Enhanced Reserve Procurement Policies for Power Systems with Increasing Penetration Levels of Stochastic Resources

by

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ABSTRACT

The uncertainty and variability associated with stochastic resources, such as wind and solar, coupled with the stringent reliability requirements and constantly changing system operating conditions (e.g., generator and transmission outages) introduce new challenges to power systems. Contemporary approaches to model reserve requirements within the conventional security-constrained unit commitment (SCUC) models may not be satisfactory with increasing penetration levels of stochastic resources; such conventional models procure reserves in accordance with deterministic criteria whose deliverability, in the event of an uncertain realization, is not guaranteed. Smart, well-designed reserve policies are needed to assist system operators in maintaining reliability at least cost.

Contemporary market models do not satisfy the minimum stipulated *N*-1 mandate for generator contingencies adequately. This research enhances the traditional market practices to handle generator contingencies more appropriately. In addition, this research employs stochastic optimization that leverages statistical information of an ensemble of uncertain scenarios and data analytics-based algorithms to design and develop cohesive reserve policies. The proposed approaches modify the classical SCUC problem to include reserve policies that aim to preemptively anticipate post-contingency congestion patterns and account for resource uncertainty, simultaneously. The hypothesis is to integrate data-mining, reserve requirement determination, and stochastic optimization in a holistic manner without compromising on efficiency, performance, and scalability. The enhanced reserve procurement policies use contingency-based response sets and post-contingency transmission constraints to appropriately predict the influence of recourse actions, i.e., nodal reserve deployment, on critical transmission elements.

This research improves the conventional deterministic models, including reserve scheduling decisions, and facilitates the transition to stochastic models by addressing the reserve allocation issue. The performance of the enhanced SCUC model is compared against contemporary deterministic models and a stochastic unit commitment model. Numerical results are based on the IEEE 118-bus and the 2383-bus Polish test systems. Test results illustrate that the proposed reserve models consistently outperform the benchmark reserve policies by improving the market efficiency and enhancing the reliability of the market solution at reduced costs while maintaining scalability and market transparency. The proposed approaches require fewer ISO discretionary adjustments and can be employed by present-day solvers with minimal disruption to existing market procedures.

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TABLE OF CONTENTS

CHAPTER Page

CHAPTER Page

CHAPTER Page

CHAPTER Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

Figure Page

NOMENCLATURE

ACPF	Alternating current power flow
ATC	Available transfer capability
c	Contingency index.
C	Set of contingency scenarios.
CAISO	California Independent System Operator
C^g	Set of generator contingencies.
$C_g(\quad)$	Variable operating cost (or production cost) for generator g.
$C^{g^{crt}} \subseteq C^g$	Subset of critical (credible) generator contingencies.
C_{gj}	Variable operational cost for generator g and segment j.
$C^{g^{ncrt}} \subseteq C^g$	Subset of non-critical generator contingencies.
C_g^{NL}	No-load cost for generator g.
C_g^{res}	Reserve cost for generator g.
C_g^{SD}	Shutdown cost for generator g.
C_g^{SU}	Startup cost for generator g.
C^l	Set of transmission element contingencies (includes non-radial transmission lines and transformers).
C_{LS}	Penalty cost to relax the node balance constraint (or cost associated with load shed/surplus) to ensure the feasibility of the contingency analysis problem.
c_n	Linear operating cost for the generator at node n.
COI	California-Oregon intertie
CRR	Congestion revenue right
DA	Day-ahead
DAM	Day-ahead market

DCOPF	Direct current optimal power flow
DDP	Desired dispatch point
D_n	Real power demand at node n (variable).
$\overline{D_n}$	Fixed real power demand at node n.
DNE	Do-not-exceed
D_{nt}	Real power demand at bus n in period t (assumed to be perfectly inelastic).
D_{nst}	Real power demand at bus n for net load scenario s in period t.
DT_g	Minimum down time for generator g.
EMS	Energy management system
EPRI	Electric Power Research Institute
ERCOT	Electric Reliability Council of Texas
FERC	Federal Energy Regulatory Commission
F_k^-, F_k^+	Pre-contingency flowgate marginal prices. Dual variables (or shadow prices) on transmission asset k's normal capacity constraints; lower and upper bounds respectively.
F_k^{c-}, F_k^{c+}	Post-contingency flowgate marginal prices. Dual variables on critical transmission asset k's emergency capacity constraints under critical contingency c; lower and upper bounds respectively.
$F_l^{RateA}, P_k^{max,a}$	Normal capacity (i.e., rate A) for the corresponding transmission asset (thermal limit or stability limit). Typically, $P_k^{min,a} = -P_k^{max,a}$.
$F_l^{RateC}, P_k^{max,c}$	Emergency capacity (i.e., rate C) for the corresponding transmission asset. Typically, $P_k^{min,c} = -P_k^{max,c}$.
F_{lt}	Real power flow for transmission element l and period t (variable).
$F_{lt_{k-z(c)}}$	Real power flow for inter-zonal transmission element l, connecting zone k and contingency zone $z(c)$, and period t (variable).
FTR	Financial transmission rights

g	Generator index.
G	Set of generators.
GDF	Generation loss distribution factor
$GDF_{n'(c),n}$	Generation loss distribution factor for contingency c at node n.
G^f	Set of fast-start generators.
$G^k \subseteq G$	Subset of generators located in zone k.
$G^n \subseteq G$	Subset of generators located at node (bus) n.
G^S	Set of slow-start generators.
i_{nct}	Net real power injection at bus location n for contingency state c and period t (variable).
i_{nt}	Net real power injection at bus location n for period t (also used to refer to the no contingency state, variable).
IROL	Interconnection reliability operating limit
ISO	Independent system operator
ISO-NE	ISO New England
k, l	Transmission asset (line or transformer) index.
K, L	Set of transmission assets (line or transformer).
$K^{crt} \subseteq K$	Subset of critical transmission assets.
KKT	Karush-Kuhn-Tucker
$L^{crt} \subseteq L$	Subset of critical transmission assets.
LMP	Locational marginal price
LODF	Line outage distribution factor
$LS^{+}_{n,c,t}$	Load shed at bus location n under contingency c in period t (variable).
$LS^{-}_{n,c,t}$	Load surplus (or over generation) at bus location n under contingency c in period t (variable).

M	Penalty cost for the OMC action of either adjusting the desired dispatch point (DDP) of a previously committed unit or modifying the commitment status of an originally offline unit.
M^{DDP}	Penalizes the OMC action of adjusting the DDP for a formerly committed unit.
MILP	Mixed-integer linear programming
MISO	Midcontinent Independent System Operator
MMS	Market management system
M^{RES}	Penalizes the OMC action of adjusting the scheduled reserve from a formerly committed unit.
n	Node (or bus) index.
N	Set of node (or bus) locations.
$n'(c)$	Node index for generator loss under contingency c.
$n(c) \in N$	Bus location of the contingency generator c.
NERC	North American Electric Reliability Corporation
$n(g) \in N$	Bus location of generator g.
NREL	National Renewable Energy Laboratory
OMC	Out-of-market correction
OOS	Out-of-sample
OPF	Optimal power flow
$P_{g,c,t}$	Real power production from generator g for contingency state c and period t (variable).
P_g^{max}	Real power maximum output (or maximum capacity bound) for generator g.
P_g^{min}	Real power minimum output (or minimum capacity bound) for generator g.
P_{gj}^{max}	Real power maximum output for generator g and segment j.

