.

4.6 Numerical Results

The performance of the market clearing designs are presented for two cases presented in Table 21. Case 1 represents the test system with 12% wind penetration and no CO_2 price, and Case 2 the system with the same wind penetration and CO_2 price equal to $10/ton.

Table 21: Cases Explored in the Numerical Results Section

Case	Wind Penetration Level (%)	CO2 Price ($/ton)
Case 1	12%	0
Case 2	12%	10

The subsections that follow compare the economic, dispatch, and environmental outcomes of the alternative market clearing designs. The results are presented as bar charts in figures with two columns, where the left column shows the result for Case 1 and the right column for Case 2. In all presented bar charts, the outcomes of DMC, as the conventional design, are taken as the baseline, and the other designs' outcomes are presented in form of positive and negative percentage differences from the baseline to assess their performance in overcoming the distortions and inefficiencies caused by not integrating the wind uncertainty characterization into the market clearing design. In this fashion, the SMC outcomes present the maximum improvements to economic and environmental outcomes that can be achieved by fully integrating the wind uncertainty characterization into the market clearing formulation. Also, the ADMC and HDMC outcomes show the partial improvement that can be achieved by these adjusted deterministic designs and their overall performance relative to SMC. ADMC's outcomes show the impacts of DA ramp products and the HDMC's outcomes the combined effects of ramp products and the SRUC.

4.6.1 Economic and Dispatch Outcomes

4.6.1.1 Operation costs and economic surplus

Figure 10 presents the economic performance of market clearing designs in Case 1 (illustrated in left panels) and Case 2 (illustrated in right panels). The plants fuel costs in Case 1 and Case 2 show SMC cuts the costs by 0.9% in Case 1 and 0.68% in Case 2 with respect to their respective baselines. ADMC and HDMC cut the costs by 0.36% and 0.41% in Case 1 and by 0.15% and 0.18% in Case 2. The cost reductions reveal two major patterns. First, the maximum improvement that can be achieved by SMC decreases by 24.4% (0.9-0.68 /0.9 %) when the CO_2 emissions are priced. The other way of interpreting

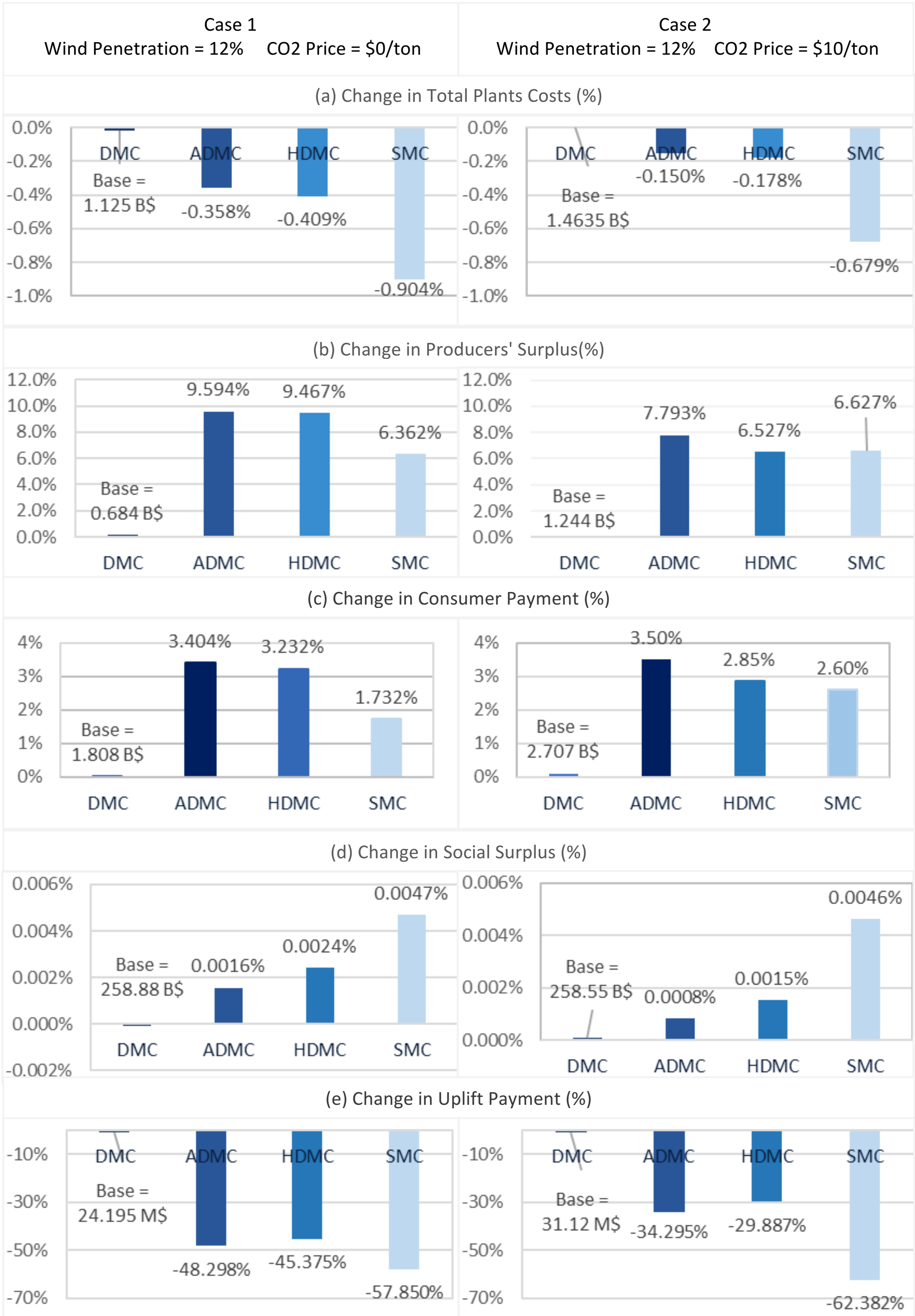

Figure 10: Economic Performance of Market Clearing Designs

this reduction is that the overall cost of not integrating the DA wind uncertainty characterization decreases by 24.4%. Second, the adjusted deterministic designs, i.e. ADMC and HDMC, become less significant in overcoming the inefficiencies when the emission price is introduced. Comparing HDMC with SMC shows it achieves 45% (0.41/0.90) of SMC's cost reduction in Case 1 that decreases to 26% (0.18/0.68) in Case 2. Both patterns are driven by the fact that NGCC producers displace coal producers in the supply curve merit order when emissions are priced. The shift increases the running hours of the NGCC producers (which are more flexible than coal-fired producers) and the average flexibility of the grid in responding to the wind uncertainty during the light- and medium-demand conditions that decreases the cost of not integrating the uncertainty characterization. However, with the shift, coal producers serve as mid-merit suppliers, but they have not been inherently designed to follow the steeper net demand trendlines and/or adjust their status in response to the uncertainty they face in this region of the supply curve. This inconsistency drives the lower significance of ADMC and HDMC in Case 2.

Panels (b) and (c) present the producers' surplus and consumers' payment outcomes. Comparing the DMC's outcomes with those of the other designs shows that not integrating the uncertainty characterization leads to underpaid electricity for consumers and significant financial losses for suppliers. In fact, under DMC, the consumers do not pay for the hidden costs of wind uncertainty (i.e. prices do not represent the true marginal operation costs), but, as discussed in sections 4.6.1.2 and

4.6.1.3, the adjusted designs correct this inefficiency by enhancing the prices and dispatch to increase the consumer payments (or equivalently producers' revenues) and producers' surplus. In Case 1, ADMC and HDMC increase the producers' surplus by 9.59% and 9.47%, and the SMC increases that by only 6.36%. In Case 2, SMC fulfills an approximately similar increase in producers' surplus, but ADMC and HDMC's enhancements decline by 18.8% (9.59-7.79/9.59 %) and 31.0% (9.47-6.53/9.47 %). These results imply that all adjusted designs improve the settlement of energy transactions and enhance the producers' surplus.

Social surplus outcomes, presented in panel (d), clarify which adjusted design offers the most efficient prices and settlement of energy transactions because it represents a combination of cost effectiveness and pricing efficiency. In fact, the most efficient design is one that not only supplies the consumers' demand at the minimum operation cost, but also delivers prices that truly represent the operation costs incurred by the producers and ensures. More efficient prices ensure more optimal allocation of costs and benefits among producers and consumers. The presented social surplus outcomes are calculated based on the assumption that the consumer's utility from consuming electricity is 3000$/MWh. ADMC and HDMC increase the social surplus by 0.0016% and 0.0024% in Case 1, and their performance declines by 50% (0.0016-0.0008/0.0016) and 38% (0.0024-0.0015/0.0024) in Case 2. In both cases, ADMC offers the least reduction in costs but the highest increase in producers' revenues and surplus. HDMC reduces both operation costs and producer's surplus slightly with respect to

ADMC that marginally enhances the social surplus. Also, Comparing the ADMC and HDMC outcomes between Case 1 and Case 2 indicates that their cost reductions are significantly lower in Case 2, but their resulting producers' surplus enhancements are not significantly lower, and their combined effect results in their lower social surplus enhancements in Case 2. HDMC's producers' surplus outcomes are more coordinated with costs in Case 2, and hence, its marginal improvements with respect to ADMC are higher in Case 2 as SRUC is more effective in Case 2 where coal producers are mid-merit producers. The SMC's outcomes indicate that SMC achieves the maximum social surplus enhancement (0.0047%) in Case 1 and maintains the same performance in Case 2, because its cost reduction and producers' surplus enhancements are well coordinated. Comparing the social surplus outcomes of HDMC and SMC shows that in Case 1 HDMC achieves 50% (0.0024 / 0.0047) of the enhancements provided by SMC, while in Case2 it achieves only 33% (0.0015 / 0.0046) of SMC's improvements.

The uplift payment outcomes are presented in panel (e). The uplift payments are out-of-market adjustments made to the producers daily to make them whole to their daily operation costs. The lower uplift payments are indicative of more transparent and efficient markets where a lower portion of producers' revenues are determined out of the market processes, and the higher indicates the lower market and pricing efficiency. The reported uplift payments imply that not integrating the DA wind uncertainty characterization accounts for a major chunk of uplift payments occurring under DMC which increases when CO_2 emissions are priced. ADMC and HDMC lower the uplift payments by 48% and 45% with respect to the baseline in Case 1, but their impact decreases to 34% and 29% in Case 2. HDMC seems to be less effective in declining the uplift payments, which is clearly because SRUC makes more commitments that are settled in the RT market and results in lower DA and RT prices it with respect to those of ADMC. SMC decreases the uplift payments by 57%, which is the largest reduction among all adjusted designs, and unlike the ADMC and HDMC, its significance increases in Case 2 because SMC internalizes the cost of uncertainty in the DA prices in the most effective way and that is not affected by CO_2 pricing.

Figure 11 illustrates the breakdown of profits among individual generation technologies. The profit outcomes indicate that in both cases, the mid-merit producers incur the greatest profit loss due to wind uncertainty. In Case 1, coal producers incur significant losses that increases dramatically in Case 2 where they serve in the middle of the supply curve. Conversely, NGCC producers incur significant losses in Case 1 where they serve in the middle of supply curve.

4.6.1.2 Dispatch Outcomes:

Figure 12 presents the aggregated RT dispatch outcomes for conventional and wind energy suppliers and clarifies how wind uncertainty distorts the scheduling and dispatch processes, how adjusted designs overcome the distortions, and how CO_2 pricing impacts the significance of adjusted designs in addressing these inefficiencies. Comparing the DMC and adjusted designs' outcomes in Case 1 demonstrate that not integrating the DA wind uncertainty characterization leads to overdispatching of coal

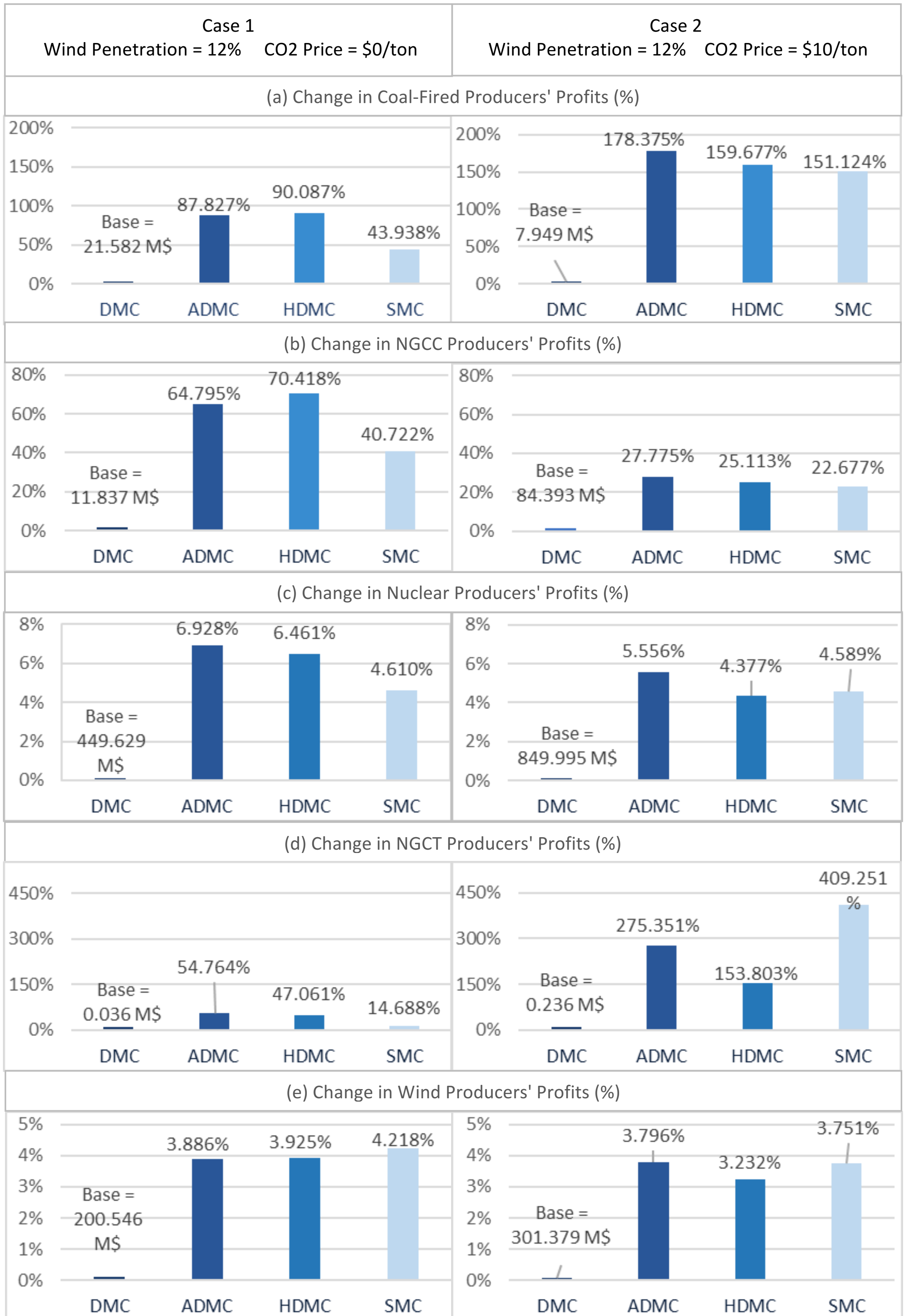

Figure 11: Technology Specific Profit Outcomes of Market Designs

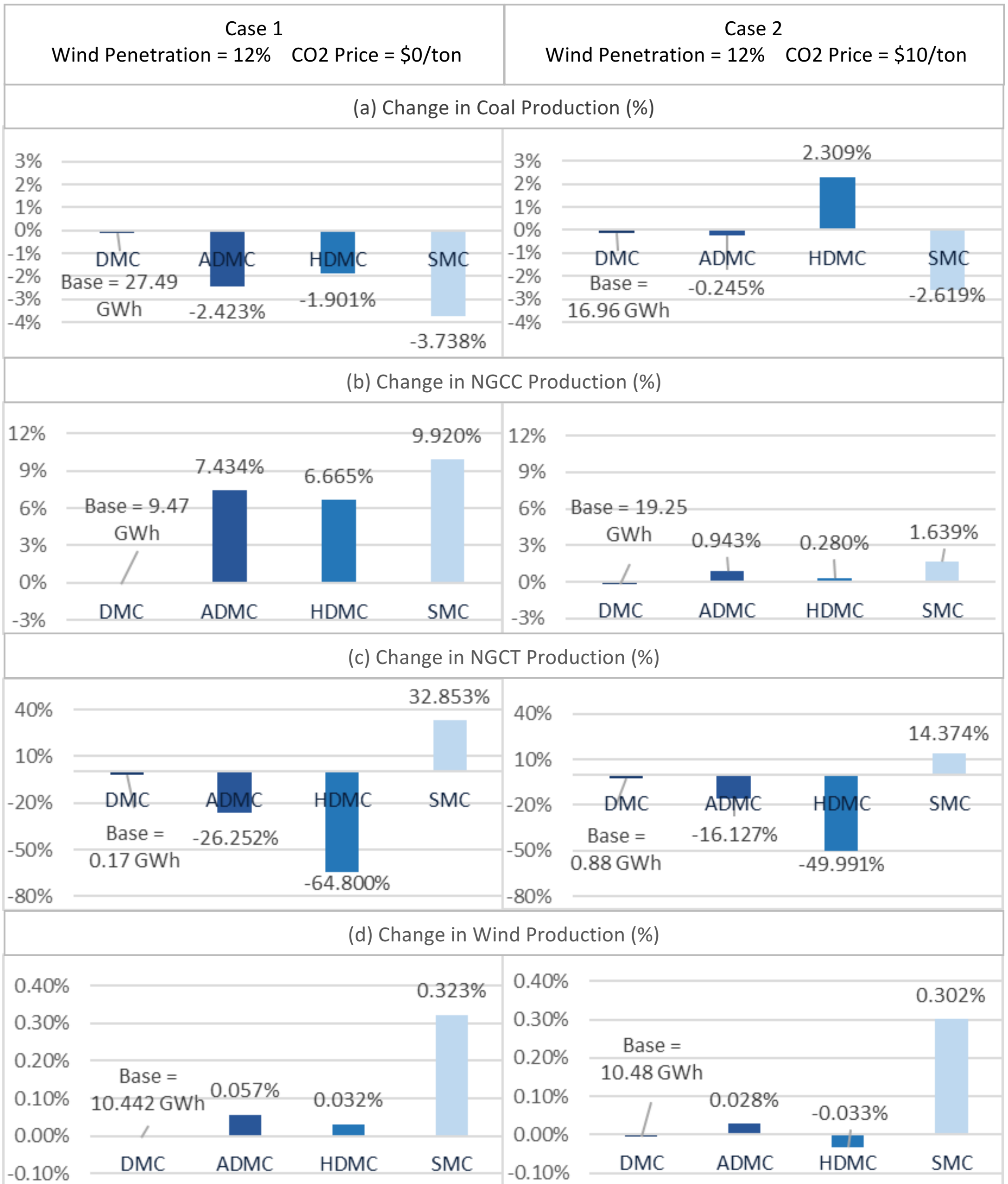

Figure 12: Dispatch Outcomes of Market Clearing Designs

and NGCT producers and underdispatching of NGCC producers. Coal producers are overscheduled in the DAM but they are not flexible enough to follow the realization of wind in RT. The coal resource inflexibility creates a resource gap during the RT operation as the slow-start producers cannot be committed at short notice during RT operation and the system operator has to dispatch quick-start yet expensive NGCT producers to follow the RT wind energy trend-line.