P_{gt}	Real power production from generator g for period t (also used to refer to the no contingency state, variable).
$\overline{P_{gt}}$	Scheduled real power production from generator g for period t (obtained and fixed from a prior scheduling stage).
PJM	Pennsylvania-New Jersey-Maryland Interconnection
P_n	Real power production from the generator at node n (variable).
P_n^c	Real power production from generator at node n under contingency c (variable).
P_n^{max}	Real power maximum capacity for the generator at node n.
PTDF	Power transfer distribution factor
$PTDF_{k,n}^R$	Proportion of flow on transmission asset k resulting from injection of one MW at node n and a corresponding withdrawal of one MW at reference node R.
$PTDF_{n,l}$	Sensitivity of real power flow on transmission asset l to an injection at node n with withdrawal at reference bus.
$PTDF_{n,l}^{BC}$	Sensitivity of real power flow on transmission asset l to an injection at bus n with withdrawal at reference bus, for the base case (i.e., the no contingency state) or for a contingency state with a generator outage.
$PTDF_{n,l}^{C}$	Sensitivity of real power flow on transmission asset l to an injection at bus n with withdrawal at reference bus, for a contingency state with a transmission element outage c.
RAS	Remedial action schemes
R_g^{10}	Maximum ten-minute ramp up/down rate for generator g.
R_g^{60}	Maximum hourly ramp up/down rate for generator g.
R_g^{SD}	Maximum shutdown ramping capability for generator g.
R_g^{SU}	Maximum startup ramping capability for generator g.
r_{gt}	Reserve from generator g for period t (variable).
$\overline{r_{gt}}$	Scheduled contingency reserve from generator g for period t (obtained and fixed from a prior scheduling stage).

r_{gt}^{c}	Activated reserve from generator g in response to generator contingency c for period t (variable).
$r_{g,s,t}^{c}$	Activated reserve from generator g in response to generator contingency c during training net load scenario s and period t (variable).
$\tilde{r}_{kt}^{c}$	Reserve in zone k that is classified as deliverable for generator contingency c and period t (variable).
RT	Real-time
RTCA	Real-time contingency analysis
s	Net load scenario index.
S	Set of net load scenarios.
SCED	Security-constrained economic dispatch
SCOPF	Security-constrained optimal power flow
SCUC	Security-constrained unit commitment
S^{FR}	Set of nodes that have generators with frequency response capability.
SFT	Simultaneous feasibility test
$S_{kt}^{z(c)}$	Reserve sharing limit from zone k to contingency zone $z(c)$ (variable).
SOL	System operating limit
$S^{OOS} \subseteq S$	Subset of out-of-sample (OOS) testing net load scenarios.
$S^{TRN} \subseteq S$	Subset of training net load scenarios.
t	Time period index.
T	Set of time periods.
UC	Unit commitment
UCTE	Union for the Coordination of the Transmission of Electricity
u_{gt}	Binary unit commitment variable for generator g and period t (0 indicates offline, whereas 1 indicates online).

$\overline{u_{gt}}$	Scheduled unit commitment status for generator g and period t (obtained and fixed from a prior scheduling stage).
u_n	Scheduled unit commitment status (0: offline, 1: online) of the generator at node n.
UT_g	Minimum up time for generator g.
v_{gt}	Startup variable for generator g and period t (1 for startup, 0 otherwise).
VOLL	Value of lost load
w_{gt}	Shutdown variable for generator g and period t (1 for shutdown, 0 otherwise).
z, k	Reserve zone index.
Z	Set of reserve zones.
$z(c) \in Z$	Reserve zone where generator contingency c is located.
α	Choice of benchmark reserve sharing policy.
α_n	Dual variable on generator's (at node n) capacity constraint; upper bound constraint.
$\overline{\beta_{g,l,t}^{c}}$	Reserve response factor for responsive generator g and critical transmission asset l under critical generator contingency c in period t.
β_n^c	Dual variable on generator's (at node n) response to contingency c constraint.
$\bar{\gamma}_{n'(c),n}$	Recognizes the node with generator loss under contingency c (1 if contingency node, else 0).
δ	Dual variable on system-wide power balance constraint (marginal energy component of LMP).
δ_{gt}	Binary variable that allows for a modification of either a unit's DDP or its commitment status through an OMC action (1 if the OMC procedure chooses to modify the DDP of a formerly committed unit or the commitment status of a previously offline unit, 0 otherwise).
δ_{gt}^{DDP}	Continuous variable that allows for a modification of the DDP of a formerly committed generating unit through an OMC action.

δ_{gt}^{RES} Continuous variable that allows for a modification of the scheduled reserve from a formerly committed generating unit through an OMC action.

$\eta\%$ Percentage of system-wide demand.

λ_n Locational marginal price (LMP) at node n. Dual variable that signifies the increase (or decrease) to the primal objective if there is slightly more (or less) consumption by the demand at node n.

$\rho^{BC}, (\rho^{C})$ Probability of occurrence of the no contingency state or the base case (outage/contingency scenario c).

$\mathit{\Gamma}_{gt}^{c}, \left(\overline{\mathit{\Gamma}_{gt}^{c}}\right)$ Reserve activation factor for generator g under generator contingency state c and period t (determined from training phase).

CHAPTER 1.

INTRODUCTION

1.1. Motivation

Maintaining a continuous supply of electricity is of paramount importance to society. The society expects high reliability because the cost to society is high if there is a blackout. This is evident from the Northeast blackout of 2003, which is estimated to have cost around $4-$10 billion [1]. Therefore, to ensure a continuous and reliable supply of electricity, electricity markets acquire ancillary services (or reserves) to protect against unexpected events. The Federal Energy Regulatory Commission (FERC) defines ancillary services as: "those services necessary to support the transmission of electric power from seller to purchaser, given the obligations of control areas and transmitting utilities within those control areas, to maintain reliable operations of the interconnected transmission system," [2]. In other words, reserve is defined as backup capability that provides flexibility to satisfy energy imbalances and mitigate uncertainty. Existing ancillary services include several types of reserves. Quick-reserve products, such as regulation and flexible ramping, respond to small forecast deviations that occur frequently, 10-minute reserves (i.e., spinning and non-spinning) respond to contingencies, and 30-minute reserves are used to replace other categories of reserve as they are depleted. It is important to note that only spinning reserve is considered in this research; however, the proposed solution methodologies can be extended to account for other reserve products.

Due to the complexities of resource scheduling (e.g., security-constrained unit commitment, SCUC) for the electric power grid while accounting for uncertainties, existing market management systems (MMS) are deterministic and incorporate various approximations in order to simplify such complex combinatorial optimization problems. Section 1.2 details a few instances of such approximations (or existing industry practices) that are commonly employed to handle large-scale complex models. One such suite of approximations includes reserve policies/products that have been introduced by system operators to ensure system reliability. Most system operators adopt deterministic criteria for contingency reserve requirements. Such deterministic criteria often necessitate the contingency reserves to be greater than the capacity of the largest online generator or a certain percentage of the peak demand, or equal to some combination of the aforementioned criteria [3]. While such deterministic criteria are generally easy to implement, they do not consider the inherent stochastic nature of such problems. Consequently, there is no guarantee that reserves, which are procured by the market, will actually be deliverable without violating transmission or voltage constraints.

A deterministic model assumes perfect forecast with no uncertainty and does not take in account post-contingency states when making the scheduling decisions, i.e., ignores the effects of stochastic resources and nodal reserve deployment on physical network limitations (e.g., congestion) post-contingency. In addition, existing approaches fail to allocate reserves at prime locations that face fewer deliverability issues due to the inadequate representation of varying system operating conditions.

The ideal solution is to model the uncertainty inside the optimization model (e.g., unit commitment, UC). This can be achieved by using stochastic programming approaches, e.g., extensive form, or two-stage stochastic programs, that determine reserve requirements implicitly by considering the corrective actions explicitly [4]–[5]. In [6]–[9], uncertainties are explicitly represented in the model and are solved simultaneously. By explicitly formulating the network constraints (and corrective actions), the reserves are ensured to be deliverable for the events that are modeled explicitly. Due to the more accurate representation of the pre- and post-contingency operating states (or the endogenous representation of uncertainty), no pre-defined reserve requirements are necessary. While stochastic programming has the benefit of ensuring reliable solutions relative to the modeling complexity, the limitation is the required computational complexity to ensure highly reliable solutions. Therefore, the computational challenges limit the potential modeling capabilities and, hence, limit the reliability and quality of the solutions. Robust optimization is another approach that has been often proposed as a method to improve solution reliability for UC problems. Robust optimization guarantees a feasible solution for any possible realization in the modeled uncertainty set. Recently, more attention has been given to robust optimization in the power systems sector [10]–[11]. However, the corresponding solutions are often very conservative, and the associated total operating costs tend to be correspondingly high. In addition, robust optimization today is still too computationally challenging for large-scale UC models.

While stochastic and robust optimization techniques are preferred since they implicitly determine reserve, these methods, by themselves, are incapable of ensuring efficient and reliable UC solutions within reasonable timeframes. Instead, a balanced approach is desirable as reserve policies can act as necessary conditions for solution feasibility and can be used to improve convergence of these algorithms as well as make up for inaccurate assumptions that are placed within these approaches in order to improve the convergence of these complicated combinatorial problems. Thus, this work aims to provide advanced yet practically implementable solutions, while striking a good balance between complexity and model accuracy. The central idea is to start with something attainable that still makes a sizeable improvement – and then march in the direction of (and enhance) advanced stochastic programming techniques.

It is noteworthy that significant improvements can be achieved by operating the system based on stochastic optimization (or Monte Carlo simulations) that leverages statistical information of an ensemble of uncertain scenarios; note that stochastic optimization is used in this work as a broader term than stochastic programming. Thus, the hypothesis is to integrate data-mining, reserve requirement determination, and stochastic optimization in a holistic manner without compromising on efficiency, performance, and scalability. This dissertation will focus on developing new reserve policies that extend beyond existing reserve procurement rules, which are static. Existing reserve policies are predominantly independent of the operating state. Thus, this dissertation will develop dynamic reserve policies that take into consideration the anticipated operational state of the network. By doing so, the reserve policies will improve the deliverability of reserves. The reserve policies will be designed to identify key locations where contingency reserve and ramping reserves for resource uncertainty are needed.