ADMC and HDMC's approach to addressing the above-referenced distortions differ from SMC's approach. ADMC reduces the dispatch of coal-fired producers by 2.4% and increases the more flexible NGCC producers' dispatch by 9.4% that alleviates the mentioned RT resource gap and result in a 24.7% decline in the dispatch of expensive NGCT producers with respect to the baseline. In fact, ADMC schedules more flexibility in the DA that provides more cost-effective ramping capability during the RT operation to reduce the over-procurement of NGCT production and the operation costs. HDMC, which is equipped with SRUC on top of DA ramp products, establishes a better balance between flexibility requirements and operation costs and results in 1.9% decrease in coal producers' dispatch and 6.6% increase in NGCC that lowers the NGCT dispatch by 64.8% (2.47 times larger than 26.2% decline observed under ADMC). However, since the coal producers have greater minimum production levels with respect to NGCC producers, this shift slightly reduces the wind integration that makes HDMC's economic enhancements marginal with respect to ADMC. Unlike ADMC and HDMC, SMC provides the lowest dispatch of coal producers (-3.73% with respect to the baseline), the highest dispatch of NGCC and NGCT producers (9.9% and 32.85% with respect to the baseline), and the largest integration of wind producers' energy (0.32% with respect to the baseline). SMC takes very aggressive DA wind schedules and enforces a remarkable displacement of coal with NGCC and wind in the DA to provide enough flexibility for following the aggressive DA wind schedules.

In Case 2, NGCC producers take the role of coal producers in supplying the baseload, and the coal producers serve in the middle of the supply curve. Due to this change, NGCC producers' dispatch is not much affected, and its variations remains within a narrow band, but the variations of dispatch between coal and NGCT producers mostly determine the economic performance of market clearing adjustments. DMC's dispatch outcomes under DMC imply that CO_2 pricing exacerbates the resource gap between the DA and RT markets; while NGCT producers are relatively more expensive than coal producers in Case 2, their dispatch increases by 417% (0.88-0.17/0.17 %). This has two major reasons; first, the uncertainty leads to under commitment of coal producers in the DAM, and second, coal producers that are in the middle of supply curve face faster net demand (demand – wind production) trend lines compared to Case 1, but they are not nimble enough to follow them. Both reasons, particularly the second one, make the NGCT the next best option and raise the operation costs. ADMC is very ineffective in impacting the dispatch of coal producers and reduce the NGCT's dispatch by only 16%. However, HDMC increases the dispatch of coal producers by 2.31% as it makes a better use of DA wind uncertainty characterization in the SRUC step and reduce the NGCT's dispatch by 49.99%. Although HDMC's impact on NGCT dispatch in Case 2 is 22.8% (64.8-49.99/64.8 %) less significant than that in Case 1, its marginal improvement with respect to ADMC is higher and that explains its more effective impacts on producers' and social surplus compared to ADMC. In short, while ADMC and HDMC tend to reduce the resource gap in a cost-effective manner to overcome the inefficiencies, the shift in merit order and flexibility of producers in the supply curve occurring in Case 2 not only increases the resource gap, but also degrades their effectiveness in alleviating the gap.

The SMC's impacts on dispatch outcomes follows a pattern similar to its impacts in Case 1, but the magnitude of its impacts are lower in Case 2. The reduction in coal dispatch decreases to 2.62%, that is 30% (2.62-3.738/3.738 %) lower than that in Case 1. Similarly, the increase in dispatch of NGCT producers decreases to 14.37%, which is 56% (14.37-32.85/32.85 %) lower than the reduction in Case 1. Thus, SMC drives similar dispatch implications even after the merit of producers changes in Case 2, and hence, maintains its superior performance in Case 2.

4.6.1.3 DA and RT Prices and Price Spread

Figure 13 illustrates the average DA and RT prices and the spread between them. The DA and RT prices in Case 1 show that the lowest DA prices (20.44 $/MWh) occurs under the conventional design. Under DMC, the average RT price is higher than the average DA price and the average spread is 0.54 $/MWh which is the highest among all designs. In fact, DMC's average DA price do not represent its high operation costs and consequently offers the minimum producers' surplus among all presented designs. ADMC increases the average DA price by 3.95% with respect to the baseline but does not affect the RT prices. That change reduces the price spread by 14% and improves the settlement of energy transactions between producers and consumers. HDMC increases the average DA price by 3.146% and reduces the average RT price by 0.68%; that is,

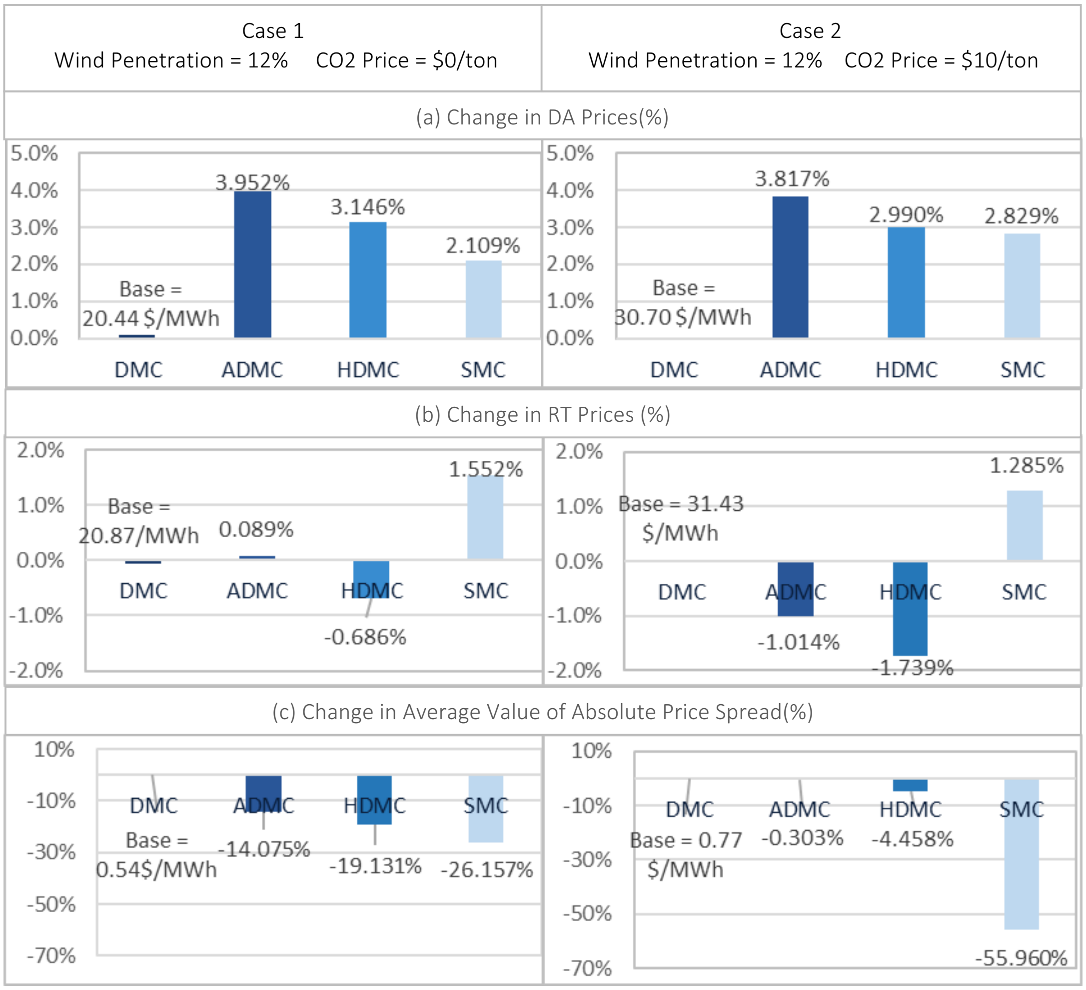

Figure 13: Price Outcomes of Market Clearing Designs

HDMC's DA and RT prices and their spread are lower than ADMC's corresponding prices and spread. HDMC's lower DA and RT price are due to the impact of SRUC on reducing the gap between the DAM and RTM. Unlike ADMC and HDMC that reduce the price spread by alleviating the resource gap, SMC increases both average DA and RT prices in a coordinated manner and results in the minimum price spread among all designs. The higher RT prices reflect the higher balancing costs under this design which stems from the aggressive DA wind schedules offered by this design, while the higher DA prices are due to the nature of SMC's pricing scheme that account for the expected balancing operation costs in the DA prices.

In Case 2, the average DA and RT price outcomes demonstrate a pattern highly representative of the corresponding dispatch outcomes. Under DMC design, the remarkable increase in NGCT producers' dispatch leads to 29.8 % (0.77 – 0.54/0.77 %) increase in price spread with respect to Case 1. ADMC and HDMC both increase the average DA price and reduce the average RT price, but their impacts are not coordinated and instead of reducing the spread, they cause spreads with similar or slightly lower magnitudes and opposite signs. Unlike ADMC and HDMC, SMC's impacts on prices in Case 2 are similar to the pattern observed in Case 1. SMC increases the average RT price and the average DA price that reflects the higher RT balancing costs. SMC's average spread in Case 2 is 0.35 $/MWh (0.77·(1-0.5596)), which is 12.5% lower than 0.4 $/MWh (0.54·(1-0.2615)) reported for SMC in Case 1.

4.6.2 Cycling effects

Figure 14 illustrates the aggregated cycling outcomes for different generation technologies under different designs. There are two panels for each technology, where the first one shows the annual number of startups and the second one energy per cycle defined as the ratio of annual generation to the number of startups for all generators with the same technology. The higher energy per cycle implies lower number of

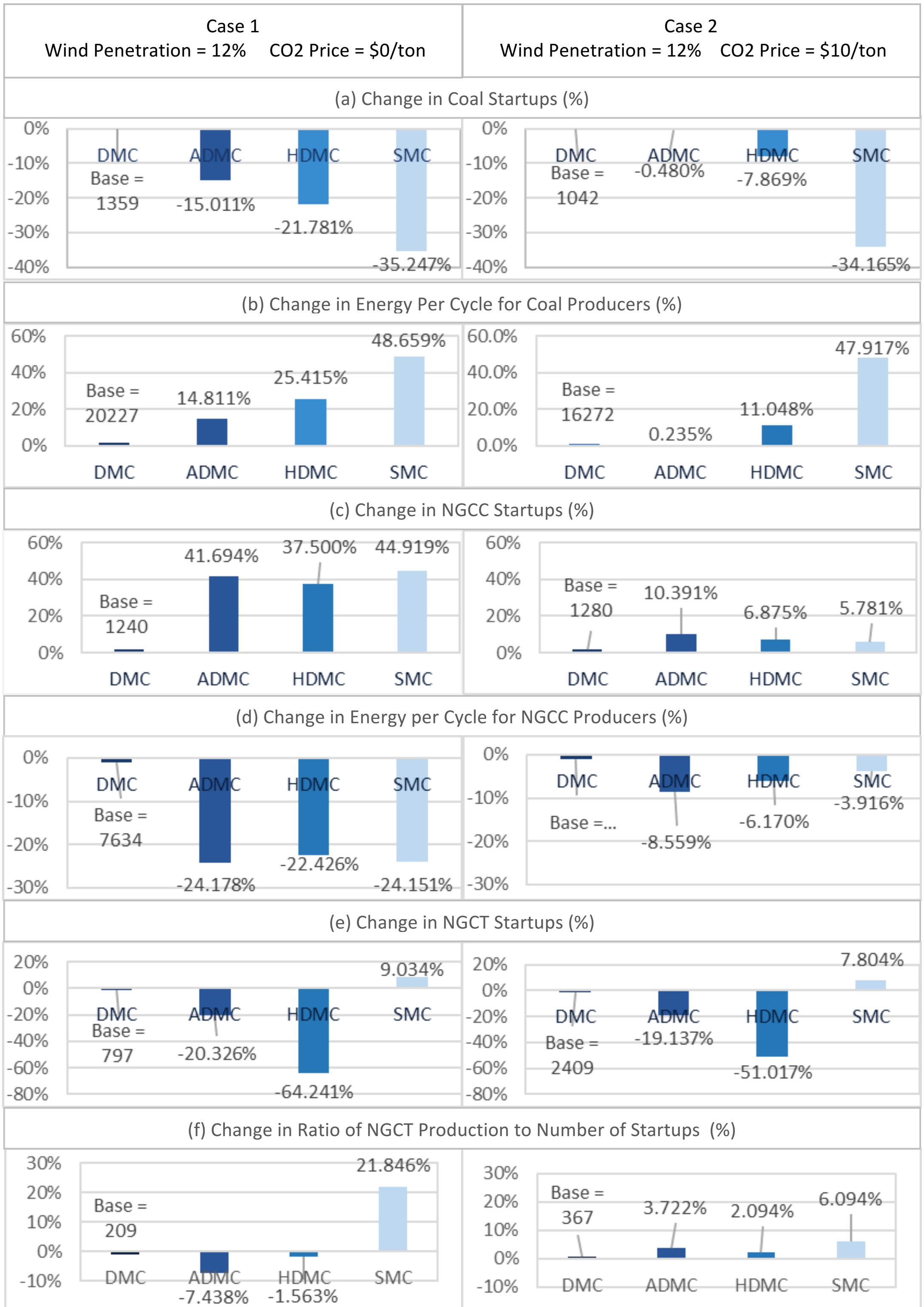

Figure 14: Cycling Outcomes of Market Clearing Designs

startups and lower startup costs and lower energy per cycle implies higher number of startup and higher costs which is not desirable.

The DMC results in Case 1 illustrate that not integrating the DA uncertainty characterization increases the energy per cycle for coal producers, which have the most expensive startups, and decreases that for NGCC producers, which have intermediate startup costs, that combined increases the system's startup costs. ADMC and HDMC partially reverse this pattern by increasing the energy per cycle for coal producers by 14.81% and 25.41 and decreasing that for NGCC producers by 24.18 and 22.43% that ultimately lower the startup costs. Additionally, they reduce the energy per cycle for NGCT producers. HDMC outcomes clarify the role of SRUC on more effective commitment and dispatch of coal producers. SMC increases the energy per cycle for coal producers by 48.66%, which is twice the increase driven by HDMC, decreases that by 24.15% for NGCC producers, which is roughly similar to ADMC and HDMC, and increases that by 9.03% for NGCT producers, which is quite opposite to the other designs' impacts on NGCT producers' startups and cycling. Unlike ADMC and HDMC, SMC increases both NGCT's startups and their energy per cycle that implies cost-effective commitment and dispatch of NGCT resources under this design.

In Case 2, the results indicate that ADMC is quite ineffective in increasing the energy per cycle for coal producers and HDMC increases that by only 11.4%, which is 43% (11.04/25.415 %) of the increase it delivers in Case 1. SMC increases the energy per cycle for coal producers by 47.91%, which is very similar to its impact in Case 1. Also, SMC increases the energy per cycle for NGCT producers but to a lower extent with respect to Case 1 as the annual generation of coal/NGCT producers decreases/increases in Case 2 compared to Case 1. In short, SMC's cycling outcomes follow a similar pattern in both cases but with different magnitudes.

4.6.3 Environmental Impacts

Figure 15 presents the CO_2, NO_X, and SO_2 emission outcomes of market clearing designs in Case 1 and Case 2. In Case 1, not integrating the DA uncertainty characterization distorts the dispatch by overcommitting coal producers that increases the emissions. ADMC and HDMC shifts the dispatch from coal to NGCC producers that reduces the CO2 emissions by 1.601% and 1.605%. SMC reduces the CO2 emissions by 3.51%, which is 219.6% higher than HDMC's CO_2 reductions, because it drives a larger shift from coal to NG-fired producers and highest wind energy integration. In Case 2, ADMC reduces the CO2 emissions by 0.35% by slightly shifting the generation from NGCT and coal to NGCC producers. However, HDMC slightly increases the CO_2 emissions because it rises the generation of coal producers with respect to ADMC. Also, the results imply that CO_2 pricing reduces the CO2 mitigation potential of SMC by 29.33% (3.515-2.484 /3.515 %), whereas its mitigation impact with respect to ADMC's mitigation increases from 119.55% in Case 1 to 609% in Case 2.

NO_X and SO_2 emissions follow a similar variation pattern in both cases, except HDMC increases SO_2 emissions in both Cases because HDMC replaces NG-fired

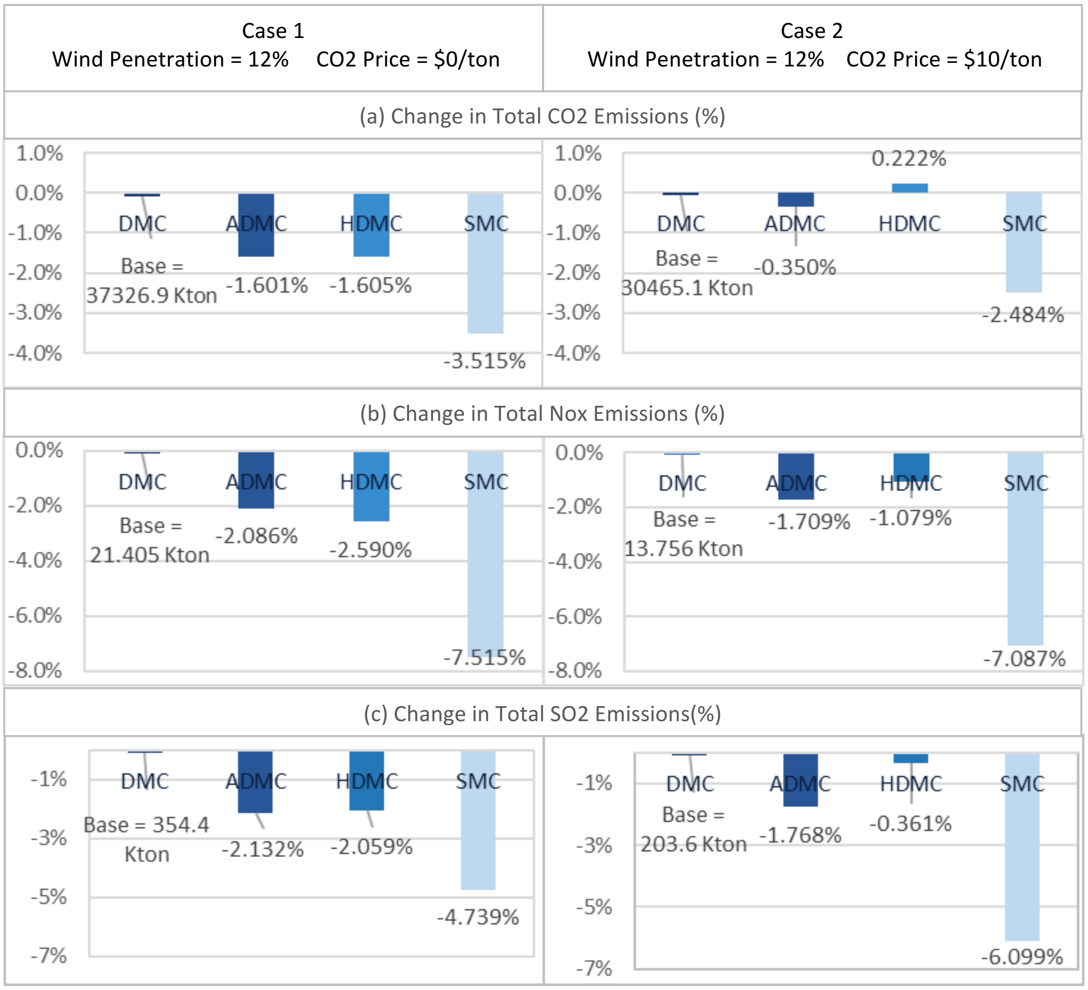

Figure 15: Emissions Outcomes of Market Clearing Designs

generation, with zero SO_2 emission rates, with coal-fired generation with non-zero SO_2 emissions.

Figure 16 illustrates the breakdown of CO_2 emissions to startup and generation emissions. As seen, the adjusted designs play a significant role in reducing the startup emissions by enhancing the cycling per ratio of coal and NGCC producers. Similar to other outcomes, this pattern is less significant in Case 2.