The research will primarily focus on two methods to develop these reserve policies. First, the utilization of data analytics-based algorithms to develop reserve policies, that approximately encapsulate the abundance of information that is available regarding other potential realizations of uncertain scenarios to improve reserve scheduling decisions, will be investigated where offline analysis based on Monte Carlo simulations (or historical data) will be used. Second, responsive based reserve policies will also be investigated. Such reserve policies establish a set of generators (resource providing reserves) that are designated to respond to an event since their reserves are deemed to be deliverable under the operating state of the network. These response sets can be determined at different time intervals and they can be fed into real-time security assessment tools to determine the security of the system. Finally, this research will also look into testing the contemporary reserve assumptions, used by independent system operators (ISOs); the new reserve policies will be compared against the traditional reserve policies to demonstrate that the new reserve policies are better at identifying critical locations for reserve procurement. Besides, without the advent of new dynamic reserve policies, those responsible and obligated by the North American Electric Reliability Corporation (NERC) to maintain system reliability will continue to rely on traditional but less effective approaches to maintaining reliability. In addition, it is pertinent to note that, this work focuses on typical forms of uncertainty like generator contingency, load uncertainty, and renewable uncertainty; line contingency is not addressed because traditional SCUC models already include transmission contingencies. In addition, since NERC mandates only N-1 reliability, this work does not focus on multiple contingencies; however, it could be extended in future to accommodate the same.

The main outcomes of this dissertation, with respect to reserve policies, include: (1) responsive-based reserve policies that are embedded inside of the UC framework in order to endogenously determine participation factors. (2) Enhanced dynamic reserve policies that acknowledge system operating conditions. (3) A methodology that utilizes offline knowledge discovery processes on historical data or leverages Monte Carlo simulations that generate hypothetical data. (4) Enhanced scheduling models for ancillary services (i.e., contingency reserves) to improve its allocation and deliverability in systems with renewable resources, while preserving the computational complexity. (5) Finally, a comprehensive evaluation of the proposed reserve models, including their impacts on market efficiency and system reliability.

1.2. Existing Industry Practices

As per the reliability standards set by NERC, the system is required to be able to withstand an N-1 event. In other words, given a system with N elements, operators are required to continue serving demand reliably following the failure of any single bulk power system element. With such reliability requirements, the ideal approach would be to model all N-1 events explicitly within the SCUC model. However, it is a challenge to model the full network model for a large-scale power system and have it solved within the required time frame for just the pre-contingency state let alone the added computational complexity of adding post-contingency states. For example, as reported in [12], the Midcontinent Independent System Operator (MISO) manages a system with about 45,000 buses. In order to meet the market clearing time requirements, MISO employs a 1200 seconds time limit and a 0.1% MIP relative gap to solve its day-ahead (DA) SCUC model. MISO further mentions that it constantly encounters performance challenges in solving its DA SCUC model, which only includes the pre-contingency state, in spite of the aforementioned limits; thus, expanding the model in order to explicitly represent contingency scenarios within the model would be computationally burdensome. Therefore, to address the performance challenges that arise from large-scale systems, the ISOs in the United States presently rely on heuristics, approximations, and policies rather than solving stochastic programs.

The utilization of such approximations is evident in industry practices. For instance, all mixed-integer linear programs (MILPs) for power systems, such as expansion planning and transmission switching, are approximations. The commonly used UC formulation is a natural evolution of approximations and heuristics that have been present in the literature for many years. The dc optimal power flow (OPF) problem uses a linear approximation of the non-linear ac power flow. Another popular practice used by the industry is the reduction of the power transfer distribution factor (PTDF) matrix used in scheduling models by omitting PTDFs, which have an absolute value less than a cutoff value. The California ISO (CAISO) uses a 2% cutoff while MISO and the Pennsylvania-New Jersey-Maryland (PJM) Interconnection employ a 5% PTDF cutoff threshold [13]–[15]. A simple yet neat heuristic policy like this can help reduce the computational burden drastically. Further approximations, such as the aggregation of radial nodes, the use of engineering judgment to reduce the PTDF matrix to model only critical components (i.e., lines and buses), the removal of inconsequential lines (i.e., lines that regularly have flows that are less than their nominal rates) from the full network model, and the use of interface limits to approximate the flows on a subset of lines are common industry practices.

ISOs use dynamic operating transfer capability and nomograms to effectively manage and control the scheduling of generation and critical line flows such that the reliability of the system is ensured. Nomograms are a set of rules that are used to describe safe operating regions and are developed to identify or define simultaneous (or multiple) operating constraints or scheduling limits without having to include the corresponding constraints in the model explicitly [16]. The central idea behind using nomograms is to operate the system, defined by the nomogram, such that no thermal, stability or voltage limits are violated following the occurrence of an uncertain scenario. Nomograms are usually developed by analyzing the results from offline studies, performed under normal and emergency system conditions, using prior operating experience with the system and by predicting future operating conditions for the system.

One widely known nomogram being used by CAISO is the one that controls the power flow on the California-Oregon intertie (COI). Nomograms are developed to identify simultaneous operating limits between COI and other transmission paths. The allowed transfer on the COI is restricted based on the flow on other critical paths. For example, the rating of the COI may be reduced to 4500 MW from 4800 MW if another path, i.e., the NW-Sierra path (Path 76), is utilizing its entire capacity of 300 MW [16]. In addition, as stated in [16], CAISO uses another nomogram to model the relationship between the hydro generation in the northern California region and the flow on the COI, which in turn affects the COI's rating. The main motivation behind these nomograms is to maintain system reliability with easier to handle proxy constraints. Dependent on how these proxy methods are implemented, such preventive actions may inappropriately reduce the economic efficiency. However, the goal of the energy market is to operate the system at least cost while maintaining reliability. Consequently, approximations remain a necessary approach to help strike a balance between model complexity and model accuracy.

1.3. Overview of the Dissertation

This dissertation is structured as follows. Chapter 2 provides a literature review. A thorough review of contemporary industry-based policy-driven approaches, which are currently embedded within forward dispatch optimization models, to ensure sufficient reserve is presented. However, the majority of these approaches have primarily focused on the quantitative aspect of reserve, whereas this research focuses on the locational and the deliverability aspects of the reserve. In addition, existing efforts by researchers from both academia and industry in the direction of advanced stochastic programs and stochastic reserve determination, in order to address uncertainties and adequately reflect changing operational conditions, are presented. However, the implementation of stochastic programs for large-scale power systems is a significant challenge due to its computational tractability and the market barriers associated with the pricing of products (i.e., energy and reserve) within such models.

Chapter 3 presents an overview of electric energy optimization problems that are germane to this dissertation. In particular, it discusses the formulation for the deterministic unit commitment problem as well as the extensive form N-1 reliable unit commitment problem. A discussion of the contingency analysis problem for assessing the effects (on security) of removing individual bulk elements (e.g., generator, transformer, transmission line, etc.) from an electric power system is presented.

Operators make uneconomic adjustments, outside of the market (or optimization engine), to ensure reliability when SCUC provides a solution that has undeliverable reserve or potential security violations. Two out-of-market correction (OMC) formulations are proposed in Chapter 4 to quantify the cost of security violations. The OMC approaches are proposed to mimic and optimize the out-of-market correction procures that are often employed by operators, wherein a market solution is traditionally modified and corrected (ex-post) by a system operator manually to find a solution that is N-1 reliable. The OMC approach provides a more appropriate and objective way to evaluate the cost to correct security violations in comparison to the value-of-lost-load (VOLL) approach. A case study is conducted on a modified IEEE 118-bus system, wherein the proposed OMC models are used to evaluate the reliability of the system and are compared with the traditional VOLL approach. Finally, the proposed OMC models are used in the future chapters to conduct a fair comparison between the various SCUC solutions that have different costs and ensure different levels of security. The proposed OMC models are designed to pull the various SCUC solutions to a valid N-1 reliable solution or achieve the same level of reliability.

Chapter 5 presents an enhanced SCUC model, which is modified to include a heuristic reserve policy that aims to preemptively anticipate post-contingency congestion patterns and account for uncertainty, simultaneously. The proposed heuristic policy uses post-contingency transmission constraints to predict the influence of recourse actions under critical generator contingencies and to cover a range of uncertain scenarios by defining reserve response factors, which are determined offline using a data-mining algorithm. The main motive is to address both the locational and the deliverability issues that are usually associated with reserve. The performance of the proposed data-driven reserve response set policy is compared against two sets of deterministic reserve policies and an extensive form stochastic UC model. Testing on a modified 2383-bus Polish test system illustrates that the proposed reserve model can improve market efficiency and enhance the reliability of the market solution at reduced costs while maintaining scalability and transparency.