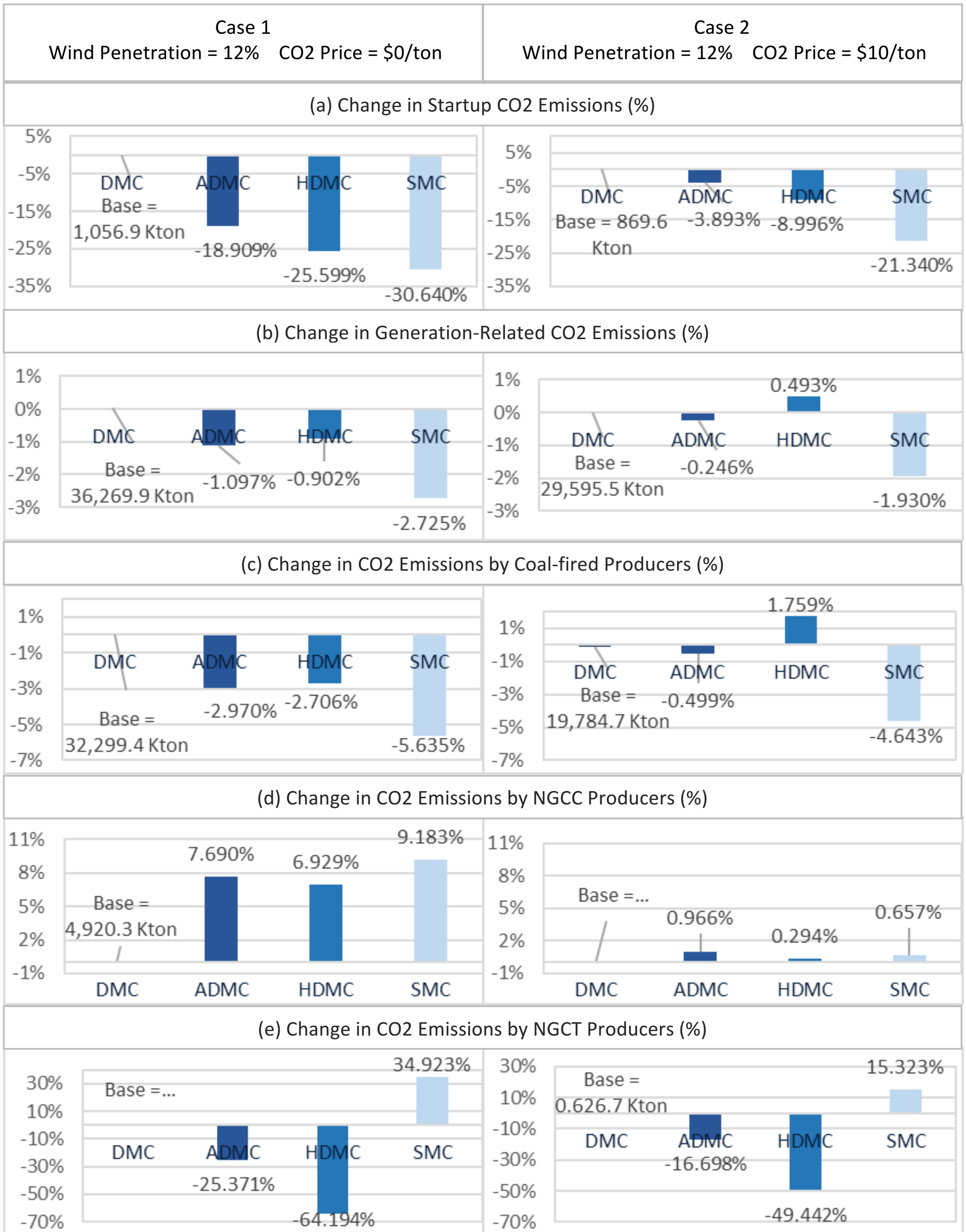

Figure 16: Breakdown of CO2 Emissions Outcomes of Market Designs

4.7 Discussion and Conclusions

Comparing the results of deterministic designs with SMC in Case 1 shows that not integrating the uncertainty characterization increases the operation cost up to 0.9% in Case 1. Integrating the wind uncertainty through ramp products and SRUC together cuts the costs by 45% of the reductions fulfilled by SMC. The ramp products fulfill the major part of the cost reductions, and SRUC marginally improves the costs. In ADMC, the additional headroom capacities scheduled around energy schedules improve the resource gap that would be realized during the RT operation and partially shift the dispatch from less flexible to more flexible resources such that the DA schedules have sufficient flexibility to follow wind uncertainty during RT operation feasibly and cost efecctively. In ADMC, the DA schedules are optimized based on deterministic estimates of DA wind energy and ramp requirements are quantified exogenously, they can lead to under- or over-scheduling energy and reserves to follow the point estimates. In HDMC, the SRUC reoptimizes the commitments, emanating from DA market clearing process, over a full characterization of uncertainty around the DA point estimates of wind. SRUC marginally improves the commitment of coal and NGCC producers that would be late and impossible to change near RT operation that saves additional RT dispatch of more expensive NGCT producers that slightly reduces the costs. In fact, the SRUC's improved commitment schedules are better coordinated with the RT operation. In addition, both ADMC and HDMC alleviate the cycling of producers and lower their startup costs accounting for a significant portion of the cost reductions achieved by them.

Unlike operation costs which increase due to not integrating the DA wind uncertainty characterization, DA and RT prices decrease with respect to the ideal levels observed in SMC and increases the price spread. Comparing the operation costs and prices of SMC and DMC shows clearly that DMC's prices do not reflect the higher operation costs. These uncoordinated costs and prices lead to the financial loss for producers and underpayment for electricity by wholesale consumers. These distortions lower the overall market surplus and discourage producers from offering their flexibility and following the RT dispatch instruction. Ramp products compensate the dampening effect of uncertainty on prices and revenues by increasing the energy prices, reducing their spread, and remunerating producers for maintaining ramp capability reserves. Conversely, SRUC marginally reduces the prices yet further reduces the spread, so the prices would be not only supportive to producers but also fair to consumers. The opposite effects of ramp products and SRUC, observed under HDMC design, lead to prices that better represent the system operation conditions, optimize the settlement of transactions between producers and consumers, and increases the welfare with respect to ADMC.

Comparison of the market outcomes in Case 2 reveals the implications of CO2 pricing. A CO_2 price forces NGCC generators to supply the base load and follow the variations mostly during light-load hours. In this scenario, coal producers become mid-merit units that makes them more susceptible to the uncertainty and more prone to fast ramps occurring near peak time for which they have not been inherently designed.

Consequently, the economic outcome distortion resulting from the uncertainty decreases compared to Case 1. However, turning of coal producers to mid-merit suppliers make it harder for ADMC and HDMC to reduce the resource gap caused by the uncertainty and to overcome the resulting inefficiencies. In this case, although NGCT generators fall behind the coal generators in the merit order, their average production increases by two to five times across deterministic designs compared to Case 1. Although the SRUC serves as an effective tool for improving the commitment of coal producers and replacing NGCT producers, the NGCT production is still remarkably higher than in Case 1 due to coal producer's insufficient flexibility to follow net demand variations at paces formerly provided by NGCC in Case 1. The other notable outcome occurring due to the merit order change is the increase in the average price spread and the inability of ramp products and SRUC in reducing them. Finally, unlike ADMC and HDMC, SMC's economic and dispatch implications are not much affected by the shift in the merit order of producers in Case 2, and its relative improvements with respect to ADMC and HDMC significantly increases in this case compared to Case 1.

The emissions implications of the uncertainty and market clearing adjustments depend on the pollutant type and cases and are driven by the variations to the dispatch change due to the scenario or the market clearing adjustments. While the percentage increase in CO_2 and NO_X emissions occurring due to wind uncertainty decrease from Case 1 to Case 2, SO_2 emissions increase. The impacts that could be made by ramp products and SRUC seem to be different in Case 1 and Case2. In Case 1, ramp products lower all emission types, while SRUC slightly decreases CO2 and NO_X and increases SO_2. In case 2, ramp products show a consistent pattern, but SRUC has an increasing impact on emissions. Also, SRUC has contradicting impacts on startup and generation-related emissions. Consistent with its impacts on cycling of coal producers, it increases the emissions from generating electricity and reduces those from starting them.

The above-mentioned conclusions are sensitive to the composition of the generation fleet, the share of slow-start coal producers, and the technical characteristics of individual generation technologies considered in the resources mix. Also, the price of coal and NG is another factor that can affect the merit order of producers and the hence results. Therefore, investigating the sensitivity of the results to the above factor seems necessary for providing a more comprehensive picture of the inefficiencies inflicted by wind uncertainty and the improvements made by market clearing enhancements.

Chapter 5: Conclusions

Electric power sector is the single largest source of CO_2 emissions whose decarbonization plays a major role in climate change mitigation efforts. The possible pathways for decarbonization of the power sector relies on clean energy standards, which increase the penetration of renewable energy resources, and carbon pricing mechanisms, which reduce the CO_2 emissions from the existing fossil-fired resources. However, the power systems have not been inherently designed for such a transition. On one hand, renewable energy resources are intermittent, variable, and in some cases highly unpredictable, and hence, their growing penetration challenges the ability of power system operators in maintaining the cost-effective, reliable, and stable operation of the grid. On the other hand, CO_2 pricing policies alter the priority order of fossil-fired technologies in the supply curve and might further complicate cost-effective and reliable operation of the grid.

This dissertation has been motivated by the challenges and peculiarities caused by the DA wind production uncertainty, their interaction with carbon pricing strategies, and the market clearing design adjustments that can overcome these challenges.

The second chapter of this dissertation explores a situation in which ramp capability reserves, introduced to manage DA wind uncertainty and intermittency, can create opportunities for market manipulation behaviors in the demand side of the market. I develop a bilevel multi-player equilibrium model to investigate the behavior of a large price responsive consumer in an electricity market with a moderate share of wind producers in the resource supply mix. The results suggest that a large consumer can leverage its reserve provision capability to understate its demand bid price and quantity in the DA market in order to reduce the DA price at which it procures its DA demand, which comprises a major share of its total demand. Although it might end up paying higher RT prices or incur unsupplied energy in the RT market, its DA market cost savings outweigh the higher RT costs, which motivate the consumer to pursue this strategy.

The scheduling/dispatch distortions, caused by consumers' strategic behavior, lead to prices that do not compensate the producers adequately for supplying energy and reserves, and hence reduces the producers' surplus and social welfare. The consumer's strategy does not succeed at ever period and its effectiveness depends on the hourly wind and demand profiles. The reserve provision capacity of the consumer, the magnitude of DA wind production uncertainty, and transmission bottlenecks are three major factors contributing to the market power of the consumer. The higher DA wind uncertainty increases the reserve requirements from both demand- and supply-side resources creating a desirable ground for the large consumer to exercise its market power. An effective strategy for mitigating the market power of such a consumer would be to limit the share of reserve requirements to be provided by the demand-side resources.

The third chapter of the dissertation focuses on perfectly competitive electricity markets and explores how DA wind unpredictability distorts the dispatch and price outcomes and how to integrate the wind uncertainty characterization into the market clearing mechanisms to overcome the distortions. The distortions stem from the classic structure of the market clearing design that optimizes the commitment of generators in the DAM based on point estimates of wind energy, which are not very accurate in the DA. The results imply that inaccurate DA wind forecasts lead to inefficient commitment of slow-start producers, which lead to a resource gap and excessive dispatch of fast but more expensive generators during RT operations. In addition, DA prices do not reflect the hidden costs of wind uncertainty occurring during the RT operation and hence do not adequately compensate producers for their operation costs. Consequently, the consumers do not pay a fair price for their demand, and producers bear the cost of uncertainty. The unfair allocation of costs and profits between consumers and producers increases the deadweight loss and reduces the social surplus.

To overcome the inefficiencies, I study three adjusted market-clearing designs that adopt different procedures to integrate the wind uncertainty characterization into the market clearing mechanisms, including ADMC, HDMC, and SMC. Integrating the uncertainty characterization informs the market clearing mechanisms of the prospective deviations of wind and enables them to position the system for dealing with such deviations cost effectively. ADMC uses ramp-capability requirements in the DAM, HDMC uses the ramp products in the DAM and stochastic optimization in the RUC phase, and SMC uses stochastic optimization in the DA unit commitment and economic dispatch mechanisms. The results suggest that SMC is superior to the adjusted deterministic designs and achieves the highest reduction in operation costs and emissions and the highest increase in social surplus with respect to the traditional design.

ADMC and HDMC deliver operationally feasible DA energy and ramping reserve schedules that allow effective deployment of slow producers' flexibility for following the RT wind energy variations, alleviate the resource gap, reduce the operation costs, and deliver supporting DA prices that are more representative of the operation costs compared to DMC's prices. HDMC is slightly superior to ADMC because it establishes a better tradeoff between flexibility and operation costs of slow producers (i.e., coal and NGCC generators) to reduce the operation costs and DA prices compared to ADMC. In short, HDMC's operation costs are marginally lower, its DA prices are more representative of the operation costs, and its DA and RT prices demonstrate slightly lower spread. Higher cost and price efficiency of HDMC results in fairer settlement of energy transactions between consumers and producers and higher social surplus. Nonetheless, HDMC achieve less than half of the cost and welfare improvements attained by SMC.

Superior cost reductions and social surplus enhancements attained by SMC have two drivers: 1) maintaining additional ramp capability reserves; and 2) accounting for the expected cost of RT corrective actions in in allocation of energy and reserves. It is the second driver that makes SMC achieve greater benefits. In fact, ADMC and HDMC can ensure those reductions gained by maintaining reserves if quantified efficiently;

however, it cannot take advantage of full characterization of wind production uncertainty and account for the expected balancing costs when scheduling energy and reserves in the DA market. This difference enables SMC to deliver a more efficient dispatch of energy and reserves that positions the system a day ahead of the system operation to effectively hedge against wind uncertainty. Uncertainty-adjusted allocations under SMC shifts the production towards producers with greater flexibility and prepares the system for integrating maximum cost-effective levels of wind power production determined in the optimization process.

Besides cost effective operation of resources, SMC is clearly more efficient in pricing resources. SMC fulfills the highest reduction in costs and yet the least increase in DA prices compared to ADMC and HDMC. The combination of costs and prices ensure the most efficient settlement of energy transaction between consumers and producers and the highest social welfare. Accounting for the expected balancing costs allows SMC to internalize those costs in the DA prices and deliver prices that are very well representative of the total cost of system operations including all the corrective actions made during the RT operation.

The adjusted deterministic and stochastic designs offer substantial environmental benefits in terms of CO_2, SO_2, and NO_X emission reductions. Similar to economic benefits, yet to a greater extent, SMC outperforms ADMC and HDMC in terms of air emissions mitigation. All the adjusted designs reduce the emissions by shifting the dispatch from less flexible coal producers to NG-fired producers. Nonetheless, SMC attains the highest emissions reduction as it causes the largest shift from coal to NG and the greatest wind energy integration.

The fourth chapter investigates the economic and environmental performance of ADMC, HDMC, and SMC in overcoming the price and dispatch distortions under a scenario that CO_2 emissions are priced at $10/ton. The CO_2 price alters the cost and flexibility merit order of generators. In the base case, the marginal cost of producers increases as their flexibility increases; that is, their ramp capability increases and their startup, min-up, and min-down times decline. However, in the carbon pricing scenario, coal producers fall between NGCC and NGCT producers that are more flexible than coal-fired resources. The results suggest that this shift exacerbates the excessive dispatch of NGCT producers and the price spread between the DA and RT prices because coal producers' commitment are now more susceptible to wind uncertainty. Moreover, coal producers are prone to faster net load ramps, but they do not have sufficient ramping capability to follow such ramps. Finally, DA ramp capability products are not capable of establishing an effective tradeoff between operation costs and flexibility, while SRUC becomes more effective as they re-optimize the commitment of coal producers using the stochastic information. As a result, ADMC and HDMC become very ineffective in overcoming the dispatch and price distortions, but the relative performance of HDMC with respect to ADMC increases under the carbon-pricing scenario.

Unlike ADMC and HDMC, SMC effectively overcomes the dispatch and price distortions and enhances the market's economic and environmental performance even after the shift in merit order of generators. HDMC is not capable of achieving even 30% of the cost and welfare improvements attained by SMC. A similar pattern is observed in the environmental performance of the adjusted designs. ADMC and HDMC are ineffective in reducing the air emissions in the CO_2 pricing scenario, but SMC achieves considerable emissions reductions.

Appendix A: Supporting Information for Chapter 2

Sections A-J in this appendix appear in the Supporting Information of a paper coauthored by the PhD candidate [115], *and have been reprinted with permission from her coauthors.*

1. Current Practice in US ISOs/RTOs

The US electric power markets, administered by ISOs/RTOs, include day-ahead and real-time markets. In the day-ahead market (DAM), the market clearing engine is based on a multi-interval model for simultaneous scheduling (co-optimization) of energy and operating reserves. Operating reserves are ancillary services required for balancing the systems demand and supply at any given moment in the future at any point of the network [1], [116]–[118]. The need to operating reserves stems from the uncertainty and variability of system variables when they occur at time resolutions shorter than the scheduling horizons of the system. The system operators must schedule sufficient amounts of operating reserves to maintain the real-time system balance [1], [116]–[118]. Scheduling sufficient amounts of reserves is a two-step process: 1) calculation of reserve requirements 2) allocation of the reserve requirements among eligible resources.

Traditionally utilities and ISOs/RTOs in the US enforce pre-specified criteria for the minimum reserve requirements. Calculation of the requirement for each type of operating reserve would be performed based on different factors. For instance, PJM's regulation requirement is equal to 1% of the forecasted valley load for the operating day for off-peak hours (00:00 – 04:59), and 1% of the forecasted peak load for the operating day for on-peak hours (05:00 – 23:59) [110]. PJM's synchronized reserve requirement is also determined based on the largest contingency in each sub-zone, usually equal to the loss of the largest unit [110]. Regulation requirement is determined based upon a statistical analysis of the historical change in net load, schedule, and frequency deviations and past up and down regulation deployment. Also contingency reserve requirements are impacted by other factors such as value of lost load (VOLL), allowable risk criteria, and loss of load expectation (LOLE).

Currently US ISOs/RTOs use deterministic market clearing models for dispatching energy and allocation of reserves to eligible resources. In this manner, the market clearing engines take as input day-ahead forecasted values of load and intermittent generation, e.g., wind and solar, and reserve requirements to achieve the reliability criteria specified by the system operators. However, many renewable integration studies have found that high penetration of variable renewable energy resources increases the uncertainty and variability of system variables such that using the current practice alone simply cannot capture these characteristics, and the systems must find alternative approaches for allocating and deploying operating reserves.

2. Alternative Solutions for Operationally Feasible Integration of Renewable Energy Resources

Alternative solutions such as new reliability products, new markets, redesigning the ancillary service markets, and stochastic market clearing engines have been proposed for tackling the problems associated with the current standards and models under high penetration of variable energy resources [7], [8], [13], [14], [18], [19], [119]–[123].

Intraday markets reduce the lead time for the forecasts, take advantage of the less uncertain load, wind, and solar forecasts, and allow the generating units and consumers to redefine their forward positions closer to real time with a lesser degree of uncertainty. In this way, intraday markets provide an effective solution for integrating intermittent supply while reducing the balancing costs and enhancing the reliability of the system. European Union (EU) members such as Germany and Spain have adopted multiple intraday markets as their main strategy for increasing the flexibility of their markets in response to higher penetration of intermittent resources particularly wind [119], [120]. Unlike many EU members, the US market operators with high penetration of wind and solar resources, e.g. California ISO (MISO) and Midcontinent ISO (MISO), have proposed the flexible ramp products as a solution for enhancing the flexibility and reliability of their systems [7], [8]. The US market operators are concerned about managing the growing extreme net load (net load= system load – solar generation – wind generation) ramp events because of the growing uncertainty on wind and solar production resources and the ramp constraints of their resources for managing such events. The goal of flexible ramp products is to provide the system with sufficient ramp capability for minimizing the severity and frequency of short-term scarcity conditions due to unexpected variations in the net load. Although the integration of intraday markets or flexible ramp products to the existing electricity markets increases the flexibility and reliability of them and reduces their balancing costs, such solutions may be inadequate for managing the anticipated uncertainty and variability of the intermittent resources at their future penetration levels.

In such situations utilizing stochastic market clearing engines for clearing day-ahead energy and reserve markets has been proposed as a good solution to cope with the expected uncertainty and variability at higher penetration of variable renewable resources. Stochastic market clearing models are look-ahead models capable of capturing the uncertainty and variability of variable resources through simulating balancing operation of the system under different scenarios for real-time realization of variable generation [13], [14], [18], [19], [121]–[123]. Stochastic day-ahead market clearing models are not currently utilized in any of the US electricity markets. However, there are significant efforts underway to increase the efficiency of the existing market clearing mechanisms by developing stochastic models for unit commitment and operating reserves. For instance, the Federal Energy Regulatory Commission (FERC) is promoting increasing real-time and day-ahead market efficiency through adopting stochastic modeling for the market clearing engine [124]. Although implementation of stochastic market clearing seems to be an interesting option for enhancing the efficiency and reliability of the electricity markets, the achievable efficiency gain is an important driver for the market operators and regulators to go into this direction. The benefits of moving to stochastic market clearing must be so tempting that market operators and regulators take the risk and implement it. Nevertheless, none of the he existing studies addresses the added value of utilizing the stochastic market clearing; instead, they are mainly focused on its other aspects, such as functioning, market outcomes, and pricing schemes.

The stochastic market clearing model used in our paper has generally two main differences with respect to the existing deterministic models used in the electricity markets: 1) estimation of the reserve requirements and 2) dispatch of energy and deployment of reserves. In deterministic market clearing models, reserve requirements are input parameters reflecting a target that system's operators pre-specify based on reliability criteria and without any consideration of the current costs of such services and/or updated information on the uncertainty and variability of intermittent energy resources. In contrast, in a stochastic market clearing model reserve requirements are endogenously determined through simulating the balancing operation of the system under different scenarios. The second difference between the stochastic and deterministic modeling stems from the dispatch of energy and reserves. The stochastic model provides an optimal pre-positioning of generating units and loads to manage the uncertain events in the balancing stage of the system. Consequently, and different from the deterministic modeling, stochastic models would not necessarily schedule all the day-ahead forecasted production from intermittent resources in the DAM, and instead, would schedule a level of production from intermittent resources determined after considering its variability and uncertainty, and the costs and availability that required reserves for managing it [13], [14], [18], [19], [121]–[123].

3. Two-Stage Stochastic Model for Clearing Day-Ahead Electricity Markets

The considered stochastic clearing engine used for clearing the day-ahead market in our work is a two-stage stochastic programming model taking into account only the uncertainty in wind power production. The scenario tree of the two-stage model is illustrated in Figure 17. The first stage of the model constitutes the day-ahead stage of the system that represents the actual DAM clearing and renders day-ahead dispatch decisions, including hourly production/consumption levels of generating units/consumers, and day-ahead electricity prices as the dual variables of the day-ahead balance constraints (See Section 2.3.2 of the paper). The day-ahead stage decisions are called here-and-now decisions as they are scenario-independent and are made with imperfect information about the future realization of wind power production during the real-time operation of the system (balancing stage). The second stage, called balancing stage, envisions the real-time balancing operation of the system under likely real-time wind power production scenarios by simulating the implementation of corrective actions to meet real-time energy imbalance needs due to wind power deviation from the day-ahead dispatch. The two-stage structure of the model allows the scheduling of energy and reserves that meets the reliability constraints of the system under all likely scenarios at the minimum cost. Depending on the realization of wind power production in each scenario and the scheduled wind production in the day-ahead stage, two situations can occur in each scenario:

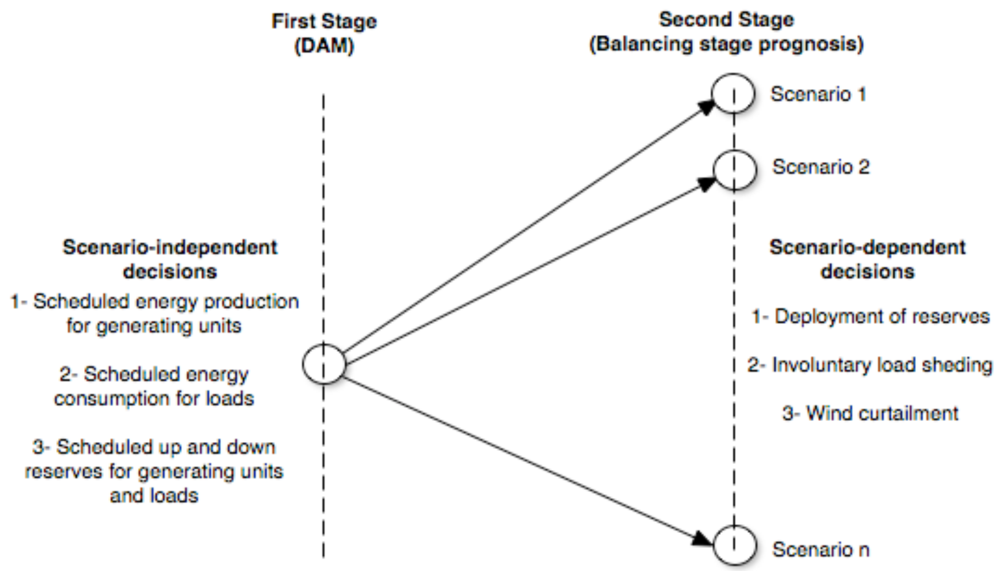

Figure 17: The Scenario Tree for the Two-Stage Stochastic Market Clearing Model

1) When the real-time wind power production is lower than the scheduled wind power production in the day-ahead stage, the system faces under generation and requires deployment of up reserve. Upward reserve deployment corresponds with more production/less consumption for producers/loads compared to their day-ahead stage schedules.
2) If the real-time wind power production is higher than the scheduled wind power production in the day-ahead stage, the system faces over generation and requires down reserve deployment. Down reserve deployment corresponds with reducing production for generating units and increasing consumption for loads relative to their day-ahead stage levels.

The two-stage structure of the stochastic market clearing model inter-relates day-ahead and balancing stage decisions such that the day-ahead schedules impact the implementation of corrective actions in the balancing stage, and the associated corrective action costs impact the dispatch of resources in the day-ahead stage. Such a structure allows pre-positioning the demand-side and generation-side resources in the day-ahead stage to manage the range of uncertainty considered in the set of scenario for production of the wind resources. Accounting for the uncertainty in scheduling of energy and reserves through modeling expected balancing stage costs ensures the reliability of the system and avoids over-scheduling and/or shortage of the reserves.

4. The Implications of Demand-Side Reserve Provision on the Outcomes of the Stochastic Day-Ahead Market Clearing

The specific features of the stochastic market clearing model, particularly scheduling an optimal level of reserves and wind power production, enable the consumers and generators to impact the scheduling of reserves and wind power production through their reserve provision capability and their respective offers. Better understanding of this interaction requires understanding different components of the stochastic model's objective function, briefly explained in Section 2.3.2 of the paper.

The objective function maximizes the expected social welfare of the market consisting of day-ahead (first) stage and balancing (second) stage costs/utilities from energy production/consumption. The four reserve types, including generation-side up and down reserves and demand-side up and down reserves, affect the objective function in different ways. Since generation-side down reserve deployment for generators correspond with the reduction in their production level in the balancing stage, it reduces the expected value of production cost in the balancing stage. Nevertheless, system incurs costs for reserving the associated capacity for down reserve provision in the day-ahead stage, which can be much higher than the generation cost reduction due to the down reserve deployment if the ratio of the total expected value of down reserve deployment to the scheduled down reserve is small. Therefore, as the number of scenarios with the generation-side down reserve deployment increases, the incurred cost of the system for scheduling and deploying down reserve decreases. When it comes to the generation-side down reserve deployment, corresponding with increasing production in the balancing stage, though generators incur opportunity costs, the system does not incur any costs in the day-ahead stage for scheduling the up reserve. The system would be only charged for the value of up reserve deployment in the balancing stage. The expected value of up reserve deployment is probability weighted which grows with increase in the number of scenarios that up reserve is deployed.

For loads, deploying down reserve in the balancing stage corresponds with increasing their consumption. The down reserve deployment in the balancing stage increases the expected value of the utility (expected utility) of the consumers and expected social welfare of the market, and does not impose any cost on the system for reserving its corresponding capacity. On the other hand, the up reserve deployment by loads increases the expected utility of the consumers in the day-ahead stage.

Additionally, the up reserve deployment reduces the expected utility of consumers and expected welfare of the system.

Managing the uncertainty of wind power production requires both up and down reserves. Up and down reserve requirements depend on factors, including the set of wind power production scenarios, the costs of generation-side and demand-side reserves, the utility of loads for providing reserves, and the availability of reserves from both generation and demand sides. The contribution of different reserve types to the objective function of the stochastic market clearing model implies that: 1) when the system needs down reserve deployment, demand-side down reserve is preferred to the generation-side down reserve and 2) when the system needs up reserve deployment, the generation-side up reserve is preferred to the demand-side up reserve. Since the demand-side down reserve deployment increases the expected social welfare of the system, the scheduled wind power production in the day-ahead would be closer to its minimum possible production provided that the system has enough down reserve capability in the demand side. Hindering demand-side resources from reserve provision increases the amount of wind that would be scheduled in the day-ahead stage with respect to the opposite case.

To further clarify the interaction of the reserves and scheduling of wind power production in an electricity market with the stochastic clearing engine, the market outcomes for the illustrative case study of the paper, i.e. Case 1 and Case 2, are studied. Case 1 and Case 2, defined in section 4.1 of Chapter 2, are only different in consumers' reserve provision capacity. In Case 1, both generators and consumers may have reserve provision capacity; however, in Case 2 consumers cannot provide reserves.

4.1. A Case Study for Illustrating the Impacts of Demand-side Reserve Capacity on the Stochastic Market Clearing Outcomes under the Competitive Demand-Side Situation

In this section Case 1 and Case 2 are compared to show how consumers' down reserve provision capability affects the scheduling of wind power production and up and down reserves under the competitive demand-side. The results are presented in Table 22. Rows two and three of Table 22 give the values of dispatched wind in the DAM and the percentage of the expected wind production that is scheduled in the DAM, respectively. The fourth and fifth rows present the total expected deployed up and down reserves by generating units. Rows six and seven show the total expected deployed up and down reserves by generating units. Row eight shows the total expected costs of all generating units. The ninth row gives the expected utility of all consumers. The last row presents the expected social welfare of the market.

Comparing the wind production scenarios, presented in Table 3, and the scheduled wind production values in the day-ahead stage in Case 1 and Case 2 imply that the system needs both up and down reserves to manage the likely wind power fluctuations in the balancing stage, yet down reserve requirement surpasses the need for up reserve. As observed in Table 22, when consumers are allowed to provide reserves (Case 1), the scheduled wind in the day-ahead stage is 146 MW (146=190-44) higher than that in Case 2. In terms of the expected wind production, the scheduled wind increases from %18.61 (=44/236.42) of the expected wind production in Case 2 to %80.38 in Case 1. Additionally, the expected deployed reserves for the two cases indicate that reserve provision by consumers alter the dispatch and deployment of reserves. For instance, in Case 2, with generators as the only providers of up and down reserves, the expected up- and down-reserve deployment values are 29.2 MWh and 69.95 MWh; that is, down reserve deployment of generators slightly surpasses their up reserve deployment. In contrast, when the consumers provide reserves, expected up reserve deployment of generators, equal to 69.86 MWh, surpasses their expected down reserve deployment, equal to 38.22 MWh; in addition, the consumers deploy a considerable amount of down reserve, equal to -233 MWh, and a modest amount of up reserve. In other words, in Case 1 that generators and consumers both provide reserves, the expected up reserve mostly come from the generation side and the expected down reserve mostly come from the demand-side, unless the system does not have enough down reserve capacity in the demand side.

The presented results in the last three rows of Table 22 indicate that demand-side's down reserve capacity increases the total expected utility of consumers and the expected social welfare of the system, while reducing the total expected cost of generating units. Above-mentioned results and implications indicate that in a wind-integrated pool with the stochastic market-clearing engine, demand-side reserve provision reduces the scheduled wind in the day-ahead stage so that the expected down reserve deployment and expected social welfare of the system increases.

Table 22: Stochastic Market Clearing Results for the Illustrative Case Study under the Competitive Demand-Side

Result	Case 1*	Case 2✤
Scheduled wind power production in the DAM (MW)	44.00	190.00
Percentage of the expected wind power production scheduled in the DAM (%)	18.61	80.38
Total expected deployed up reserve by the generating units (MWh)	69.86	29.20
Total expected deployed down reserve by the generating units (MWh)	38.22	69.95
Total expected deployed up reserve by the consumers (MWh)	3.19	0.00
Total expected deployed down reserve by the consumers (MWh)	226.5	0.00
Total expected cost of all generating units ($)	29230	29593
Total expected utility of all consumers ($)	25554	22645
Expected social welfare ($)	39771	39563

* Case 1: demand-side is allowed to provide reserves
✤Case 2: demand-side is not allowed to provide reserves

5. Literature Review and Contributions

A large literature exists on demand response. One thread of research related to this work is concerned with the impacts of enhanced demand-side elasticity on improving efficiency, operational flexibility, and reliability of the grid and integration of intermittent energy resources. For instance, [125] investigates the benefits of short-term demand elasticity to consumers and more efficient operation of the grid considering challenges of enhancing demand-side elasticity. [126] addresses the challenges and benefits of implementing demand-side management alternatives in the UK electric power system. [127] considers the impacts of enhanced demand-side elasticity on mitigating the market power of strategic producers and increasing the market efficiency in an oligopolistic market environment. [128] explores the impacts of adopting real-time retail electricity pricing, as an efficient way of increasing demand elasticity, on the market efficiency in a competitive electricity market. [129] develops a model for the elasticity of the demand for electricity through which studies the impacts of different electricity market designs on the demand-side ability to influence the market prices. [130] analyses the effects of price-based load shifting and load curtailment, as two common demand-response programs, on locational marginal prices (LMPs) of electricity. Demand-side elasticity as an operational flexibility resource has been studied in [131]–[135]. [131], [132] analyze the provision of ancillary services by the demand-side resources in the US Western Interconnection grid to understand its impacts on operational flexibility of the grid and estimate its economic value. They show the provision of ancillary services increases the grid flexibility to manage the variable output of renewable energy resources like wind and solar, enables retail customers to manage their energy costs, and enhances overall system efficiency. [133]–[135] analyze the value of price-responsive demands in competitive energy-only markets for electricity under the uncertainty of wind power production and its impacts on wind power integration and operational costs of the grid, considering the uncertainty of wind power production.

Another thread of research related to this work is concerned with the bidding strategy of the demand-side in electricity markets. Most literature in this domain regards electricity purchasers as price takers. For instance, references [20]–[22] optimize the bidding strategy of a price-responsive retailer, with different responsiveness levels to electricity prices. Similarly, [23], [24]optimize the contracting policies for energy purchase of an energy buyer participating in forward and day-ahead markets using stochastic programming models. In addition, [136] designs the robust electricity procurement strategy of a large consumer in a DAM and a subsequent adjustment market using information gap decision theory. However, very little attention has been paid to the strategic demand-side bidding with endogenous formation of electricity prices. [26] proposes a non-linear programming approach (where optimality of its solution is not guaranteed) for the optimal bidding strategy of a retailer procuring electricity in the DAM and several subsequent intra-day markets. The retailer's impact on the clearing prices is represented through its residual offer curves in each market. [27] proposes a complementarity bilevel model for deriving strategic bidding curves of a large consumer, supplying its demand in a day-ahead pool, under the uncertainty of supply offer curves of producers.

Complementarity modeling, or specifically bilevel optimization has been applied before to different electricity market problems. This technique has been used to study the offering strategy of a producer [28], the offering strategy of investor-owned storage units [29], the bidding strategy of a large consumer participating in day-ahead markets [27], strategic generation investment [30], [31], transmission expansion planning [32], [33], vulnerability assessment [34], yearly generation maintenance scheduling [35], and yearly transmission maintenance scheduling [36]. Among these papers, [27] is the only one investigating the strategic behavior of a large price-responsive consumer through complementarity modeling. However, [27] determines the strategic day-ahead bidding curves without considering the benefits the strategic consumer can obtain from provisioning balancing services. Moreover, [27] also leaves out of the analysis the uncertainty of wind power production and its impacts on provision of balancing services and other market outcomes determining the benefits of the strategic consumer. To fill these gaps, this paper extends the model presented in [27] in three ways: a) it allows demand-side resources to provide reserves, b) it accounts for the benefits of this provision in the determination of the bid of the strategic consumer, and c) it accounts for the uncertainty on wind power generation and its impacts on the strategic consumer's ability to manipulate the market to its benefit. To the best of our knowledge, our approach of using a two-stage stochastic market clearing model in the lower-level program of a complementarity model to determine the day-ahead dispatch of energy and reserves under wind power uncertainty is the first of its kind. None of the previous works have addressed the impacts of the participation of the strategic consumer on the reserve provision and the impacts of wind power production uncertainty on the design of this consumer's day-ahead bidding strategy. Accordingly, the contributions of this paper are threefold:

1) A two-stage stochastic complementarity model that derives an optimal bidding strategy for a large strategic consumer in an electricity market (including day-ahead trading stage and real-time operation) under wind power production uncertainty, and demand-side reserve provision.

2) A transformation of the proposed stochastic complementarity model into an equivalent mixed-integer linear programming (MILP) problem.

3) Use of the proposed model to explore the effects of allowing large consumers to participate in the reserve's market under uncertainty on wind-power production.

6. Mathematical Program with Equilibrium Constraints (MPEC)

This section provides a general introduction to a special class of mathematical programs called bilevel optimization and its connection to Mathematical Problems with Equilibrium Constraints (MPEC). We start with introducing bilevel optimization, which will be followed by the introduction to the concept of MPEC, and how it can be used to model bilevel programs.

Bilevel programming problems are hierarchical optimization problems where the constraints of an optimization problem, referred to as upper-level problem, includes other optimization problems, referred to as lower-level problems, which are parameterized by the so-called upper-level variables. The general formulation of a bilevel optimization problem is as follows [137]:

$$\underset{\{x\}\cup\{y_1^L,\dots,y_n^L\}\cup\{\lambda_1^L,\dots,\lambda_n^L\}\cup\{\mu_1^L,\dots,\mu_n^L\}}{\text{Minimize}} F^U(x, y_1^L, \dots, y_i^L, \dots, y_n^L, \lambda_1^L, \dots, \lambda_i^L, \dots, \lambda_n^L, \mu_1^L, \dots, \mu_i^L, \dots, \mu_n^L) \quad \text{(A.1)}$$

Subject to:

0) Upper-level equality and inequality constraints:

$$H^U\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L, \lambda_1^L, \dots, \lambda_i^L, \dots, \lambda_n^L, \mu_1^L, \dots, \mu_i^L, \dots, \mu_n^L\right) = 0 \quad \text{(A.2)}$$

$$G^U\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L, \lambda_1^L, \dots, \lambda_i^L, \dots, \lambda_n^L, \mu_1^L, \dots, \mu_i^L, \dots, \mu_n^L\right) \le 0 \tag{A.3}$$

1) Lower-level problem 1:

$$\begin{cases} \underset{y_1}{\text{Minimize}}\, f_1^L\,(x, y_1^L, \dots, y_i^L, \dots, y_n^L) \\ \qquad\qquad \text{subject to:} \\ h_1^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) = 0 : \ \lambda_1^L \\ g_1^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) \le 0 : \ \mu_1^L \end{cases} \tag{A.4}$$

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i) Lower-level problem *i*:

$$\begin{cases} \underset{y_i}{\text{Minimize}}\, f_i^L\,(x, y_1^L, \dots, y_i^L, \dots, y_n^L) \\ \qquad\qquad \text{subject to:} \\ h_i^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) = 0 : \ \lambda_i^L \\ g_i^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) \le 0 : \ \mu_i^L \end{cases} \tag{A.5}$$

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n) Lower-level problem *n*:

$$\begin{cases} \underset{y_n}{\text{Minimize}}\, f_n^L\,(x, y_1^L, \dots, y_i^L, \dots, y_n^L) \\ \qquad\qquad \text{subject to:} \\ h_n^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) = 0 : \ \lambda_n^L \\ g_n^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) \le 0 : \ \mu_n^L \end{cases} \tag{A.6}$$

Bilevel model (A.1)-(A.6) includes an upper-level optimization task (A.1-A.3) consisting of an upper-level objective function (A.1), constrained by upper-level equality and inequality constraints (A.2)-(A.3), and a set of *n* lower-level optimization tasks (A.4-A.6). The elements of the upper-level problem are identified by the superscript U. Variable vector $x \in \mathbb{R}^{n_0}$ denotes the set of lower-level primal variables. Also the lower-level elements are distinguished by the superscript L. Variable vector $y_i^L \in \mathbb{R}^{n_i}$ represent the set of primal variables for the lower-level problem *i*, and variable vectors $\lambda_i^L \in \mathbb{R}^{m_i^E}$ and $\mu_i^L \in \mathbb{R}^{m_i^I}$ respectively represent the set of dual variables associated with equality and inequality constraints of lower-level problem *i*.