Chapter 6 presents an enhanced reserve procurement approach, which improves upon existing deterministic reserve rules and can potentially facilitate the transition to stochastic models. The proposed approach aims to address the allocation and deliverability issues associated with reserve by using reserve response-set policies and by appropriately modeling the predicted effects of nodal reserve deployment on critical transmission lines post-contingency. Here, the reserve response-set policies include scenario-specific reserve activation factors, which incorporate deliverability information. In other words, the reserve activation factors reflect the quotient of scheduled reserve that is potentially deliverable in a specific scenario. The results show that the proposed approach improves the deliverability of reserve post-contingency at reduced system operating costs, and with minimal added computational burden. In addition, the proposed approach is demonstrated to perform between traditional deterministic approaches and futuristic stochastic models. Numerical studies are conducted on the IEEE 118-bus test case and on the 2383-bus Polish test case respectively.

Chapter 7 analyzes the market implications of recent industry movements that modify the traditional market auction models to model generator contingencies more appropriately. A primal auction (and the corresponding dual) formulation that accounts for the proposed changes is provided to enable a theoretical analysis of the anticipated changes including, but not restricted to, effect on market prices, settlements and revenues. A comparison to existing market structures is also included.

Finally, chapter 8 concludes this dissertation along with a discussion on potential future work.

CHAPTER 2.

LITERATURE SURVEY

With the increasing integration of non-dispatchable (or semi-dispatchable) resources, such as wind and solar, managing system operations while maintaining system reliability is a critical challenge. This chapter reviews the state-of-the-art approaches to respond to these challenges including an overview of existing deterministic reserve policies that are included in present-day SCUC formulations; stochastic programming; robust optimization; and stochastic optimization-based approaches.

2.1. Existing Deterministic Reserve Rules and Practices

The majority of the large balancing authorities employ deterministic reserve criteria that primarily focus on the quantitative and not the locational aspect of reserves and are predominantly independent of the system operating state. The underlying reason for this assumption is that the procured reserve is assumed to be deliverable irrespective of the system congestion/operating state. In order to improve the deliverability of reserves in large-scale power systems while maintaining the computational tractability of the model, one potential solution is to utilize policy-driven approaches to provide enhancement to existing scheduling models, i.e., SCUC and security-constrained economic dispatch (SCED) models. Due to the limitations of stochastic programs, today, the industry uses a deterministic approach to model scheduling problems, wherein the reserve requirements (system-wide or zonal) are modeled as inputs to the model and are determined a priori based on heuristics (e.g., N-1 reliability criterion, or based on predicted information regarding intermittent resource output and system demand, etc.).

2.1.1. Myopic Policies

A policy is defined as "a rule (or function) that determines a decision given the available information in a specific state," [17]. Myopic policies are regarded as elementary policies since they do not explicitly use forecasted information or any direct representation of decisions in the future [17]. An instance of once such myopic policy, in the context of reserve rules, is the existing practice to approximate the *N*-1 reliability criterion for generator contingencies. *N*-1 reliability is achieved by ensuring the system can withstand the loss of any single bulk system element. For generator contingencies, *N*-1 is often approximated by something similar to (2.1); (2.1) simply requires a MW level of contingency reserve to be acquired somewhere in the system for any particular generator contingency. This MW level of contingency reserve is a system-based quantity requirement. Today, most of the existing reserve rules involve some sort of approximations. Equation (2.2) describes a variant of the approximate *N*-1 policy and requires the system-wide reserve to be no less than a certain percentage (η) of the system-wide demand. Furthermore, in [18], the National Renewable Energy Laboratory (NREL) suggests that the creation of such simplified linear rules, such as the 3+5 rule, hold promise to be used by market operators to allocate reserves to handle load and wind variability. The 3+5 rule suggests that the system-wide reserve should be no less than 3% of load plus 5% of the short-term forecasted wind. Such conservative heuristic rules do not ensure that the reserve is not stranded behind a congested portion of the network.

$$\sum_g r_{gt} \geq P_{gt} + r_{gt}, \forall g \in G, t \in T \tag{2.1}$$

$$\sum_g r_{gt} \geq \eta\% \sum_n D_{nt},\ \forall t \in T. \tag{2.2}$$

It is evident that myopic policies generally employ such tunable parameters to potentially produce decent performances over time. However, since contemporary mathematical programs, used within MMS, rely on such simplistic proxies for reserve requirement, the market solutions may procure reserves that are not deliverable. Furthermore, with the integration of stochastic resources, it is becoming increasingly more challenging to maintain system reliability at least cost.

2.1.2. Reserve Zones

Myopic policies do not guarantee reliable operations (or ensure reserve deliverability) because they are formulaic rules that only capture the quantitative aspect. Therefore, in the recent years, the paradigm has shifted to regional (or zonal) reserve policies that disperse the reserves across the system, thereby, improving the deliverability of reserve by ensuring that sufficient reserve is held within import-constrained regions. Today, system operators use the following approximations to address the locational aspect of reserves: 1) reserve zones, 2) artificially de-rate critical transmission interfaces that connect neighboring regions, and 3) nomograms that approximate the available transfer capability (ATC) on critical transmission paths. Enforcing reserve requirements on a zonal basis rather than a system-wide basis is a policy choice. Besides, the myopic policies detailed in Section 2.1.1 can be viewed as equivalent single-zone reserve models.

It is pertinent to note that, most of the transmission system operators treat reserve zones as static in spite of the varying operational conditions. In fact, a few of the popular ways to determine reserve zones are either based on geographical boundaries or on the similarity in the impact (i.e., PTDFs) that a cluster of buses have on the flows on a set of selected pre-defined critical paths (i.e., inter-zonal interfaces or commercially significant interfaces) instead of basing it on system operating conditions [19]. Furthermore, zonal reserve models typically include reserve zone configuration studies that are dependent on pre-defined and rarely updated guesstimates of anticipated transmission constraints, despite the constantly changing system operating conditions. Thus, operators are usually forced to manually disqualify generators (behind unanticipated bottlenecks) or turn on additional units in local areas to account for modeling inaccuracies and to overcome the aforementioned shortfalls. Such operator-initiated modifications, which are made after the fact (i.e., outside the market), reduce market efficiency and referred to as out-of-market corrections (OMCs). The terminology used for such actions varies between entities; for instance, such mediations are categorized as exceptional dispatches in CAISO [20], out-of-merit capacity/energy in the Electric Reliability Council of Texas (ERCOT) [21], and reserve disqualifications in MISO [22].

In order to account for changing congestion patterns, recent literature suggests updating zones on a more frequent basis. Reference [23] proposes a model for updating zones on a daily or an hourly basis by using probabilistic power flows to reflect changing system operating conditions. As the level of penetration of renewables increases, traditional static zones will no longer be able to adequately reflect the changing operating conditions in the system; thus, dynamic reserve zones are proposed to account for the variability and uncertainty associated with renewable resources in addition to N-1 contingencies. In addition, the authors in [23] employ a statistical clustering algorithm (K-means), which uses a centrality measure based on weighted power transfer distribution factors (PTDFs), to produce the reserve zones. However, [23] does not consider reserve sharing between zones. MISO typically performs their reserve zone reconfiguration studies in conjunction with their quarterly network model updates, however, the studies can be performed within a quarter if the system state deviates considerably [22], [24]-[25].

It is pertinent to note that, the adoption of dynamic reserve zones has faced significant implementation barriers due to opposition from market participants/stakeholders regarding the potential uncertainty over which zone they will be a part of because of how it would impact their profit and bidding strategy and due to the costs associated with updating the market clearing software. However, updating zones more frequently may improve the efficiency of the market model and reduce the need for uneconomic adjustments, like reserve disqualification, which cause further market distortions.

Today, many ISOs have developed ways to account for reserve sharing when there is ATC on inter-zonal links. A simplistic representation of one such benchmark static zonal reserve model [26] used in this work, which is an extension of the model used by ISO New England (ISO-NE) [27], is described below.

$$\sum_{k \in Z} \tilde{r}_{kt}^{c} \geq P_{ct} + r_{ct}, \forall c \in C^{g}, t \in T \tag{2.3}$$

$$\tilde{r}_{kt}^{c} \leq \sum_{g \in G^{k}} r_{gt}, \forall c \in C^{g}, k \in Z, t \in T \tag{2.4}$$

$$\tilde{r}_{kt}^{c} \leq S_{kt}^{z(c)}, \forall c \in C^{g}, k \in Z, t \in T \tag{2.5}$$

$$S_{kt}^{z(c)} \leq \alpha \left(F_{l_{k-z(c)}}^{RateC} \right) \pm F_{lt_{k-z(c)}}, \forall c \in C^{g}, k \in Z, t \in T\,. \tag{2.6}$$

The aforementioned model accounts for reserve sharing or artificial derating of critical transmission interfaces that connect adjacent zones. Here, $\tilde{r}_{kt}^{c}$ is described as the reserve in zone k that is classified as deliverable for contingency c in contingency zone $z(c)$ and period t. In addition, P_{ct} and r_{ct} are the pre-contingency real power-production and the scheduled reserve from generator g, respectively. $F_{lt_{k-z(c)}}$ is the power flow on the inter-zonal line connecting zones k and the contingency zone $z(c)$. $F_{l_{k-z(c)}}^{RateC}$ is the emergency line rating of the corresponding inter-zonal line. The reserve model presented in [26] does not account for uncertainties from stochastic resources. Note that the aforesaid reserve-sharing model formulation is for mutually exclusive (adjacent) zones; however, the model can be reformulated to model nested zones.

Equation (2.3) requires the sum of the imported reserves and the reserve in contingency zone $z(c)$ to be sufficient to replace the underlying generator contingency, (2.4) requires the quantity of the exported reserves to be no greater than the amount of reserves that are held within the corresponding exporting zone (or zone k), and (2.5) restricts the amount of reserves that can be shared (i.e., exported or imported) between adjacent zones, i.e., zone k and the contingency zone $z(c)$. Constraint (2.6) limits the maximum amount of reserves that can be shared between two adjacent zones to the ATC (i.e., emergency line rating less the line flow) of the corresponding inter-zonal interface connecting the two zones. In other words, the transfer capability is equal to the ATC when α is equal to one in (2.6). In the context of this work, such a policy will be referred to as a liberal policy since there is no restriction on the percentage of the ATC (100%) that is allotted for reserve sharing. Alternately, the smaller the value of α the more conservative the corresponding reserve sharing policy. In other words, α controls and reflects the level of conservatism of the corresponding reserve sharing policy. Note that the algebraic sign of the second term in (2.6) is chosen based on the designated interface flow direction. For instance, the reserve import capability of $z(c)$ is increased ($+$ sign) if the "*from*" bus of the inter-zonal line is in $z(c)$ due to counter flow. Contrarily, the reserve import capability of $z(c)$ is decreased ($-$ sign) if the "*to*" bus of the inter-zonal line is in $z(c)$.

Here, the reserve sharing limit is system-dependent and can be pre-determined based on offline studies. Nevertheless, such estimates may be imprecise due to unanticipated congestion on the inter-zonal lines. Furthermore, effectively determining the optimum amount of reserves to be shared between zones still remains a challenge. Finally, such zonal reserve models are still rough approximations, since they treat all locations in the same zone as equal, ignoring intra-zonal congestion and leading to imprecise estimates of inter-zonal flows [28]. Thus, such models fail to address local congestion within zones. In other words, such a zonal model only partly addresses the inter-zonal deliverability issue; it does not address the intra-zonal reserve deliverability issue. Therefore, due to the limitations of the aforementioned approximations that aim to address the locational aspect of reserves, system operators are forced to rely on OMCs to correct for procured reserve that may not be deliverable to meet reliability standards [23].

2.1.3. Response Sets

To overcome the limitations of the aforementioned reserve models, recent papers in the literature have suggested introducing contingency-based sets/factors to allocate reserves at appropriate locations to better address reserve deliverability. Reference [29] constrains power flows based on participation factors that estimate how generators will respond to uncertain scenarios. In [26], the authors introduce contingency-specific response sets to suspend/disqualify reserve held at unfavorable locations. Here, a two-stage decomposition algorithm that dynamically updates the response sets (to account for changing system conditions) is proposed as an alternative market mechanism to determine OMCs.

The reserve modeling approach presented in this research is motivated by the enhanced co-optimization process proposed and adopted by MISO in [22]. MISO suggests enhancing the market clearing process by incorporating post zonal reserve deployment transmission constraints for a pre-defined set of transmission elements, which can be obtained from processes like simultaneous feasibility test, state estimation, or contingency analysis, to improve the transfer of reserves between zones in manageable time. By incorporating the post-contingency transmission constraints into the model explicitly, the zonal reserve quantity requirement is implicitly determined by the model rather than being provided as an input or a pre-determined policy. This removes the need to impose strict zonal reserve requirements since the reserve deployment constraints ensure adequate dispersion of reserve procurement. However, the pre-defined set of critical transmission assets in MISO's case can only include inter-zonal transmission elements; therefore, the approach presented in [22] does not address intra-zonal congestion related issues. The primary motive is to evaluate the aggregated impact of deployed zonal reserve, i.e., regulation, spinning, and supplemental reserve, on the pre-determined set of commercially significant transmission lines (such as the interconnection reliability operating limit (IROL) and the significant transmission system operating limit (SOL) constraints), in the post-generator contingency state explicitly to enhance reliable operations. In other words, these constraints capture the effects of critical generator contingencies and the underlying reserve deliverability issue on a zonal level. Note that to reduce the computational complexity, MISO restricts the reserve model to include only the largest generator contingency event per zone. Furthermore, MISO uses zonal aggregated sensitivities and pre-determined zonal reserve deployment factors to meet the reserve zone requirements, including market-wide reserve requirements and deliverability requirements, and to approximate actual reserve deployment for the modeled event. Such a zonal approach does not capture the effect of post-contingency reserve deployment on critical transmission paths aptly. Furthermore, MISO uses a simplistic approach to pre-determine the zonal reserve deployment factors to do away from the associated complexity in determining the corresponding nodal factors, as a result of which all the acquired reserves are then deployed on a zonal basis (potentially causing increased flow violations). An analogous approach for allocating and pricing operating reserves by modifying the SCED formulation is introduced in [30]. In addition, [30] includes an analysis on the effect of reserve allocation on generation scheduling.

Two-stage scenario-based stochastic programs are often proposed to enhance operations under uncertainties [6], [8]. Such two-stage stochastic programs optimize the recourse decision variable (or reserve activation) on a nodal (or zonal) basis inherently, whereas in [22], the primary difference is that MISO is implementing a zonal approximation with a pre-determined fixed reserve deployment factor. With this change, the industry is moving away from deterministic program formulations to a stochastic program structure; consequently, the solution is expected to be closer to the valid solution obtained from two-stage stochastic programs proposed in [6], [8].

Analogous to the generator contingency modeling approach adopted by MISO in [22], CAISO intends to enhance its scheduling models to include generator contingencies and pre-determined special protection schemes or remedial action schemes (RAS) explicitly without utilizing second-stage recourse decision variables [31]. Here, the post-contingency transmission constraints include generator loss distribution factors (GDF) analogous to the more familiar participation factors that are used today in real-time contingency analysis (RTCA) when simulating generator contingencies. Thus, there is evidence to the use of pre-determined participation (deployment) factors to model the reserve response to generator contingencies explicitly without utilizing second-stage recourse decisions. The key issue with such approaches lies in the appropriate determination of participation/deployment factors and the associated market pricing implications. Currently, system operators and market designers are exploring new policies to accommodate stochastic resources. This research proposes to improve upon existing industry practices to determine more appropriate nodal and zonal factors by leveraging stochastic optimization.

2.2. Advanced Stochastic Programming Techniques

The anticipated growth of intermittent resources, such as wind and solar, in the United States, has raised concerns about how system operators will maintain energy balance between generator production and demand because the availability of such resources is beyond human control and largely unpredictable. Today, to handle *N*-1 reliability, the industry solves deterministic SCUC and security-constrained optimal power flow (SCOPF) problems, with reserve requirements modeled within SCUC and SCOPF, which does not explicitly capture the uncertain event. Thus, there is a need to modify and enhance the existing deterministic formulations, while ensuring both reliability and economic efficiency, in order to capture the operating states pre- and post-contingency more accurately and to adapt to the challenges posed by stochastic resources [32]-[33].

2.2.1. Stochastic Programming

In the recent years, stochastic programming has been widely proposed as a solution to the task of optimizing reserve operations, to address system uncertainty, due to the fact that reserve dispatch decisions are optimized endogenously in the program formulation. One potential solution is to use scenario-based multistage stochastic programs [34]-[35]. For instance, two-stage stochastic programs explicitly model multiple scenarios and consider the cost for corrective actions (or recourse decisions); the obtained solution is both efficient and robust with respect to the scenarios considered in the stochastic program.