A general bilevel model must have a hierarchical structure so that the lower-level primal and dual decision variables impact the upper-level's objective function and constraints, and not the other way around. For instance, in the bilevel model (A.1)-(A.6) the variable set of the upper-level problem includes the upper-level decision variables (x) and all lower-level primal variables (y_i^L, $i = 1, .., n$) and dual variables (λ_i^L and μ_i^L, *i*=1,…,n). However, each lower-level problem is optimized on only their own set of variables. For instance, the lower-level problem *i* is optimized on y_i^L assuming upper-level decision variable set x is fixed. On the contrary, the upper-level problem is solved assuming lower-level decision variables y_i^L are constrained to be the optimal solution of lower-level problem i. In other words, the upper-level problem is solved accounting for the response of the lower-level problem to decision vector x such that the feasible region of the upper-level optimization problem is implicitly determined by the global optimal solutions of the lower-level problems.

Bilevel decision making is closely associated with leader-follower problems where the leader desires to optimize her own decision taking the decisions of the follower into account. Thus, the upper-level decision maker corresponds to the leader and the lower-level decision maker corresponds to the follower. The hierarchical process means that the leader makes a decision first and thereafter the follower chooses his/her strategy according to the leader's action. In this process, the leader can influence but cannot control the decision of the follower. Great examples of such problems are Stackelberg games in economic models especially in market problems. In our case, the leader is the strategic consumer who seeks to maximize its expected utility, and the follower is the clearing of the day-ahead market. The leader affects the clearing of the market through day-ahead bidding curves, and the market clearing impacts the strategic consumer's decision through the clearing prices.

The most common way to deal with a bilevel problem is to recast it into a single-level optimization problem. If the lower-level problems are convex and some mild constraint qualifications are satisfied, each lower-level problem (if more than one) can be substituted by its equivalent Karush-Kuhn-Tucker (KKT) optimality conditions as constraints to the upper-level problem. The resulting problem is a special class of the optimization problems called mathematical programming problem with complementarity constraints (MPCC). Since the KKT conditions are necessary and sufficient for the global optimality of the lower-level problems, the resulting MPCC problem is globally and locally equivalent to the bilevel programming problem (A.1)-(A.6). If the equivalent optimality conditions correspond with equilibrium in a system, e.g., traffic network equilibrium and oligopolistic market equilibrium, the resulting problem is called mathematical programming problem with equilibrium constraints (MPEC).

An MPEC is a constrained nonlinear optimization problem in which some or all of the constraints are formulated in terms of the solution of an equilibrium problem, which appear as a parameter-dependent variational inequality or complementarity problem. In our case, the resulting equilibrium constraints take the form of a complementarity problem resulting from taking the KKT optimality conditions from the stochastic market clearing problem. The bilevel problem (A.1)-(A.6) can be recast as an MPEC as follows [137]:

$$\underset{\{x\}\cup\{y_1^L,\dots,y_n^L\}\cup\{\lambda_1^L,\dots,\lambda_n^L\}\cup\{\mu_1^L,\dots,\mu_n^L\}}{\text{Minimize}} F^U(x, y_1^L, .., y_i^L, .., y_n^L, \lambda_1^L, .., \lambda_i^L, .., \lambda_n^L, \mu_1^L, .., \mu_i^L, .., \mu_n^L) \quad \text{(A.7)}$$

subject to:

0) Upper-level equality and inequality constraints:

$$H^U\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L, \lambda_1^L, \dots, \lambda_i^L, \dots, \lambda_n^L, \mu_1^L, \dots, \mu_i^L, \dots, \mu_n^L\right) = 0 \quad \text{(A.8)}$$

$$G^U\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L, \lambda_1^L, \dots, \lambda_i^L, \dots, \lambda_n^L, \mu_1^L, \dots, \mu_i^L, \dots, \mu_n^L\right) \le 0 \quad \text{(A.9)}$$

1) Corresponding KKT conditions of lower-level problem 1:

$$\nabla_{y_1^L} f_1^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) + {\lambda_1^L}^T \nabla_{y_1^L} h_1^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) + \cdots \tag{A.10}$$

$$+ {\mu_1^L}^T \nabla_{y_1^L} g_1^L(x, y_1^L, \dots, y_i^L, \dots, y_n^L) = 0$$

$$h_1^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) = 0 \tag{A.11}$$

$$0 \leq g_1^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) \perp \mu_1^L \geq 0 \tag{A.12}$$

$$\lambda_1^L : \text{free} \tag{A.13}$$

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i) Corresponding KKT conditions of lower-level problem *i*: (A.14)

$$\nabla_{y_i^L} f_i^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) + \cdots + {\lambda_i^L}^T \nabla_{y_i^L} h_i^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) + \cdots \tag{A.15}$$

$$+ {\mu_i^L}^T \nabla_{y_i^L} g_i^L(x, y_1^L, \dots, y_i^L, \dots, y_n^L) = 0$$

$$0 \leq g_i^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) \perp \mu_i^L \geq 0 \tag{A.16}$$

$$\lambda_i^L : \text{free} \tag{A.17}$$

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.

n) Corresponding KKT conditions of lower-level problem *n*:

$$\nabla_{y_n^L} f_n^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) + {\lambda_n^L}^T \nabla_{y_n^L} h_n^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) + \cdots + \tag{A.18}$$

$${\mu_n^L}^T \nabla_{y_n^L} g_n^L(x, y_1^L, \dots, y_i^L, \dots, y_n^L) = 0$$

$$h_n^L\left(x, y_1^L, \dots, y_i^L, \dots, y_n^L\right) = 0 \tag{A.19}$$

$$0 \le g_n^L(x, y_1^L, \dots, y_i^L, \dots, y_n^L) \perp \mu_n^L \ge 0 \tag{A.20}$$

MPEC (A.7-A.21) is obtained by replacing the lower-level problems (A.4-A.6) by their corresponding KKT conditions. For instance, constraints (A.14)-(A.17) are the corresponding KKT conditions of lower-level problem *i*. Constraints (A.16) represents the complementarity conditions associated with the inequality constraints of lower-level problem *i* which can be also written as follows [137]:

$$\text{diag}\left[g_n^L(x, y_1^L, \dots, y_i^L, \dots, y_n^L)\, .\ \mu_n^L\right] = 0 \tag{A.22}$$

$$g_n^L(x, y_1^L, \dots, y_i^L, \dots, y_n^L) \ge 0 \tag{A.23}$$

$$\mu_n^L \ge 0 \tag{A.24}$$

7. Wind Power Production Data for Wind Farms K1 to K3

In order to generate the set of scenarios for production of wind farms K1 to K3, aggregated wind power production data from wind farms in Belgium [39] and Ireland [40] are scaled down and used. We use the first half of the available data from Feb 1, 2012 to October 28, 2014, corresponding to 500 days of the available data, to generate the set of scenarios. Aggregated wind production data from transmission system-connected wind farms in Belgium are used as the data for wind farm K1 [39]. Aggregated production data from the Ireland's wind farms is used for wind farm K2 [40]. Aggregated wind power production data of distribution system-connected wind farms of the Belgium's grid is used for wind farm K_3. The characteristics of the scaled data

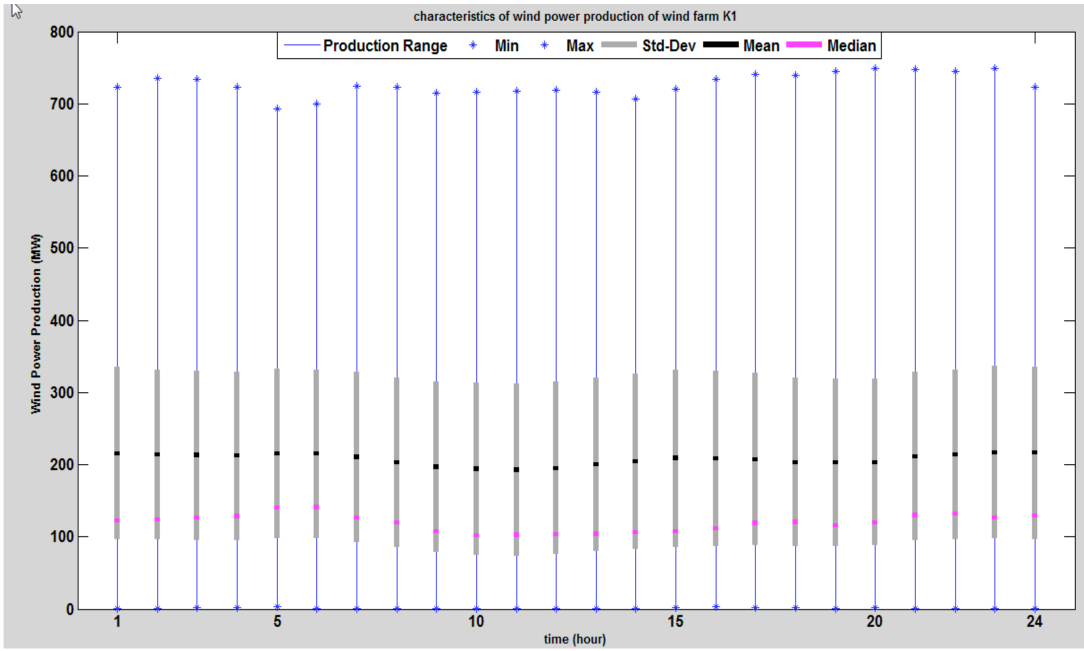

Figure 18: Production Range, Mean, Median, and Standard Deviation for Production of Wind Farm K1

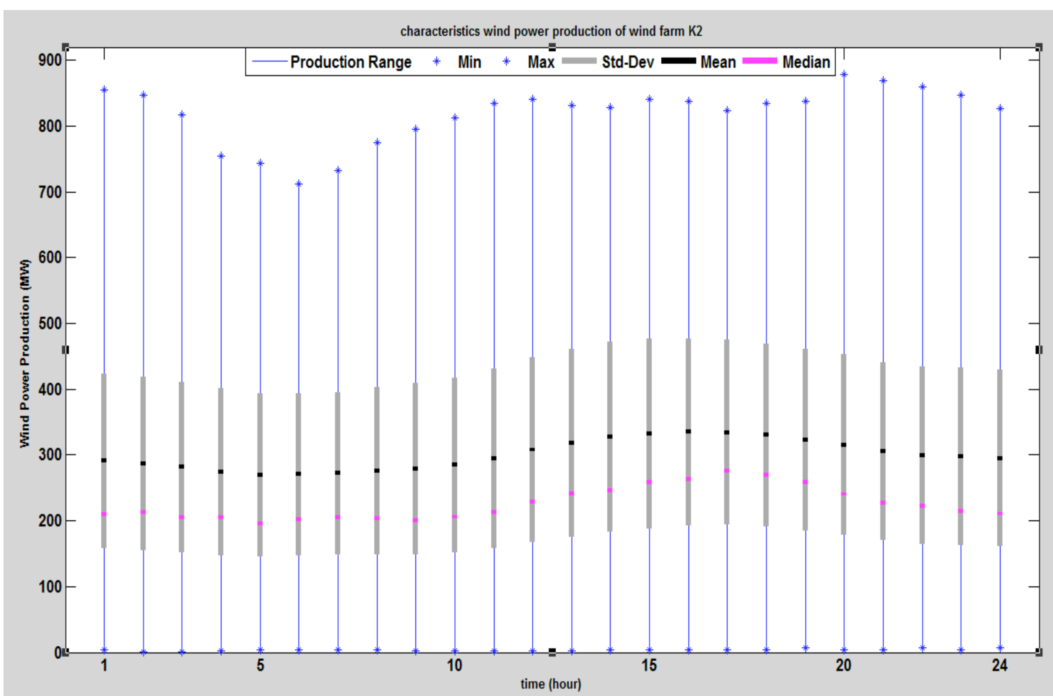

Figure 19: Production Range, Mean, Median, and Standard Deviation for Production of Wind Farm K2

used for wind farms K1 to K3, including production range, mean, standard deviation, and median are illustrated in Figure 18 to Figure 20, respectively. In Figure 18 to Figure 20, the upper and lower blue whiskers respectively show the minimum and maximum wind power production for each hour. The grey box shows the standard deviation of wind production for each hour. The black line through the box shows the mean wind production for each hour. The purple line through the box shows the median for wind power production of each hour.

8. Constructing Wind Power Production Scenarios

A scenario in our paper is the possible realization of wind power production for the set of wind farms for a single time period. Hence, in the large-scale case study of the paper, which has three wind farms, each scenario represents the production values of three farms for that particular hour. Constructing the set of scenarios for production of wind farms K1 to K3 consists of two successive modules: 1) scenario generation module and 2) scenario reduction module. The first module generates a large set of scenarios for production of the wind farms ensuring the uncertainty of wind power production is well characterized in the set of scenarios, and different states that may occur for

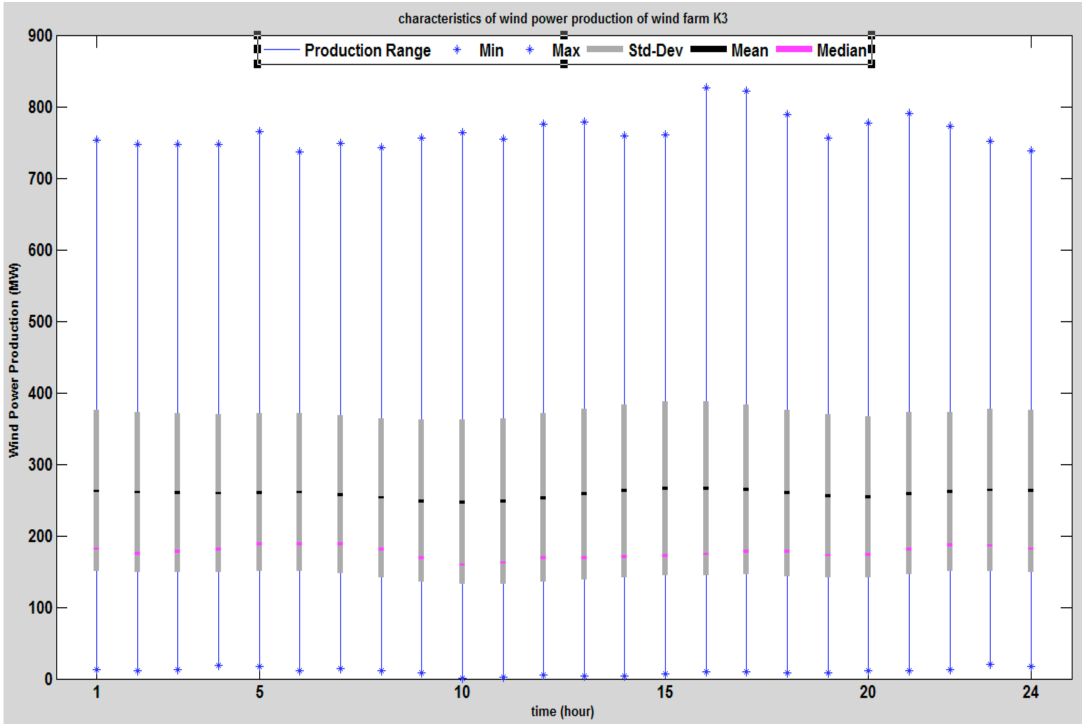

Figure 20: Production Range, Mean, Median, and Standard for Production of Wind Farm K3

production of the wind farms are seen in the set of scenarios. The scenario reduction module is fed with the large set of scenarios and gives a smaller set of scenarios that not only keeps the information and uncertainty content of the scenario set as intact as possible but also keeps the computational tractability of the strategic bidding model. Note that the scenario generation module is performed individually for each time period (t=1,…,24). The scenario generation and reduction modules are introduced in the following subsections.

8.1. Scenario Generation Module

For each hour of the case study, the scenario generation is performed in the following step-by-step procedure:

Step 1) Determining different states associated with power generation of each wind farm: The output of this step consists of multiple states for power generation of each wind farm. For each wind farm, a state corresponds with the expected production and the probability of that state. This step is performed in the following way:

1) The available historical data associated with production of each wind farm at hour *t* is collected. Note we have scaled down the collected data to fit the case studies of our paper.
2) Equal-length intervals corresponding to different possible states of power generation for each wind farm are defined. In our case, we have selected 5 states, including very low, low, medium, high, and very high. The defined states and their corresponding intervals for wind farms K1 to K3 for time period t=21 are presented in Table 23.
3) In this step a wind production value and a probability are assigned to each state. The historical observations for each wind farm are allocated into their corresponding states. Based on the allocated observations to each state, the centroid of any defined state is calculated and assigned as the anticipated production value associated with that particular state. The centroid of each state is the mean value of that particular state. The calculated centroid values associated with the states defined in Table 23 are given in Table 24. The probability of a state is also calculated based on the number of observations in

each interval. Thus, the anticipated production and the probability values associated with the defined states for all wind farms are calculated.

Step 2) Constructing the set of scenarios for production of the set of wind farms: The set of scenarios consists of all possible combinations of the defined states for generation of the wind farms in the previous step. In our case study with three wind farms and five states for generation of each wind farm, there are 5^3=125 scenarios. The probability of

Table 23: Defined Intervals in Step 1 for Production of Wind Farms K1 to K3

Wind	Interval 1		Interval 2		Interval 3		Interval 4		Interval 5	
Farm	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
K1	4.00	140.5	140.5	277.0	277.0	413.5	413.5	550.0	550.3	686.8
K2	0.86	174.6	174.6	348.3	348.4	522.1	522.1	695.8	695.8	869.5
K3	11.8	167.6	167.6	323.4	323.5	479.3	479.3	635.2	635.2	791.0

Table 24: Calculated Centroid Values for the Defined Intervals

Wind	Centroid				
Farm	Interval 1	Interval 2	Interval 3	Interval 4	Interval 5
K1	65	211	361	518	669
K2	88	254	430	604	763
K3	107	233	390	543	713

each scenario is calculated by multiplying the probabilities associated with the states of the wind farms in that scenario.

8.2. Scenario reduction module

A forward scenario reduction method presented in [78], [138] is used to choose a representative set of scenarios (containing 30 scenarios in our case) among the original set of scenarios (125 scenarios in our case). This scenario reduction method works based on minimizing the Kantorovich distance between the discrete probability distributions of the original set of scenarios and the reduced set of scenarios. In fact, the selected scenarios in the reduced set are iteratively selected from the original set to minimize the Kantorovich distance between the two sets. Given that the stochastic market-clearing model used in our paper only present stochasticity in the objective function and right-hand side of the constraints, the Kantorovich distance between the original set (Ω_O) and the reduced set (Ω_R) of scenarios can be equivalently determined as follows [78], [138]:

$$D_K(Z^O, Z^R) = \sum_{\omega \in \Omega_O \setminus \Omega_R} \phi_\omega \min_{\omega' \in \Omega_R} c(\omega, \omega') \tag{B 25}$$

where D_k (Z^O, Z^R) denotes the Kantorovich distance between probability distributions Z^O (associated with the original scenario set Ω_O) and Z^R (associated with the reduced scenario set Ω_R), Φ_ω represents the probability of scenario $\omega \in \Omega_O$, and $c(\omega, \omega')$ is the cost function defined for every possible combination of $\omega \in \Omega_O$ and $\omega' \in \Omega_R$ explained in details later. Note that the above minimization problem can be solved for any given number of scenarios in the reduced set. Solution to problem (A4) can be also obtained through an iterative approach presented in [78], [138]:

Step 0) Cost function value is calculated for every two scenarios in the original scenario set Ω_O as follows:

$$c^0(\omega, \omega') = \sum_{k=1}^{K} \left| W_{k,\omega}^{act} - W_{k,\omega'}^{act} \right| \tag{B 26}$$

$c^0(\omega,\omega')$ is equal to norm of the sum of differences of generation for wind farms k=1,..,K between scenarios ω,ω'. Therefore, the results can be represented as a zero diagonal square matrix.