Current research has also aimed to address the uncertainty in day-ahead unit commitment, e.g., discrete disturbances including generator and transmission line outages and continuous disturbances including demand and renewable uncertainty, with the use of stochastic programming. For example, one of the modeling approaches to handling *N*-1 reliability is to use a two-stage stochastic unit commitment formulation, wherein the two stages represent the pre- and post-contingency states respectively. The two stages are linked together by constraints that govern how the system will respond to the contingency. A general, two-stage stochastic programming formulation for the unit commitment problem is investigated in [34], where reserve requirements are enforced to overcome the limitations of using a reduced scenario set. Reference [36] uses a two-stage stochastic programming framework to determine the required levels of reserve in systems with high wind penetration.

Extensive form stochastic unit commitment problems can be solved with decomposition techniques, where the master problem contains the modeling of the initially chosen scenarios as well as feasibility cuts generated by the sub-problem due to infeasibilities of remaining scenarios. The authors in [36] use the progressive hedging algorithm proposed in [37] to solve the stochastic unit commitment problem by decomposing it into *n* single-scenario sub-problems. Reference [38] employs a decomposition algorithm based on an augmented Lagrangian technique to solve a multistage stochastic unit commitment problem. Reference [39] proposes a heuristic solution methodology to solve multistage stochastic mixed-integer programming models. Furthermore, multiple techniques have been proposed, including, but not limited to, scenario selection techniques to reduce the number of scenarios, probability distributions for uncertain parameters, as well as chance-based constraints, [40]-[46]. However, these types of approaches (for example, Benders' decomposition, Lagrangian relaxation, etc.) are known for having long tails regarding convergence, which is why stochastic programming is still not used today for large-scale unit commitment problems. In addition, adding feasibility cuts to the master problem not only adds constraints but also variables.

In spite of its appealing features, the application of stochastic programming presents numerous challenges. For instance, a large number of scenarios may be required to obtain a solution with reasonable accuracy, which is computationally intensive. Another challenge is to develop a methodical approach for selecting and aptly weighing the uncertain scenarios that are to be included in the stochastic program. Furthermore, the implementation of stochastic programs for large-scale power systems is a significant challenge due to its computational tractability when it comes to solving large-scale stochastic programs within required timeframes. Other barriers that prevent such models from practical consideration include, but are not limited to, complications/market barriers associated with the pricing of products (e.g., energy and ancillary service) in a stochastic market environment, consistency of solution quality subject to solution timeframe, lack of transparency for stakeholders, scalability, and stakeholder opposition to drastic changes in existing market structures. Thus, one solution is to create proxy reserve requirements or policy functions for the quantity and location of reserves needed in the grid.

2.2.2. Robust Optimization

Recently, robust optimization has also been considered as an appealing formulation, in order to address uncertainty, due to the fact that system operators have a predisposition to operate the system in order to avoid worst-case consequences, and also because stochastic programming needs an excessive amount of information about the underlying uncertainty. In addition, robust optimization has the added advantage of providing a solution that is immune against all realizations of the uncertain data within the uncertainty set. For example, ISO-NE is exploring the use of robust optimization to determine what they define as do-not-exceed (DNE) limits for intermittent renewable power producers [47]-[49]. These DNE limits, however, are zonally structured limits; they do not take into consideration the locational aspect of the resource that causes the uncertainty, nor do they take into consideration the ramping reserve product that is meant to respond to such events. Such an approximation is made since the computational complexity of robust optimization exponentially increases for optimal power flow problems when the uncertainty is modeled on a locational basis. Reference [50] focuses on determining DNE limits for wind generators on a nodal basis; however, solving this class of optimization problems on a large-scale power system is a significant challenge given the modeling complexity.

A two-stage adaptive robust unit commitment model for the SCUC problem in the presence of nodal net injection uncertainty is proposed in [11], which requires a deterministic uncertainty set (i.e., moderate information about the underlying uncertainty) in comparison to a hard-to-obtain probability distribution on the uncertain data in the conventional stochastic programming approaches. Similar robust optimization UC models are proposed in [51]-[54]. Here, the authors use Benders' decomposition to solve the problem and illustrate that the addition of transmission capacity and ramp rate limits complicates the problem significantly. A unified stochastic and robust unit commitment model that combines the advantages of both the approaches, i.e., a low expected total cost while ensuring robustness, by introducing weights that control the corresponding part's effectiveness in the objective function is proposed in [55]. However, the aforementioned models only consider continuous uncertainty sets, i.e., intermittent renewable and demand uncertainty; in other words, such models do not extend to account for discrete uncertainties, such as generator and line outages, in an uncomplicated manner.

Robust optimization-based models have also proposed to address reserve deliverability. In [56], a robust optimization model with time-coupled affine policies is designed to improve reserve allocation in real-time operation. In addition, a clearing model for the policy-based reserves is designed. In [57], an affinely adjustable robust OPF formulation is developed. Participation factors are utilized in the model to adjust generation dispatch after renewable uncertainty is realized. In [58], a robust optimization framework is designed to address increased renewable uncertainties. Reserve deliverability is enhanced by using robust optimization techniques. A new concept named uncertainty marginal price is developed to price and allocate the cost of uncertainty. In [59], adjustable robust optimization is utilized to address generator and line contingencies in systems with renewable resources. Costs associated with reserve deployment are explicitly considered in the optimization model. While the aforementioned papers can effectively enhance reserve deliverability, these robust optimization-based models are computationally challenging when applied to SCUC problems for large-scale systems. More importantly, the implementation of such models would necessitate a complete market design overhaul because it is not aligned with existing market structures.

2.3. Stochastic Optimization-Based Techniques

Today, the uncertainty associated with renewable resources is handled by using operating reserves capacity. There is a general consensus that significant improvements could be achieved by devising a flexible operational plan that can follow different realizations of the future in an effective fashion. Effectively and efficiently controlling the quantity, location, and deliverability of contingency reserves (i.e., spinning and non-spinning) can lead to substantial cost savings and reliability enhancements in large-scale power systems. The hypothesis of this work is that a significant amount of the surplus lost in following the traditional and inefficient approaches can be regained by operating the system based on stochastic optimization that leverages statistical information of an ensemble of scenarios. The goal is to complement similar existing efforts in the industry.

An instance of the use of offline stochastic simulations for reserve determination, such as stochastic reserve determination, in the industry is evident in [60]. The Electric Power Research Institute (EPRI) proposes to use an offline stochastic programming approach for the CAISO to produce potential reserve quantities and locations (i.e., dynamic reserve procurement policies) in [60]-[61]. Here, a stochastic program is solved before the real-time (RT) model, i.e., during the intra-day scheduling period, and the results are used to determine dynamic reserve requirements that are to be included within

CAISO's RT market, which is a deterministic program. The authors in [61] simulate and deploy dynamic reserve policies based on stochastic OPF and study its potential benefits. Such an approach should make improvements beyond CAISO's existing reserve rules because it determines a quantity of reserve to procure within each of the CAISO's zones. However, this process can be enhanced because it relies on static reserve zones and neglects intra-zonal congestion.

2.4. Summary

With the current trend towards higher levels of intermittent renewable resources, the location, i.e., deliverability, of reserves will become more critical in addition to the quantity. Higher levels of renewables not only increase the reserve level but also increase the difficulty in predicting the network flows and the resulting bottlenecks. Furthermore, voltage transfer limits may limit the ability to deliver reserves. Today's static reserve policies, will, thus, be even more inefficient at achieving system reliability at least cost. Additional reserves will need to be acquired, thereby forcing generators to operate at undesirable production levels for the sake of providing reserves. While it is possible to rely on existing static reserve policies that inadequately reflect changing operational conditions, such procedures drive down the market surplus and it is anticipated that generator compensation will decrease as well in spite of the fact that they will be needed to provide even more reserves as the level of non-dispatchable resources increases. As a result, advanced stochastic programming techniques are being proposed to overcome the shortcomings of deterministic models. However, while more robust solutions can be obtained from stochastic programming models, stochastic programs are less computationally tractable when compared to deterministic models. This work aims to combine advanced reserve policies with stochastic optimization-based approaches to address the impacts of stochastic resources and improve the deliverability of reserve. The main motive is to support the existing efforts by academia and industry to schedule reserve appropriately with minimal added computational burden [60]-[63].

CHAPTER 3.

REVIEW OF ELECTRIC ENERGY OPTIMIZATION PROBLEMS

This chapter provides background information on the optimization problems that are pertinent to this dissertation; specifically, the deterministic unit commitment problem, the extensive form *N*-1 reliable unit commitment problem, and a preview of the contingency analysis problem.

3.1. Deterministic Unit Commitment Formulation

Unit commitment is the problem of scheduling generators in response to the anticipated system demand while accounting for physical network constraints. Numerous solution techniques for the unit commitment problem have evolved over time. This includes dynamic programming [64], Lagrangian relaxation [65]-[66], and MILP [67]-[68]. In this research, the day-ahead security constrained unit commitment model (DA SCUC) is formulated as a MILP. The objective (3.1) is to minimize the total operating costs, which includes the fuel costs (i.e., variable operating costs and fixed costs – no-load costs, startup costs, and shutdown costs) and the cost of reserves, subject to generator and network constraints. One potential formulation of the DA SCUC problem is described in (3.1)-(3.18). It is pertinent to note that, the demand is assumed to be perfectly inelastic in the formulation described below; consequently, minimizing total operating costs is equivalent to maximizing social welfare.

Minimize: $\sum_{g,t} C_g\left(P_{gt}\right) + C_g^{NL} u_{gt} + C_g^{SU} v_{gt} + C_g^{SD} w_{gt} + C_g^{res} r_{gt}$ (3.1)

Subject to:

$i_{nt} = \sum_{g \in G^n} P_{gt} - D_{nt}\,, \forall n \in N, t \in T$ (3.2)

$$\sum_n i_{nt} = 0, \forall\, t \in T \tag{3.3}$$

$$F_{lt} = \sum_n PTDF_{n,l} i_{nt}\,, \forall l \in L, t \in T \tag{3.4}$$

$$-F_l^{RateA} \le F_{lt} \le F_l^{RateA}, \forall l \in L, t \in T \tag{3.5}$$

$$P_{gt} + r_{gt} \le P_g^{max} u_{gt}, \forall g \in G, t \in T \tag{3.6}$$

$$P_g^{min}\, u_{gt} \le P_{gt}, \forall g \in G, t \in T \tag{3.7}$$

$$\sum_{q=t-UT_g+1}^{t} v_{gq} \le u_{gt}\,, \forall g \in G, t \in \{UT_g, \dots, T\} \tag{3.8}$$

$$\sum_{q=t-DT_g+1}^{t} w_{gq} \le 1 - u_{gt}\,, \forall g, t \in \{DT_g, \dots, T\} \tag{3.9}$$

$$0 \le r_{gt} \le R_g^{10} u_{gt}, \forall g \in G, t \in T \tag{3.10}$$

$$P_{gt} - P_{g,t-1} \le R_g^{60} u_{g,t-1} + R_g^{SU} v_{gt}, \forall g \in G, t \in T \tag{3.11}$$

$$P_{g,t-1} - P_{gt} \le R_g^{60} u_{g,t} + R_g^{SD} w_{gt}, \forall g \in G, t \in T \tag{3.12}$$

$$\sum_g r_{gt} \ge P_{gt} + r_{gt}\,, \forall g \in G, t \in T \tag{3.13}$$

$$\sum_g r_{gt} \ge \eta\% \sum_n D_{nt}\,, \forall t \in T \tag{3.14}$$

$$v_{gt} - w_{gt} = u_{gt} - u_{g,t-1}, \forall g \in G, t \in T \tag{3.15}$$

$$u_{gt} \in \{0,1\}, \forall g \in G, t \in T \tag{3.16}$$

$$0 \le v_{gt} \le 1, \forall g \in G, t \in T \tag{3.17}$$

$$0 \le w_{gt} \le 1, \forall g \in G, t \in T\,. \tag{3.18}$$

In the above formulation, constraint (3.2) models the power injection at every bus, whereas constraint (3.3) guarantees energy balance between the demand and the supply at the system level. The load at a bus is modeled as a withdrawal while generator supplies are injections. Constraint (3.4) represents the dc approximation of the power flow on each line and (3.5) imposes the transmission line capacity limits, i.e., either the thermal or the stability limits. Generators have physical/operational limitations with respect to their capacity and ramping ability. Constraints (3.6) and (3.7) represent the generator output limit constraints. Facet-defining valid inequalities that help improve the computational time of the unit commitment problem are used to describe the minimum up and down time constraints and are shown in (3.8)-(3.9) [69]. The minimum up (or down) time constraint requires a generator to be on (or off) for a pre-determined number of hours once it has been turned on (or off) due to the physical limitations of the corresponding generator. Constraint (3.10) represents the ramp rate restriction for spinning reserves, which is a ten-minute ancillary service product. It is important to note that, in this dissertation, contingency reserves are modeled by spinning reserves, and are subsequently used to mitigate the contingencies in the system. The hourly ramp rate constraints, shown in (3.11) and (3.12), describe the speed at which a unit can ramp up and ramp down its production levels between two consecutive hours or while starting up and shutting down, respectively. System-wide spinning reserve requirements are modeled in (3.13) and (3.14). Constraints (3.13) and (3.14) together require that the system-wide reserve be no less than the single largest generator contingency or $\eta\%$ of the total demand in the system, whichever is greater, in order to ensure system reliability. In other words, they describe a single-zone reserve model, which is also referred to as a myopic policy in the context of this dissertation. Constraint (3.15) models the relationship between the unit commitment variables and the startup and shutdown variables. Lastly, constraints (3.16)-(3.18) model the binary commitment (u) decision and the continuous startup (v) and shutdown (w) decisions respectively.

3.2. Extensive Form *N*-1 Reliable Unit Commitment Formulation

Prior studies of managing uncertainty in the unit commitment problem can be classified into two subgroups. The first subgroup, i.e., the deterministic unit commitment problem described above, uses conservative heuristic reserve rules to handle the uncertainty implicitly. However, the real-time condition may deviate significantly from the expected value of the operating condition resulting in capacity inadequacy. The second subgroup uses stochastic programming techniques that include a probability distribution of the uncertainty explicitly and depend upon a pre-sampled set of discrete scenarios of the uncertain realizations [11]. Thus, the reserve dispatch decisions are optimized endogenously. Uncertainty in power system operations is usually caused either by continuous disturbances (e.g., demand and renewable energy forecast errors) or by discrete disturbances (e.g., generator, transmission line, and transformer outages). The extensive form stochastic unit commitment formulation to manage discrete disturbances (i.e., for *N*-1 reliability) is defined by (3.19)-(3.55). The objective is to minimize the expected cost over a wide range of uncertain outage realizations.

Minimize: $\sum_{g,t} \rho^{BC} C_g(P_{gt}) + C_g^{NL} u_{gt} + C_g^{SU} v_{gt} + C_g^{res} r_{gt} + \sum_{g,c,t} \rho^c C_g(P_{g,c,t})$ (3.19)

Subject to:

Base-case modeling of generation:

$$P_g^{min} u_{gt} \le P_{gt}, \forall g \in G, t \in T \tag{3.20}$$

$$P_{gt} + r_{gt} \le P_g^{max} u_{gt}, \forall g \in G, t \in T \tag{3.21}$$

$$0 \le r_{gt} \le R_g^{10} u_{gt}, \forall g \in G, t \in T \tag{3.22}$$

$$P_{gt} - P_{g,t-1} \le R_g^{60} u_{g,t-1} + R_g^{SU} v_{gt}, \forall g \in G, t \ge 2 \tag{3.23}$$

$$P_{g,t-1} - P_{gt} \leq R_g^{60} u_{gt} + R_g^{SD}\left(v_{gt} - u_{gt} + u_{g.t-1}\right), \forall g \in G, t \geq 2 \tag{3.24}$$

$$P_{g1} - P_{g,T} \leq R_g^{60} u_{g,T} + R_g^{SU} v_{g1}, \forall g \in G \tag{3.25}$$

$$P_{g,T} - P_{g1} \leq R_g^{60} u_{g,1} + R_g^{SD}\left(v_{g1} - u_{g1} + u_{g,T}\right), \forall g \in G \tag{3.26}$$

$$\sum_{q=t-UT_g+1}^{t} v_{g,q} \leq u_{gt}, \forall g \in G, t \geq UT_g \tag{3.27}$$

$$\sum_{q=T+t-UT_g+1}^{T} v_{g,q} + \sum_{q=1}^{t} v_{g,q} \leq u_{gt}, \forall g \in G, t \leq UT_g - 1 \tag{3.28}$$

$$\sum_{q=t+1}^{t+DT_g} v_{g,q} \leq 1 - u_{gt}, \forall g \in G, t \leq T - DT_g \tag{3.29}$$

$$\sum_{q=1}^{t+DT_g-T} v_{g,q} + \sum_{q=t+1}^{T} v_{g,q} \leq 1 - u_{gt}, \forall g \in G, t \geq T - DT_g + 1 \tag{3.30}$$

$$v_{gt} \geq u_{gt} - u_{g,t-1}, \forall g \in G, t \geq 2 \tag{3.31}$$

$$v_{g1} \geq u_{g1} - u_{g,T}, \forall g \in G \tag{3.32}$$

$$0 \leq v_{gt} \leq 1, \forall g \in G, t \in T \tag{3.33}$$

$$u_{gt} \in \{0,1\}, \forall g \in G, t \in T \tag{3.34}$$

Base-case modeling of power flow:

$$i_{nt} = \sum_{g \in G^n} P_{gt} - D_{nt}, \forall n \in N, t \in T \tag{3.35}$$

$$\sum_n i_{nt} = 0, \forall\, t \in T \tag{3.36}$$

$$-F_l^{RateA} \leq \sum_n PTDF_{n,l}^{BC} i_{nt} \leq F_l^{RateA}, \forall l \in L, t \in T \tag{3.37}$$