Step 1) This step is an iterative process; the total number of iterations in this step is equal to the designated number of scenarios in the reduced set (N). Note that $\Omega_R^{[i]}$ represents the reduced scenario set at the end of iteration i, and $c^{[i]}(\omega,\omega')$ denotes the calculated cost matrix at the beginning of iteration i.

Iteration 1: In this iteration the first scenario is added to the reduced set $\Omega_R^{[i]}$. The first scenario selected from the original set Ω_O is determined as follows:

$$\omega_1 = \arg\{\min_{\omega'\in\Omega} \sum_{\omega\in\Omega} \pi_\omega c(\omega,\omega')\} \tag{B 27}$$

In fact, ω_1 is the scenario with minimum distance from all other scenarios in the original set.

Iteration i: The cost function matrix is updated at the beginning of iteration i as follows:

$$c^{[i]}(\omega,\omega'), = \min[c^{[i-1]}(\omega,\omega'), c^{[i-1]}(\omega,\omega_{i-1})] \qquad s.t. \quad \omega,\omega' \epsilon \Omega_L^{[i-1]} \tag{B 28}$$

where $\omega_{i\text{-}1}$ is the scenario that is added to the reduced set $\Omega_s^{[i-1]}$ (in iteration *i*-1). After the update, $c^{[i]}(\omega,\omega')$ and $c^{[i]}(\omega',\omega)$ are not necessarily equal anymore; They are only equal in the first iteration. The scenario ω_i added to the reduced set is obtained as follows:

$$A_{\omega}^{[i]} = \sum_{\omega' \epsilon \Omega_L^{[i-1]} \backslash \{\omega\}} \pi_{\omega'} \times v^i(\omega',\omega) \quad , \omega \epsilon \Omega_L^{[i-1]} \tag{B 29}$$

$$\omega_i = \arg\{ \min_{\omega \epsilon \Omega_L^{[i-1]}} A_{\omega}^{[i]} \} \tag{B 30}$$

where $\Omega_L^{[i-1]}$ contains the leftover scenarios from the original set that have not been selected.

Iteration N: After this iteration, the scenarios in the original set are divided into two sets $\Omega_R^{[N]}$ and $\Omega_L^{[N]}$ where $\Omega_R^{[N]}$ contains N selected scenarios, and $\Omega_L^{[N]}$ contains the leftover scenarios that must be discarded.

Step 2) After the last iteration of the last step, the probability values for the leftover scenarios in $\Omega_D^{[N]}$ must be distributed between the selected scenarios in $\Omega_R^{[N]}$. The probability of each scenario $\omega \epsilon \Omega_L^{[N]}$ must be added to the scenario $\omega' \epsilon \Omega_R^{[N]}$ such that $\omega' = \arg\left\{ \min_{\omega' \epsilon \Omega_R^{[N]}} c^{[0]}(\omega,\omega') \right\} \omega \epsilon \Omega_L^{[N]}$. In other words, ω' is the scenario with the minimum initial cost function value $c^{[0]}(\omega,\omega')$ with ω.

9. Out-of-Sample Simulation

Different steps for performing the out-of-sample simulations are illustrated by a flowchart in Figure 21.

10. Market Design and Policy Implications

According to the observations of our work, in a situation that the strategic consumer manipulates the market, the strategic consumer underbids its expected demand in the day-ahead market (DAM) to withhold its demand from being scheduled in the DAM. The withheld demand depresses the day-ahead prices by hindering the dispatch of a more expensive unit that would be the marginal generator otherwise. That is, its price-responsiveness and large share of the total market demand enables it to tolerate a non--zero amount of unscheduled demand and supply its demand at a lower price with respect to competitive levels. In addition, down reserve deployment capability that corresponds to consumption increase in the balancing stage enables the strategic consumer to supply a fraction of the unscheduled demand in the DAM. Through down reserve provision capability, the strategic consumer impacts the scheduling of wind power production and down reserve deployment in the balancing stage that increases its market power. In other words, reserve provision capability

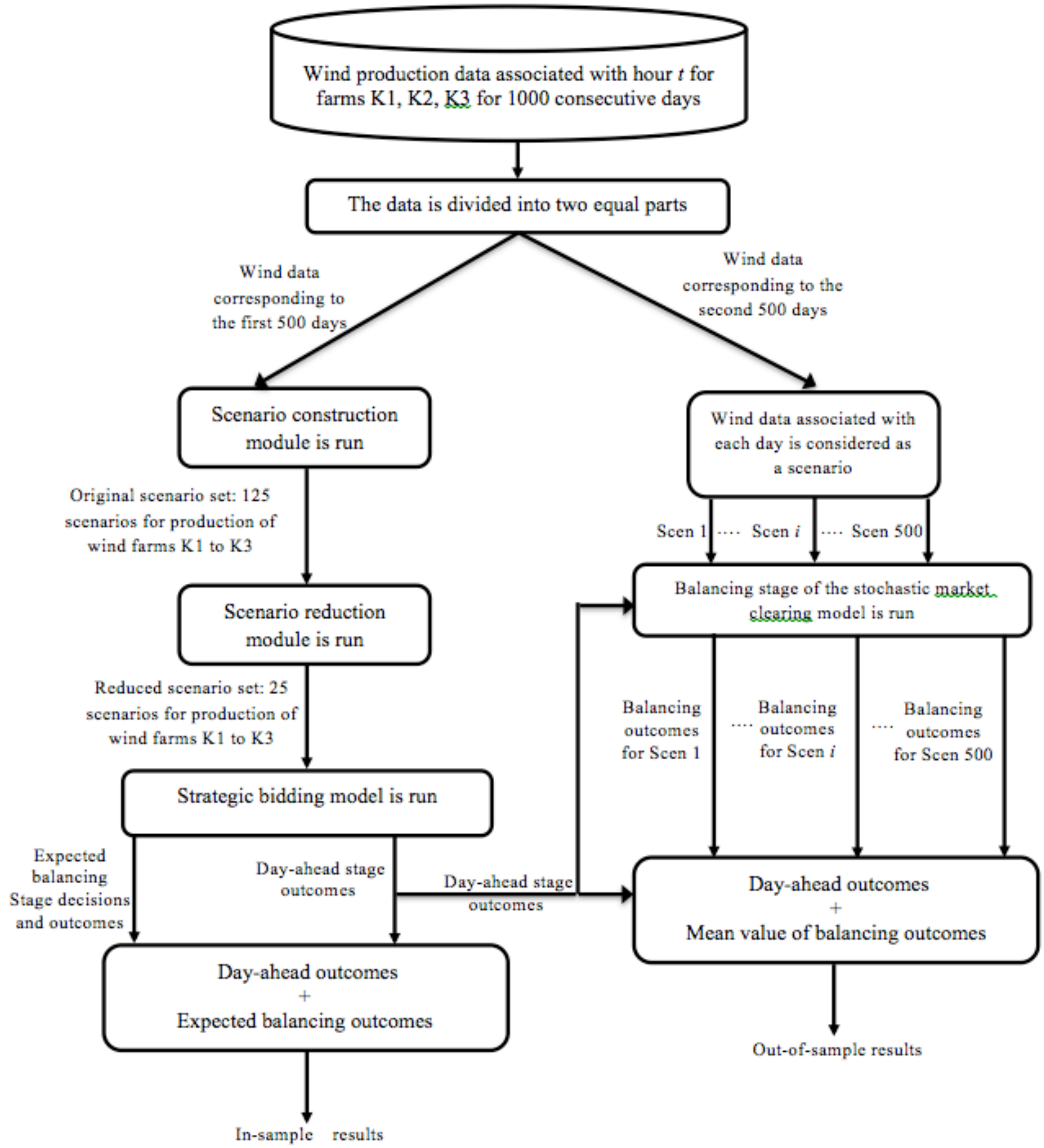

Figure 21: Flowchart of the In-Sample and Out-of-Sample Simulations

enables the strategic consumer to achieve its desirable prices with lower amount of unserved demand compared to the situation that does not have such capability. The above results have a number of implications for market designers, regulators, and policy makers to consider. These implications are described in the following paragraphs summarizing key considerations.

These observations have two important policy implications:

Exercise of market power by a large consumer capable of proving up and down balancing reserves can occur enough of the time to suppress electricity prices and increase the expected utility[2] of the large consumer compared to the competitive levels; The exercise of market power also reduces the generating units' expected profit and total expected social welfare of the market. However, the other consumers, which behave competitively, benefit from such a behavior as they fully supply their demand at reduced prices compared to the competitive levels. Therefore, the electricity markets with progressive price-based demand response programs need to take such exercise of market power serious and design efficient monitoring processes for the demand-side resources to ensure well-functioning, liquidity and competitiveness of their markets.

The observed values for the dispatch of wind power production in the day-ahead and balancing stages in the competitive and strategic case studies indicate that the dispatch of wind power production is impacted by the exercise of market power. As explained in Section 4 of this Appendix, the strategic consumer's behavior tends to further reduce the scheduled wind power production in the DAM relative to the competitive levels to increase the demand for down reserves in the balancing stage.

From the market design's point of view, the observed results indicate the following implications:

[2] Consumer welfare

The strategic consumer takes advantage of its two capabilities to suppress electricity prices: 1) It can withhold a fraction of its demand from being scheduled in the DAM (price responsiveness) and 2) part of the unscheduled demand is supplied in the balancing stage through down-reserve deployment (reserve provision capability). Nevertheless, these two features are not the only factors contributing to the exercise of market power by the strategic consumer.

Having a stochastic engine for clearing the market increases the ability of market manipulation by the strategic consumer. In fact, two characteristics distinguishing the stochastic market clearing model from the deterministic ones, i.e., estimation of the reserve requirements and dispatch of energy and reserves, create opportunities for the strategic consumer to manipulate an electricity market with the stochastic clearing engine. As explained in section 4 of Appendix A, the amount of wind power production scheduled in the DAM using the stochastic market clearing model is optimized based on the uncertainty of wind production, and the availability and costs of the reserve requirements. When the demand-side resources are allowed to provide reserves, they can affect the scheduling of wind in the DAM and reduce it from the levels that would be dispatched otherwise. The higher the demand-side reserve provision capability, the lower the amount of wind scheduled in the DAM, so the strategic consumer would rather offer its consumption as down reserve to be later deployed in the balancing stage, than being scheduled as consumption in the DAM.

Since there is no restriction or pre-specified criteria on the provision of reserves by the consumers, the strategic consumer leverages its reserve deployment capability to reduce the amount of wind production that would be scheduled in the DAM. Thus, joint optimization of wind production and deployment of reserves with no cap on the demand-side reserve provision further increases the ability of the strategic consumer for withholding its demand from the DAM and surpassing electricity prices. That is, it can achieve its goals (reducing the clearing prices and maximizing its utility) with comparatively lower expected energy not supplied.

The particular features of a market with the stochastic clearing engine can enable the strategic consumer to use its reserve deployment capability on top of its elasticity for manipulating the market, suppressing electricity prices, and harming the welfare and the generating units. Therefore, certain actions such as limiting the reserve provision capability of the demand-side resources and/or total share of reserves to be provided by them must be taken into account to avoid the situations that lead to the exercise of market power by the strategic consumer.

The other important implication of the observed results is that the occurrence of market power and the magnitude of its effects on the market outcomes would be sensitive to factors, including marginal utility of the strategic consumer's loads, share of the strategic consumer from the total market demand, reserve provision capability of the strategic consumer, the volatility of wind power production, and congestion in the transmission system. Among above factors, the marginal utilities and the share of the strategic consumer are the keystone for the exercise of market power, so the exercise of market power would be impossible if the strategic consumer's marginal utilities are too high (its loads are not elastic enough) and/or its market share is lower than a threshold required for manipulating the market. The other factors impact the extent of the strategic consumer's market power and the magnitude of its impacts on the market outcomes. Among the other factors, reserve provision capability and volatility of wind power production contribute to the benefits and market power of the strategic consumer in all aspects. For instance, enhancing the reserve provision capability of the strategic consumer increases its expected utility while decreases its expected energy not supplied. Similar effects result from higher volatility of wind power production because it increases the demand for reserves that enables the strategic consumer to make more efficient use of its reserve provision capability. In contrast, network congestion has mixed effects on the strategic consumer's targets. Additionally, the magnitude of its impact depends on the topology of the grid and distribution of the strategic loads throughout the grid. For the particular test case of our paper, network congestion enables the strategic consumer to suppress the electricity prices to the levels lower than no congestion condition leading to higher expected utility for the strategic consumer. Nevertheless, the enhanced benefits come at the cost of incurring larger amounts of expected energy not supplied.

Appendix B: Supporting Information for Chapter 3

Sections 1-7 in this appendix appear in the Supporting Information of a working paper coauthored by the PhD candidate [89], *and have been reprinted with permission from her coauthors.*

1. Scenario Reduction Module

The scenario reduction module takes the full set of generated error scenarios, referred to as *original scenario set*, for each of the simulation days, and selects a representative set of scenarios, called the *reduced scenario set*. The scenario reduction process is based on an iterative method, presented in [77], [78], which finds the *reduced scenario set* with the minimum Kantorovich distance from the *original scenario set*. The Kantorovich distance is a probability distance metric that sums the absolute deviations between distributions of two random variables for all possibilities of the variables. The number of scenarios in the *reduced scenario set* are determined prior to the scenario reduction, which in our case is limited to the maximum number that maintains the computational tractability of the electricity market simulations with stochastic market clearing mechanism. Full description of the iterative scenario-reduction method and how it equivalently approximates the minimum Kantorovich distance between the original and reduced sets can be found in [77], [78], [139].

The scenario reduction process occurs in two stages. The first stage adds one scenario from the *original scenario set* to the *reduced scenario set* until the latter reaches its target size. The scenario selected in each iteration creates the greatest reduction in the

Kantorovich distance between the associated distribution functions of the original and reduced sets. The second stage distributes the probabilities of not selected scenarios to the scenarios in the reduced set. Step-by-step implementation of the scenario reduction method is presented below:

Step 0 – Initialization: For every two scenarios ω and ω' in the *original scenario set*, denoted Ω_O, a cost function $c^0(\omega, \omega')$ is calculated as:

$$c^0(\omega, \omega') = \sum_{t=1}^{T} \left| WFE_{\omega,t} - WFE_{\omega',t} \right| \tag{B.1}$$

Where *t* represents hours 1-24 and $WFE_{\omega,t}$ is the hourly Wind production Forecast Error for hour t under scenario ω. Hence, $c^0(\omega, \omega')$ is a zero-diagonal square matrix of dimension 24. Each component is equal to the absolute value of the difference between the WFE for the two scenarios ω, ω'.

Step 1: This step is an iterative process in which the cost function and the reduced scenarios set are updated where $\Omega_R^{[i]}$ represents the reduced scenario set at the end of iteration *i,* and $c^{[i]}(\omega, \omega')$ denotes the calculated cost matrix at the beginning of iteration *i*. The total number of iterations in this step is equal to the designated number of scenarios *N* in the reduced set.

Iteration 1: In this iteration, the first scenario is added to the reduced set $\Omega_R^{[1]}$. The first scenario selected from the original set Ω_O is determined as follows:

$$\omega_1 = \arg\{\min_{\omega' \in \Omega} \sum_{\omega \in \Omega} \pi_\omega c(\omega, \omega')\} \tag{B.2}$$

ω_1 is the scenario with minimum distance from all other scenarios in the original set.

Iteration i: The cost function matrix is updated at the beginning of iteration *i* as follows:

$$c^{[i]}(\omega, \omega') = \min[c^{[i-1]}(\omega, \omega'), c^{[i-1]}(\omega, \omega_{i-1})] \qquad s.t. \quad \omega, \omega' \epsilon \Omega_L^{[i-1]} \tag{B.3}$$

where ω_{i-1} is the scenario that is added to the reduced set $\Omega_s^{[i-1]}$ (in iteration *i*-1). After the update, $c^{[i]}(\omega, \omega')$ and $c^{[i]}(\omega', \omega)$ are not necessarily equal anymore. They are only equal in the first iteration. The scenario ω_i added to the reduced set is obtained as follows:

$$A_\omega^{[i]} = \sum_{\omega' \epsilon \Omega_L^{[i-1]} \setminus \{\omega\}} \pi_{\omega'} \times v^i(\omega', \omega) \quad , \omega \epsilon \Omega_L^{[i-1]} \tag{B.4}$$

$$\omega_i = \arg\{\min_{\omega \epsilon \Omega_L^{[i-1]}} A_\omega^{[i]}\} \tag{B.5}$$

where $\Omega_L^{[i-1]}$ contains the leftover scenarios from the original set that have not been selected.

Iteration N: After this iteration, the scenarios in the original set are divided into two sets $\Omega_R^{[N]}$ and $\Omega_L^{[N]}$ where $\Omega_R^{[N]}$ contains *N* scenarios added to the reduced set, and $\Omega_L^{[N]}$ contains the leftover scenarios that must be discarded.

Step 2: After the last iteration of the last step, the probability values for the leftover scenarios in $\Omega_D^{[N]}$ must be distributed between the selected scenarios in $\Omega_R^{[N]}$. The probability of each scenario $\omega \epsilon \Omega_L^{[N]}$ must be added to the scenario $\omega' \epsilon \Omega_R^{[N]}$ such that $\omega' = \arg\left\{ \min_{\omega' \epsilon \Omega_R^{[N]}} c^{[0]}(\omega, \omega') \right\} \omega \epsilon \Omega_L^{[N]}$. In other words, ω' is the scenario with the minimum initial cost function value $c^{[0]}(\omega, \omega')$ with ω.

2. **Flowchart of the Process of Generating Wind Production Scenarios Carried Out by the Scenario Construction**

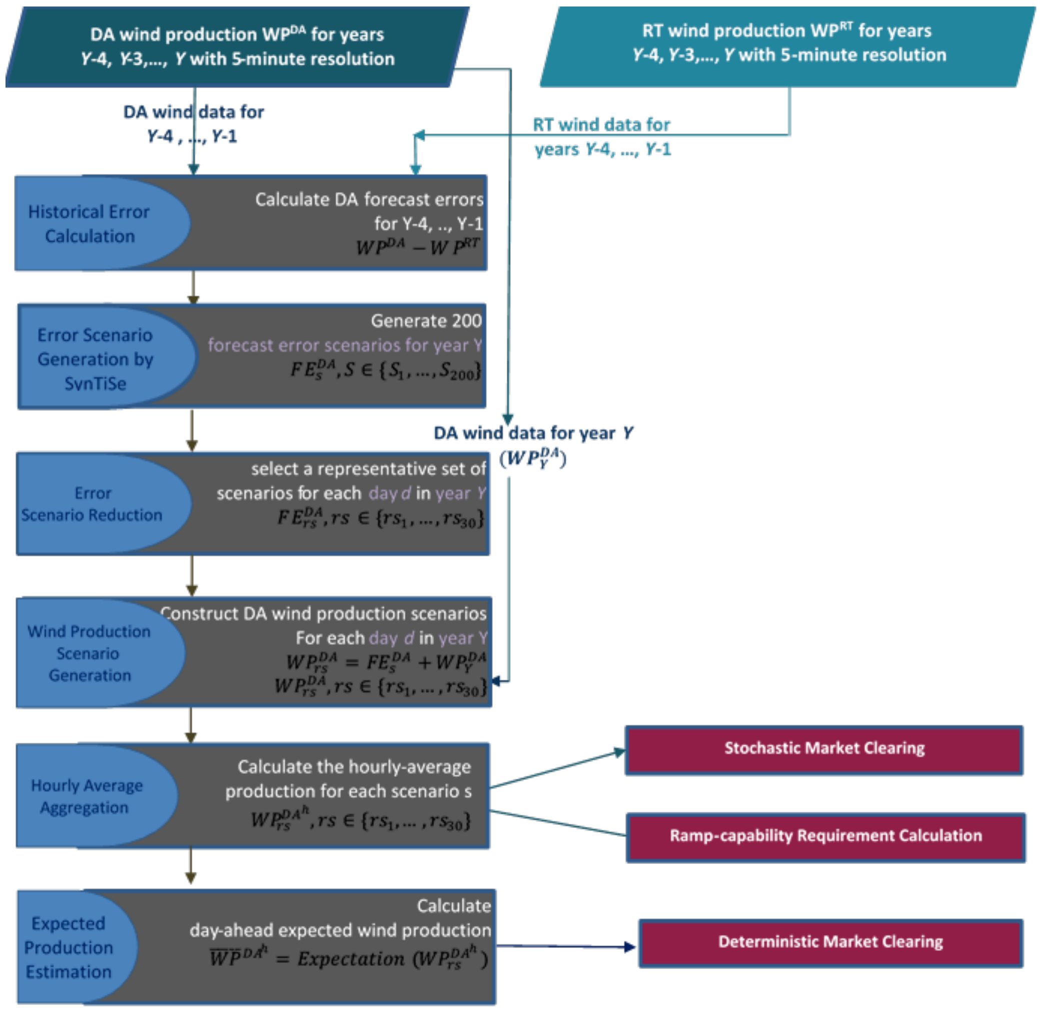

Figure 22: Process for Generating Day-Ahead Hourly Wind Power Production Scenarios

3. Market Settlement Scheme and Supply-Side Revenue Sufficiency

3.1 Consistent Supply-Side Revenue Scheme for a Fair Comparison of the Alternative Market Clearing Mechanisms

Following [13], [14], the two-stage stochastic market clearing model addressed in this study is based on an energy-only clearing scheme, where no payments are made to suppliers for maintaining the additional reserve capacity in the day-ahead market. In fact, all so-far proposed stochastic market clearing models are on the basis of energy-only scheme and do not propose any schemes for jointly pricing energy and reserves [13]–[15]. Nonetheless, this does not mean energy-only clearing schemes do not remunerate provision of ramp capability reserves by producers. As shown in section 5 of the manuscript, DA energy prices delivered by SMC incentivize the provision of ramp capability reserve by producers very well. This mainly stems from SMC's feature that day-ahead prices account for the uncertainty in wind production variations and its associated expected costs.

3.2 Energy-Only Pricing and Settlement

As indicated in the manuscript, the SMC follows an energy-only scheme to remunerate producers for the energy and reserves they provide, whereas ADMC remunerates them for producing energy as well as maintaining ramp capability reserves when the system-wide ramp constraints are binding. To have a fair estimate of the producers' revenues and profits, the producers' revenues under ADMC are calculated both based on the energy only scheme and the more general scheme including reserve payments. This section first describes the principles of the energy-only pricing scheme and then discusses reserve capacity payments and cost allocation.

In the energy-only scheme, only day-ahead energy schedules and balancing energy —to react to deviations from day-ahead schedules— are settled. Under this scheme, the producers/consumers are paid/charged for their day-ahead energy schedules at the day-ahead energy price. Balancing deviations are also settled at the balancing energy price.

In the energy-only scheme, the day-ahead energy transactions are settled between the producers (both conventional and wind power producers) and consumers. However, since the demand uncertainty is not taken into account in this study, the real-time deviations are induced only by wind producers from their DA forecasts. Thus, the RT transactions are settled between the conventional and wind power producers. According to the scheme, for each time period *t*, each generating unit *g* is paid based on the equation below:

$$R_g^{EO}(t) = \left[P_{g,t}^{DA} \times \pi_{E,t}^{DA}\right] + \left[(p_{g,t}^{RT} - P_{g,t}^{DA}) \times \pi_{E,t}^{RT}\right] \tag{B.6}$$

where $R_g^{EO}(t)$ denotes total revenues of unit *g* at hour *t* under and energy-only scheme. $P_{g,t}^{DA}$ and $p_{g,t}^{RT}$are day-ahead and real-time production of unit *g* at hour *t*, and $\pi_{E,t}^{DA}$ and $\pi_{E,t}^{RT}$ represent day-ahead and real-time energy prices at *t*.

When the ramp capability reserve payments are taken into account (i.e. under an ADMC framework), the producers' revenues are calculated as follows:

$$R_g^{E+R}(t) = [P_{g,t}^{DA} \times \pi_{E,t}^{DA}] + [(RC_{g,t}^{Up} \times \pi_{RU,t}^{DA}) + (RC_{g,t}^{Dn} \times \pi_{RD,t}^{DA})] + [(p_{g,t}^{RT} - P_{g,t}^{DA}) \times \pi_{E,t}^{RT}] \quad \text{(B.7)}$$

In which $R_g^{E+R}(t)$ represents the total revenues collected by producer g at time t and for providing energy and reserves, $RC_{g,t}^{Up}$ and $RC_{g,t}^{Dn}$ respectively notate the scheduled up and down ramp capability reserves for producer g at time t, and $\pi_{RU,t}^{DA}$ and $\pi_{RD,t}^{DA}$ express the prices for up and down ramp capability reserves at t. See section 4 for similarities and differences of MISO's ramp products and the ramp products considered in this paper.

3.3. Uplift Payments

Uplift payments are necessary out-of-market adjustments to cover the non-convexities of the pricing schemes, such as start-up and no-load costs, and assure the supply side's short-run revenue sufficiency. So the true estimate of the supply-side revenues must include the uplift payments. Uplift payment is also an important market efficiency indicator that must be addressed in the comparison of the deterministic and stochastic market clearing mechanisms.

Consistent with the conventional practice in PJM and other electricity markets in the US, uplift payments in this study are calculated on a daily basis. At the end of each day d, the generating units with positive losses are identified and receive the minimum uplift payment, $UP_g(d)$, calculated below to compensate their losses:

$$UP_g(d) = \left|\sum_{t=1}^{24} R_g^{E+R}(d,t) - \sum_{t=1}^{24}(OC_{g,(d,t)} + SUC_{g,(d,t)})\right| \quad \text{(B.8)}$$

In Equation B.8, $R_g^{E+R}(d,t)$ represents the total revenues earned by producers from generating electricity and providing ramp capability reserves, plus total operating costs $OC_{g,(d,t)}$ and startup costs of generator *g* in day *d* and hour *t* $SUC_{g,(d,t)}$. When the uplift payments are calculated in an energy-only scheme, the revenues are calculated based on equation (B.6), so do not include the reserve capacity payments. This formulation does not include no-load costs or shut-down costs which are both assumed to be zero.

To clarify the impact of alternative design on the uplift payments, the uplift payments are decomposed into two components: *Uplift payment 1*, denoted by UP_g^1, and *Uplift payment 2*, denoted by UP_g^2. UP_g^1 represents a portion of the payment made to cover the start-up costs, and UP_g^2 the other pricing non-convexities.

$$UP_g^1(d) = \left|\sum_{t=1}^{24} R_g^{E+R}(d,t) - \sum_{t=1}^{24}(SUC_{g,(d,t)})\right| \tag{B.9}$$

$$UP_g^2(d) = UP_g(d) - UP_g^1(d) \tag{B.10}$$

4. Differences Between the EMST and PJM and between ADMC with Ramp Capability Requirements and MISO's Ramp Capability Products

There are several differences between the Electricity Market Simulation Tool (EMST) and the algorithms governing PJM operations. First, EMST is focused on short-term daily operation and trades and does not represent the long-and mid-term forward and futures markets because these are irrelevant to the paper's objectives. Likewise, capacity markets that deal-with long revenue sufficiency and resources adequacy are not modeled either.

The representation of the real-time market operation has also been simplified to reduce the computational burden of the comparative analysis, or to isolate the effects of the different ways for coping with wind power uncertainty. In order to reduce computational complexity, the EMST runs on a test-system that includes 67 fossil-fired generators (20,000MW of capacity) representing the 1300 conventional generators of PJM (159219 MW of capacity as reported in NEEDS v.5.13). Also, the EMST runs a look-ahead unit commitment and a single-period economic dispatch for hour-long periods, instead of 5-minute periods as done in PJM. Also, the EMST assumes power transmission constraints are not binding and hence does not represent the transmission system. Additionally, as stated in the manuscript, to isolate the effects of wind-power uncertainty, the EMST assumes perfect foresight on electricity demand, and does not consider or represents the scheduled or forced outages of the generation fleet. Finally there are two important differences in the representation of the market clearing. The first is that PJM has not introduced load-following reserve requirements or ramp capability products. The EMST instead, when running the ADMC market clearing mechanism, includes the provision of these reserves in the DA. The second difference, is that the timing and frequency of the intraday re-optimization processes are a bit different between the EMST and PJM, as explained below.

PJM's daily operations have a two-stage hierarchical structure following the sequence of financial markets operations and physical delivery of energy in real time. The financial commitments are first determined a day in advance of the system operation and revised in real-time markets in minutes to an hour of the real-time delivery, as all market participants have the opportunity to revise their day-ahead bids/offers during the rebidding period a few hours prior to the operating day. After the rebidding period and prior to the operating day, other out-of-market operations are carried to assure sufficiency of resources that provide reactive power supply, voltage support and stability, and black start services, which is referred to as Reliability Assessment Commitment (RAC) [60]. During the operation day, real-time operations are optimized by two economic dispatch engines, Intermediate-Term Security Constrained Economic Dispatch (IT-SCED) and Real-Time Security Constrained Economic Dispatch (RT-SCED). IT-SCED is a multi-interval model that guides the commitment of fast resources for 4 periods within a 2-hour look-ahead period. RT-SCED is a single-interval dispatch model that runs every 5 minutes to produce the optimal real-time dispatch of all resources and the financially binding Locational Marginal Prices (LMP) [60], [94].

It is also important to note that, the implementation of flexibility-reserves or ramp-capability requirements in the EMST under ADMC is different than what has been implemented in MISO or CAISO. MISO's design includes both DA and RT ramp capability products. Similar to DA ramp products, RT ramp products are enforced to ensure that resources are positioned at any period, so the system has sufficient upward and downward ramping capability to follow wind production fluctuations within the upcoming 5-minute intervals between 15-minute RT unit commitment runs [7]. Also, CAISO has only introduced RT ramp products and has not included DA ramp products in its proposed design [8]. Therefore, EMST shares the design of DA ramp products with MISO, though the ramp capability targets are quantified differently in EMST. EMST differs from both MISO and CAISO in that it does not include RT ramp products. This is because EMST does not replicate the intra-hour market operations in RT to reduce the computational time of running the yearly simulations.

5. Quantifying system-wide up and down ramp capability requirements

This section describes the procedure for determining the up and down ramp capability requirements, denoted by RC^{Up} and RC^{Dn}. This process occurs in three steps: 1) determination of how much of the uncertainty on future deviations must be covered by RC^{Up} and RC^{Dn}. We call this, determination of "Ramp Capability Requirement Rule", 2) characterization of the DA uncertainty on hourly wind power production by determining the probability distribution function or the DA forecast error for each hour, and 3) determination of RC^{Up} and RC^{Dn} based on the rule found in the first step and the cumulative probability distribution function of wind power deviations from the DA forecast found in the second step. The next sub-sections describe these three steps in a way that facilitates the explanation. In 5.1 we describe the third step and then the second step. In 5.2 we describe the first step.

5.1 Determining Ramp Capability Requirements

The example below shows how hourly up and down ramp capability requirements are calculated. Let's assume that *Dev* is a random variable representing the deviation in MW of wind production from a day-ahead forecast. If the production is less than the forecast, Dev takes a negative value. If it is more than the forecast it takes a positive value. If the production is identical to the forecast, Dev takes a value of zero.

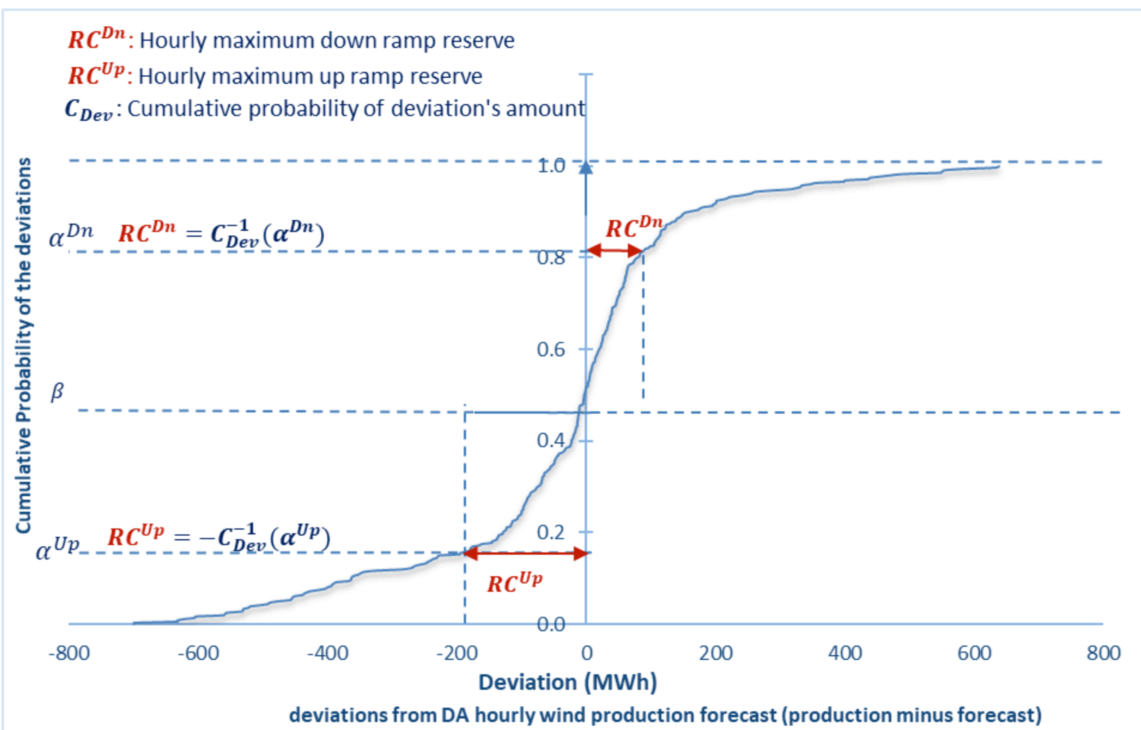

Figure 23: Relationship between Ramp Capability Requirements and CDF of the RT Deviations from DA Wind Production Forecasts for a Sample Hour

Hence, the range of this random variable is between minus infinite and infinite, with a cumulative probability distribution function C_{Dev} as depicted in Figure 23. Let's also assume that it has already been determined that it is cost-effective to set RC^{Dn} such that the probability of Dev being less than RC^{Dn} is α^{Dn} (a number closer to one). Similarly, let's assume that it has been established that it is cost effective to set RC^{Up} in a way such that, the probability of Dev being less than $-RC^{Up}$ is α^{Up}(a number closer to zero). In other words, the values of RC^{Dn} and $RC^{Up}$are set in terms of the inverse of the cumulative probability function of Dev $C_{Dev}$and the "rules" α^{Up} and α^{Dn}as stated in equations B.11 ad B.12 below:

$$RC^{Dn} = C_{Dev}^{-1}(\alpha^{Dn}) \tag{B.11}$$

$$RC^{Up} = -C_{Dev}^{-1}(\alpha^{Up}) \tag{B.12}$$

The first step in the determination of ramp-capability requirements consists of characterizing the uncertainty on deviations of production from DA forecasts through the calculation of an empirical cumulative probability distribution function. The cumulative probability distribution of deviations is calculated for each hour from the set of scenarios used in the stochastic market clearing following three steps:

Step 1) for each scenario in hour *h,* deviation from the expected production, as the DA wind production forecast, is calculated;

Step 2) the calculated deviations are sorted in an ascending order; and

Step 3) an empirical cumulative distribution function is formed by summing the associated probabilities of sorted deviations.

5.2. Estimating the Ramp Capability Requirement Rule

The optimal values of α^{Up} and α^{Dn} are identified using an iterative search method that runs the Electricity Market Simulation Tool (EMST) for multiple combinations of α^{Up} and α^{Dn} and fine-tunes them after each run until the optimal outcomes are found. The procedure begins with an initial value for α^{Up} and no down ramp capability requirement and proceeds with setting the optimal value for α^{Up}. The next step maintains α^{Up}constant and increases α^{Dn} and down ramp capability requirement until the optimal α^{Dn} is found. At every step of the iterative process, the reliability criteria (annual not-supplied energy must equal zero) is also checked to assure it is not violated. However, in all cases studied in this paper, when the penalty for under generation is set at $3000/MWh (or VOLL), the reliability criteria is not violated even when the capability requirements are set to zero. After the reliability is checked and ensured, RC^{Up} is decremented until its optimal is found. Conversely, the search process increases α^{Dn} from zero to determine its optimal value. The iterative procedure has been illustrated in Figure 24 and summarized by the following steps:

Step 1) Initial values are assigned to α^{Up} and α^{Dn} to determine the initial deviation uncertainties covered by ramp capability requirements ($\alpha^{Up} = \beta - 0.25$ and $\alpha^{Dn} = \beta$ meaning $RC^{Dn} = 0$).

Step 2) The annual system simulation is run with Augmented Deterministic Market Clearing (ADMC) and the pre-specified α^{Up} and α^{Dn} to determine the annual operation cost and not supplied energy.

Step 3) If the annual not-supplied energy is greater than zero, reduce α^{Up} by 0.1 and repeat Step 2, and go to Step 4 otherwise.

Step 4) Increase α^{Up} by decrements of 0.05, simulate the system operation, and calculate the annual not-supplied energy and operation cost.

Step 5) If the annual operation cost is lower than the previous iteration, go back to step 4; otherwise, $\alpha^{Up} - 0.05$ (corresponding to the value of α^{Up} in the previous iteration) is the optimal value.

Step 6) Keep α^{Up} constant, increase α^{Dn} by 0.05, simulate the system operation, and calculate the annual operation cost.

Step 7) If the annual operation cost is lower than the previous iteration, go back to step 6; otherwise, $\alpha^{Dn} - 0.05$ is the optimal value (corresponding to the value of α^{Dn} in the previous iteration) is the optimal value.

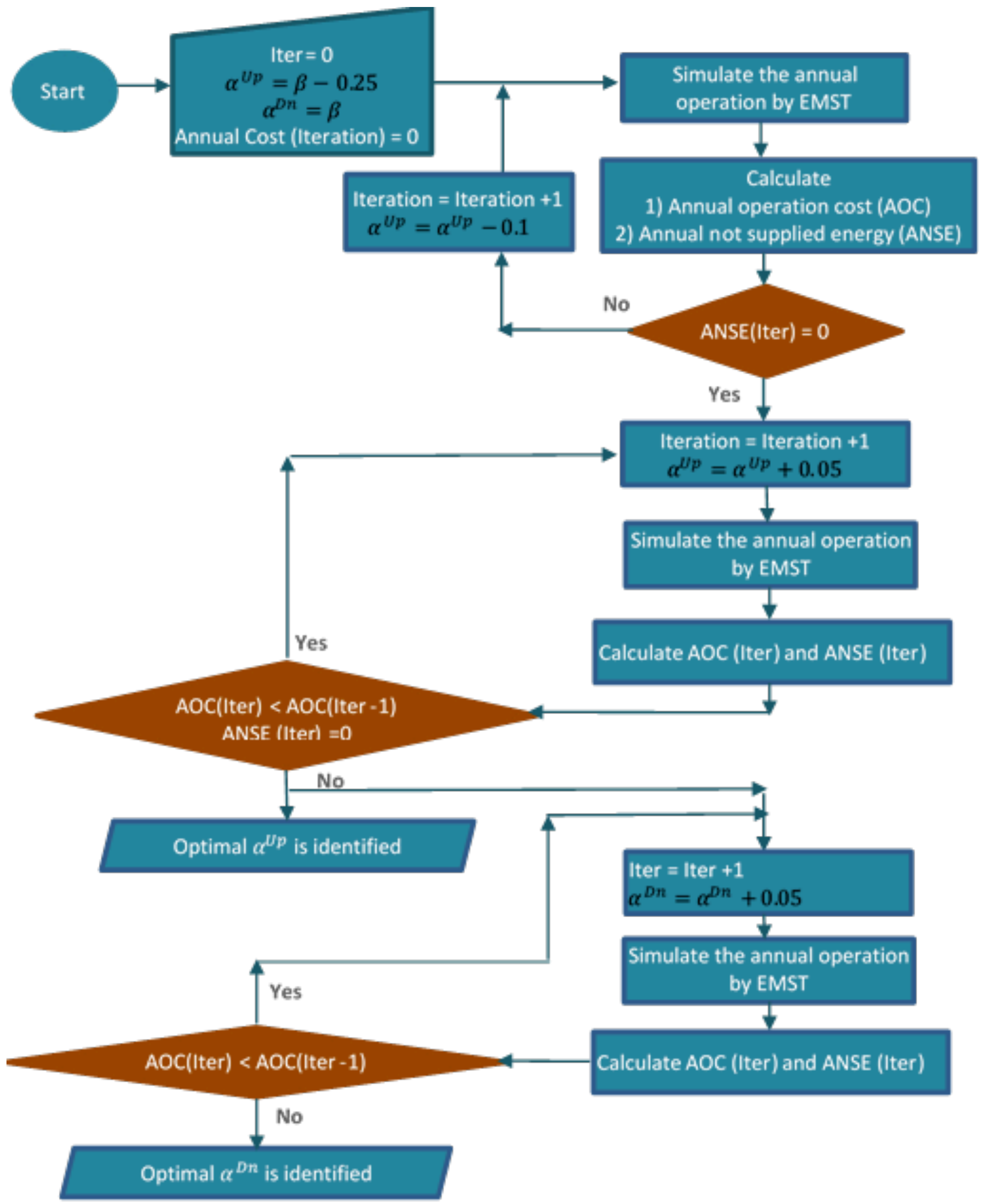

Figure 24: Flowchart of the Iterative Procedure for Identifying the Ramp Capability Requirement Rule

6. Case Study

6.1. Aggregation Procedure of the PJM's Generation Mix

Step 1: PJM's generation fleet data is obtained from NEEDS v5.13.

Step 2: 45 different groups are defined for categorizing similar plants, where each group is represented by 4 specific ranges for capacity, technology, fuel, and heat rate based on the PJM's generation mix.

Step 3: The reported plants are categorized into the defined groups based on their technology, fuel, capacity, and heat rate.

Step 3: After the set of plants in each group is specified, total nameplate capacity of plants within each group and the respective share of each cluster from PJM's installed capacity is calculated. This is to determine the corresponding chunk of each group in a down-scaled system such that each cluster in the scaled system represents the whole set of units in PJM's test grid. Table A presents the set of 30 major groups.

Step 4: Weighted average heat and emission rates of the units that represent each group are calculated.

Step 5: For the down-scaled system, which has 20000 MW installed fossil-fired capacity, respective installed capacity of each group is calculated. This is to determine the total nameplate capacity of each group in the scaled system.

Step 6: Given the capacity range of each group and its installed capacity in the scaled system, a proper number of units are selected to represent the group in the scaled system. For each group, the number of units and their associated capacities are selected to ensure their overall capacity matches the total nameplate capacity of that group in the scaled system, and their assigned capacities do not violate the specified capacity range of the group.

Table 25: Sample Set of Electricity Production Plant Categories Defined Based on Production Technology, Capacity, and Heat Rate to Group the PJM Fossil-Fired Generation Fleet

Coal-fired steam turbine					
Capacity range (MW)	Heat rate range 1 (Btu/MWh)	Heat rate range 2 (Btu/MWh)	Heat rate range 3 (BTU/MWh)	Heat rate range 4(BTU/MWh)	
<100	9000-12000	12000-15000			
100-200	9000-12000				
200-400	9000-10000	10000-11000			
400-600	8000-10000	10000-11000			
600-1000	8000-10000	10000-12000			
>1000	>=8000				
NG-fired combined cycle (NGCC)					
<100	7000-9000	9000-11000			
100-200	6000-8000	8000-10000			
200-400	6000-8000	9000-12000			
NG-fired combustion turbine (NGCT)					
<50	10500-11500	11500-12500	12500-13500	13500-14500	14500-15500
50-100	9500-10000	10000-10500	10500-12000	12000-14000	14000-15500
100-150	10500-12000	16000-17000	17000-18000	18000-19000	
150-250	10000-11000	11000-12000	12000-13000	13000-14500	14500-16000
Oil-fired combustion turbine (oil CT)					
<50	9500-11500	11500-13000	13000-15000		
50-100	14000-15000	15000-16000	16000-17000	17000-18000	18000-19000
100-150	14000-16000				
Nuclear					
800-1288	10500-11000				

6.2. Specification of the Test Grid's Fossil-Fired Generating Units

Table 26 to Table 28 present the cost and emission specifications of the fossil-fired generating units included in the test-system. Table 29 and Table 31 summarize technical characteristics, including ramp rates, as well as min-up-time and min-down-time constraints. Finally, Table 32 presents all technical specifications of generating units and the sources from which they were collected.

Table 26: Fuel, Cost, and Emission Specifications of Test Grid's Coal Units

ID	Type	Max gen (MW)	Min gen (MW)	Heat rate (mmbtu/MWh)	Startup (SU) heat & cost		Emission rates (ER) (lb/mmbtu)		
					SU Heat input (mmbtu/SU)	Fixed cost ($/SU)	SO_2	NO_x	CO_2
1	Coal	161	64	10.822	1502	989	1.97	0.31	220
2	Coal	93	37	10.828	868	571	1.97	0.31	220
3	Coal	204	81	10.835	1903	1253	1.97	0.31	228.9
4	Coal	92	37	12.921	858	565	1.93	0.39	209.6
5	Coal	65	26	12.928	606	399	1.93	0.39	209.6
6	Coal	279	112	10.406	2603	1713	2.8	0.33	226.3
7	Coal	173	69	10.414	1614	1062	2.8	0.33	226.3
8	Coal	438	175	10.420	4087	3495	2.8	0.33	226.3
9	Coal	265	106	9.633	2472	1627	2.86	0.3	230.8
10	Coal	346	138	9.639	4844	2761	2.86	0.3	230.8
11	Coal	242	97	10.347	2258	1486	1.88	0.29	222.3
12	Coal	422	169	10.354	5908	3368	1.88	0.29	222.3
13	Coal	461	184	9.537	6454	3679	3.29	0.17	250
14	Coal	664	266	9.544	9296	5299	3.29	0.17	250

15	Coal	392	157	10.519	5488	3128	0.14	0.11	224.9
16	Coal	1046	418	9.559	14644	8347	2.79	0.1	232.4
17	Coal	1152	461	9.565	16128	9193	2.79	0.1	232.4
18	Coal	980	392	10.250	13720	7820	1.83	0.08	213.5
19	Coal	1254	502	9.703	17556	10007	0.32	0.12	226.2

Table 27: Fuel, Cost, and Emission Specifications of Test Grid's NGCC, Nuclear, and Oil CT Units

ID	Type	Max gen (MW)	Min gen (MW)	Heat rate (mmbtu/MWh)	Startup (SU) heat & cost		Emission rates (lb/mmbtu)		
					SU Heat input	SU Fixed	SO_2	NO_x	CO_2
20	NGCC	283	141.5	8.513	68	849	0	0.07	131.4
21	NGCC	104	52	9.490	25	312	0	0.0312	99.7
22	NGCC	138	69	9.498	33	414	0	0.0312	99.7
23	NGCC	69	34.5	15.117	17	207	0	0.12	228.9
24	NGCC	200	107	7.278	51	642	0	0.0164	142
25	NGCC	214	107	7.285	51	642	0	0.0164	142
26	NGCC	224	107	7.289	51	642	0	0.0164	142
27	NGCC	226	114	7.293	55	684	0	0.0164	142
28	NGCC	228	114	7.298	55	684	0	0.0164	142
29	NGCC	230	114	7.305	55	684	0	0.0164	142
30	NGCC	232	114	7.315	55	684	0	0.0164	142
31	NGCC	150	75	9.183	36	450	0	0.049	129.7
32	NGCC	224	112	11.185	54	672	0	0.024	94.5
33	NGCC	474	237	7.466	114	1422	0	0.014	140.5
34	Nuclear	1037	1037	10.520	0	74000	0	0	0

35	Nuclear	1271	1271	10.525	0	74000	0	0	0
36	Nuclear	1037	1037	10.530	0	74000	0	0	0
37	Nuclear	1271	1271	10.535	0	74000	0	0	0
38	Oil CT	40	15	10.170	70	87	0.86	1.36	199.8
39	Oil CT	46	15	12.050	70	87	1.77	2.09	197.4
40	Oil CT	52	15	13.760	70	87	1.8	0.8	186.3
41	Oil CT	99	33	14.630	151	188	1.01	0.65	187.1
42	Oil CT	67	22	15.497	103	127	1.37	0.63	181.5
43	Oil CT	83	28	16.426	127	158	1.18	0.72	178.2
44	Oil CT	94	31	18.615	144	179	0.55	0.94	91.7
45	Oil CT	150	50	15.287	33	143	0.65	0.69	188.6

Table 28: Fuel, Cost, and Emission Specifications of Test Grid's NGCT Units

Gen Unit ID	Type	Max gen (MW)	Min gen (MW)	Heat rate (mmbtu/MWh)	Startup (SU) heat & cost		Emission rates (lb/mmbtu)		
					SU Heat input (mmbtu/SU)	SU Heat input (mmbtu/SU)	SO_2	NO_x	CO_2
46	NGCT	92	31	9.624	141	175	0	0.07	133.5
47	NGCT	55	18	10.204	84	105	0	0.08	132.8
48	NGCT	51	17	10.756	78	97	0	0.08	132.8
49	NGCT	48	16	11.172	73	91	0	0.12	117.9
50	NGCT	35	12	12.213	54	67	0	0.72	126.8
51	NGCT	76	25	13.437	116	144	0	0.36	125.7
52	NGCT	27	9	14.409	41	51	0	0.59	121.5
53	NGCT	35	12	15.247	54	67	0	0.38	126.7

54	NGCT	152	51	16.756	233	289	0	0.4	124.7
55	NGCT	128	43	18.143	196	243	0	0.5	131.7
56	NGCT	120	40	10.988	26	114	0	0.13	124
57	NGCT	207	69	12.158	46	197	0	0.06	124.6
58	NGCT	180	60	12.165	40	171	0	0.06	124.6
59	NGCT	184	61	13.060	40	175	0	0.09	129.3
60	NGCT	214	71	15.268	47	203	0	0.14	141.8
61	NGCT	281	94	10.861	62	267	0	0.12	147.1
62	NGCT	210	70	12.213	46	200	0	0.09	132.1
63	NGCT	115	38	17.248	25	109	0	0.38	112.9
64	NGCT	188	63	11.064	41	179	0	0.05	133.4
65	NGCT	188	63	11.069	41	179	0	0.05	133.4
66	NGCT	221	74	12.422	49	210	0	0.06	117.9
67	NGCT	221	74	12.428	49	210	0	0.06	117.9

Table 29: Technical Specifications of Test Grid's Coal Units

ID	Type	Ramp rates (MW/Min)		Min Up time (hour)	Min Down time (hour)
		Up	Down		
1	Coal	3.2	3.2	10	8
2	Coal	1.8	1.8	10	8
3	Coal	4.1	4.1	10	8
4	Coal	1.8	1.8	10	8
5	Coal	1.3	1.3	10	8
6	Coal	5.6	5.6	10	8
7	Coal	3.5	3.5	10	8

8	Coal	8.8	8.8	10	8
9	Coal	5.3	5.3	10	8
10	Coal	6.9	6.9	10	8
11	Coal	4.8	4.8	10	8
12	Coal	8.4	8.4	10	8
13	Coal	9.2	9.2	10	8
14	Coal	13.3	13.3	10	8
15	Coal	7.8	7.8	10	8
16	Coal	20.9	20.9	10	8
17	Coal	23.0	23.0	10	8
18	Coal	19.6	19.6	10	8
19	Coal	25.1	25.1	10	8

Table 30: Technical Specifications of Test Grid's NGCC, Nuclear, And Oil CT Units

ID	Type	Ramp rates (MW/Min)		Min Up Time (hour)	Min Down Time (hour)
		Up	Down		
20	NGCC	14.2	14.2	5	4
21	NGCC	5.2	5.2	5	4
22	NGCC	6.9	6.9	5	4
23	NGCC	3.45	3.45	5	4
24	NGCC	10.7	10.7	5	4
25	NGCC	10.7	10.7	5	4
26	NGCC	10.7	10.7	5	4
27	NGCC	11.4	11.4	5	4

28	NGCC	11.4	11.4	5	4
29	NGCC	11.4	11.4	5	4
30	NGCC	11.4	11.4	5	4
31	NGCC	7.5	7.5	5	4
32	NGCC	11.2	11.2	5	4
33	NGCC	23.7	23.7	5	4
34	Nuclear	20.7	20.7	24	24
35	Nuclear	25.4	25.4	24	24
36	Nuclear	20.7	20.7	24	24
37	Nuclear	25.4	25.4	24	24
38	Oil CT	3.5	3.5	2	1
39	Oil CT	3.5	3.5	2	1
40	Oil CT	3.5	3.5	2	1
41	Oil CT	7.5	7.5	3	3
42	Oil CT	5.1	5.1	3	3
43	Oil CT	6.3	6.3	3	3
44	Oil CT	7.1	7.1	3	3
45	Oil CT	11.4	11.4	3	3

Table 31: Technical Specifications of Test Grid's NGCT Units

ID	Type	Ramp rates (MW/Min)		Min Up Time (hour)	Min Down Time (hour)
		Up	Down		
46	NGCT	7.0	7.0	3	3
47	NGCT	4.2	4.2	2	1

48	NGCT	3.9	3.9	2	1
49	NGCT	3.6	3.6	2	1
50	NGCT	2.7	2.7	2	1
51	NGCT	5.8	5.8	3	3
52	NGCT	2.1	2.1	2	1
53	NGCT	2.7	2.7	2	1
54	NGCT	11.6	11.6	3	3
55	NGCT	9.7	9.7	3	3
56	NGCT	9.1	9.1	3	3
57	NGCT	15.7	15.7	3	3
58	NGCT	13.7	13.7	3	3
59	NGCT	14.0	14.0	3	3
60	NGCT	16.3	16.3	3	3
61	NGCT	21.4	21.4	3	3
62	NGCT	16.0	16.0	3	3
63	NGCT	8.7	8.7	3	3
64	NGCT	14.3	14.3	3	3
65	NGCT	14.3	14.3	3	3
66	NGCT	16.8	16.8	3	3
67	NGCT	16.8	16.8	3	3

Table 32: Test Grid's Operational Parameters and Data Sources

Parameter	Unit	Description	Source	Value
Min generation	% per MW of installed capacity (NPC)	Minimum generator output level	Coal Plants: Report by Renewable Northwest Project [140] and paper [6] NGCT Plants: value also match the approximate averages from table 27, page 66 of [141] by the German Institute for Economic Research (DIW Berlin)	PC[1] (0-800 MW): ~40% of NPC PC (>800): ~40% of NPC (Ref: approximate averages from table 4 of [140]) NGCC: 40-60% of NPC (assuming an average of 50%) page 3 of [142], consistent with a Siemens report [143] NGCT: 33% of NPC (Average value as per estimates in [144], [145]
Start-up C&M	Start-up Capitalized		Median values for warm start from Page 12, table 1-1 of [146]	PC (0-299): 157 $/MW

[1] Pulverized Coal (PC) power plant

Costs	Cycling and Maintenance costs ($/ MW of NPC) (Capitalized cycling and maintenance costs occur due to higher non-routine maintenance and capital replacement costs as a result of cycling)			PC (>300): 65 $/MW NGCC: 55 $/MW NGCT(>=65): 126 $/MW NGCT(<65 MW): 24 $/MW NGST: 58 $/MW
Fixed costs for start-ups	Auxiliary power, water additives etc.	$/MW NPC	Table 1-3, Page 30 of NREL report on power plant cycling costs [146] * The given number for nuclear units comprises of fixed and variable costs for startups as reported in [90] * The nuclear unit starts once and remains on afterwards	PC (0-299): 6.14 $/MW-Start PC (>300): 7.98 $/MW-Start NGCC: 3$/MW-Start [147] NGCT (>=65 MW): 0.95 $/MW-Start NGCT (<65 MW): 1.90 $/MW-Start

				NGST: 6.86 $/MW-Start Nuclear: 74000 $/Start [90]
Start-up heat input	mmbtu/MW-start	It is multiplied by fuel price to calculate the variable cost for startup	Table 1-3, pg 30 of NREL report on power plant cycling costs [146]	PC (0-299): 9.33/MW-Start PC (>300): 14/MW-Start NGCC: 0.24/MW-Start NGCT: 1.53/MW-Start
Ramp Rates	% NPC/min	Max. allowable change in dispatched power between two consecutive intervals for given generator	Report by European Local Electricity Production [A10], Data from GE Website [145] All values match the approximate averages from table 26, page 64 of [141] by DIW Berlin	PC: 2% of NPC Table 3, pg 22 [A10] NGCC: 5% Table 3, pg 22 [148] NGCT- 7.6 % [145]
Min up time	hours	Minimum time required for unit to start up and reach full load	PJM Monitoring Analytics report [149] * Nuclear units operate at full load at all time after they start	Coal units: 10 h NGCC: 5 h NGCT (<65 MW): 2 h NGCT (>=65 MW): 3 h

				Nuclear: 8760 h *
Min down time	hours	Minimum time required for generator following a shut-down needed before starting up again	PJM monitoring analytics report [149] * Nuclear units operate at full load at all time after they start	Coal units: 8 h NGCC: 4 h NGCT (<65 MW): 1 h NGCT (>=65 MW): 3 h Nuclear *
Fuel Prices	$/mmbtu		NG, Oil, and Coal: EIA database	Coal, NG, and Oil: Average monthly prices of coal, oil, and natural gas delivered to power as reported by the EIA's Electricity Data Browser for the PJM region in year 2016 [114] Nuclear: Total cost of reactor fuel including

				raw fuel price, conversion, enrichment, and fabrication [83], [84]
Emission Rates				[112], [113]
Quick start capability			Lawrence Berkeley National Laboratory report [144]	NGCT: Yes Coal: No NGCC: No Oil CT: Yes Nuclear: No
Reserves to meet peak load and LOLE			PJM report, page 9 [81] Comments: May vary by region or by state. Present variation is from 14.2% (MISO) to 18% (PJM)	15.5%

7. Numerical Results

7.1. Simulated DMC Versions to be Compared with SMC

Table 33: Simulated DMC Versions to Be Compared With SMC

	Ramp-capability requirements	Ramp capability reserve payments
DMC	----	----
ADMC	✓	✓
ADMC-RP	✓	----

7.2. Market Settlement and Cost Implications of DMC and SMC Mechanisms (M$)

Table 34: Market Settlement and Cost Implications of DMC and SMC Mechanisms (M$)

Outcomes (M$)	DMC	ADMC-RP	ADMC	SMC
Total plants Cost	Base (1,125)	-0.36%	-0.36%	-0.90%
DA plants' cost	Base (1,124)	-0.29%	-0.29%	-3.38%
RT plants' costs	Base (0.5)	-152.31%	-152.31%	5536.93%
Total Start-up costs	Base (27.5)	-17.00%	-17.00%	-27.40%
Producers' revenue	Base (1,809)	3.32%	3.40%	1.73%
Producers' surplus	Base (684)	9.36%	9.59%	6.36%
Consumers' surplus	Base (258,205)	-0.023%	-0.024%	-0.012%
Social Surplus	Base (258,888)	0.002%	0.002%	0.005%
UP 1	Base (21)	-45.13%	-47.27%	-58.25%
UP 2	Base (3)	-49.85%	-55.17%	-55.20%

7.3. Shift in Distribution of Revenues Among Different Production Technologies

Table 35: Shift in Distribution of Revenues Among Different Production Technologies (%)

Share of revenues (%)	DMC	ADMC-RP	ADMC	SMC
Coal	Base (33.45%)	-1.15%	-1.13%	-1.83%
NGCC	Base (10.95%)	0.93%	0.95%	1.28%
Nuclear	Base (44.22%)	0.25%	0.21%	0.22%
Oil	Base (0.00%)	0.00%	0.00%	0.00%
NGCT	Base (0.29%)	-0.08%	-0.08%	0.05%
Wind	Base (11.09%)	0.05%	0.05%	0.28%

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Biography

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