Modeling of generator outage:

$$P_{gt} - P_{g,c,t} \leq R_g^{10} u_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.38}$$

$$P_{gt} - P_{g,c,t} \leq r_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.39}$$

$$P_{g,c,t} - P_{gt} \leq R_g^{10} u_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.40}$$

$$P_{g,c,t} - P_{gt} \leq r_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.41}$$

$$P_g^{min} u_{gt} \leq P_{g,c,t} \leq P_g^{max} u_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.42}$$

$$P_{g,c,t} = 0, \forall g: g = c, c \in C^g, t \in T \tag{3.43}$$

$$i_{n,c,t} = \sum_{g \in G^n} P_{g,c,t} - D_{nt}, \forall n, c \in C^g, t \in T \tag{3.44}$$

$$\sum_n i_{n,c,t} = 0, \forall c \in C^g, t \in T \tag{3.45}$$

$$-F_l^{RateC} \le \sum_n PTDF_{n,l}^{BC} i_{n,c,t} \le F_l^{RateC}, \forall l \in L, c \in C^g, t \in T \tag{3.46}$$

Modeling of *non-radial* transmission line or transformer outage:

$$P_{gt} - P_{g,c,t} \le R_g^{10} u_{gt}, \forall g \in G, c \in C^l, t \in T \tag{3.47}$$

$$P_{gt} - P_{g,c,t} \le r_{gt}, \forall g \in G, c \in C^l, t \in T \tag{3.48}$$

$$P_{g,c,t} - P_{gt} \le R_g^{10} u_{gt}, \forall g \in G, c \in C^l, t \in T \tag{3.49}$$

$$P_{g,c,t} - P_{gt} \le r_{gt}, \forall g \in G, c \in C^l, t \in T \tag{3.50}$$

$$P_g^{min} u_{gt} \le P_{g,c,t} \le P_g^{max} u_{gt}, \forall g \in G, c \in C^l, t \in T \tag{3.51}$$

$$\sum_n PTDF_{n,l}^{C} i_{n,c,t} = 0, \forall l: l = c, c \in C^l, t \in T \tag{3.52}$$

$$i_{n,c,t} = \sum_{g \in G^n} P_{g,c,t} - D_{nt}, \forall n, c \in C^l, t \in T \tag{3.53}$$

$$\sum_n i_{n,c,t} = 0, \forall c \in C^l, t \in T \tag{3.54}$$

$$-F_l^{RateC} \le \sum_n PTDF_{n,l}^{C} i_{n,c,t} \le F_l^{RateC}, \forall l: l \ne c, c \in C^l, t \in T \tag{3.55}$$

In comparison to the deterministic unit commitment formulation, presented in Section 3.1, the above formulation includes the added explicit representation of a set of uncertain scenarios, wherein each scenario represents a contingency (i.e., the loss of a single bulk power system element) that occurs with a probability ρ^c. Thus, the second-stage decisions are indexed by contingency, $P_{g,c,t}$, and the objective is to minimize the expected operating costs across all scenarios, including the base-case pre-contingency scenario that occurs with a probability ρ^{BC}. In addition, the net injection $i_{n,c,t}$ at all nodes can change in the second stage and is therefore indexed by contingency. Here, C^g is the set of generator contingencies and C^l is the set of transmission element contingencies excluding the radial transmission lines.

It is important to note that, in this formulation, the deviation (both upward and downward) in a generator's output level, from the base-case schedule to the post-contingency schedule, is limited either by its 10-minute ramp rate (R_g^{10}) or by its reserve dispatch decision (r_{gt}) from the first-stage, and is denoted by constraints (3.38)-(3.41) and (3.47)-(3.50), for generator and transmission element (line or transformer) outages, respectively. Constraints (3.42) and (3.51) restrict the post-contingency dispatch schedules to lie within the corresponding generator bounds, for generator and transmission element contingencies, respectively. Generator contingencies are modeled by constraint (3.43), which forces the post-contingency dispatch decision for the corresponding generator outage to equal zero; similarly, transmission element contingencies are modeled by constraint (3.52), which forces the post-contingency power flow on the corresponding transmission element outage to equal zero. Finally, constraints (3.44)-(3.46) and (3.53)-(3.55) model the post-contingency power flows, for the generator and transmission element outages, respectively. Since power transfer distribution factors (PTDFs) depend on the topology of the network, the PTDFs have to be updated ($PTDF_{n,l}^{C}$) for each possible realization of a transmission element outage, whereas this is not the case when modeling generator outages because the topology remains the same. Lastly, in the case of an emergency or an outage, the power flow on a transmission line is allowed to exceed its nominal thermal rating (rate A) and reach up to its emergency line rating (rate C), which is indicated in (3.46) and (3.55).

3.3. Contingency Analysis

The *N*-1 reliability standard that is typically enforced for operations specifies that the system must be able to withstand the loss or failure of any single bulk system element (e.g., generator, transmission line, or transformer), which is also referred to as an unplanned outage, in order to avoid a blackout. Present-day energy management systems (EMS) are equipped with preview tools to analyze the effect of contingencies in an automatic manner, and to check for the feasibility of the SCUC solution to continue serving the demand reliably in the event of a statistically likely outage (i.e., to evaluate power system security or *N*-1 reliability).

The contingency analysis software application can be used both as an offline analysis or an online tool to assist the operators or planners in being more prepared to respond to disturbances by taking certain prescribed procedures, thereby, avoiding potential security violations (i.e., load shedding, over-generation, or line overloads) in the post-contingency state. Contemporary unit commitment formulations do not enforce strict *N*-1 requirements due to the corresponding increase in the modeling complexity; instead, reserve constraints are used as a proxy to ensure sufficient backup capacity would be available to respond to a contingency. In this dissertation, only 10-minute spinning reserves are used to respond to a contingency; however, the model can be extended to include other reserve types. The contingency analysis problem formulation is given below.

Minimize: $\sum_{n,c,t} c^{LS}\left(LS^{+}_{n,c,t} + LS^{-}_{n,c,t}\right)$ (3.56)

Subject to:

Post-contingency ramping restriction on generation and modeling of generator contingencies:

$$-P_{g,c,t} \leq \overline{r_{gt}} - \overline{P_{gt}}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.57}$$

$$P_{g,c,t} \leq \overline{r_{gt}} + \overline{P_{gt}}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.58}$$

$$P_g^{min}\overline{u_{gt}} \leq P_{g,c,t} \leq P_g^{max}\overline{u_{gt}}, \forall g: g \neq c, c \in C^g, t \in T \tag{3.59}$$

$$P_{g,c,t} = 0, \forall g: g = c, c \in C^g, t \in T \tag{3.60}$$

$$-P_{g,c,t} \leq \overline{r_{gt}} - \overline{P_{gt}}, \forall g \in G, c \in C^l, t \in T \tag{3.61}$$

$$P_{g,c,t} \leq \overline{r_{gt}} + \overline{P_{gt}}, \forall g \in G, c \in C^l, t \in T \tag{3.62}$$

$$P_g^{min}\overline{u_{gt}} \leq P_{g,c,t} \leq P_g^{max}\overline{u_{gt}}, \forall g \in G, c \in C^l, t \in T \tag{3.63}$$

Post-contingency modeling of power flow and transmission element (non-radial transmission line or transformer) contingencies:

$$i_{n,c,t} = \sum_{g \in G^n} P_{g,c,t} - D_{nt} + LS_{n,c,t}^{+} - LS_{n,c,t}^{-}, \forall n \in N, c \in C^g, t \in T \tag{3.64}$$

$$\sum_n i_{n,c,t} = 0, \forall c \in C^g, t \in T \tag{3.65}$$

$$-F_l^{RateC} \leq \sum_n PTDF_{n,l}^{BC} i_{n,c,t} \leq F_l^{RateC}, \forall l \in L, c \in C^g, t \in T \tag{3.66}$$

$$i_{n,c,t} = \sum_{g \in G^n} P_{g,c,t} - D_{nt} + LS_{n,c,t}^{+} - LS_{n,c,t}^{-}, \forall n \in N, c \in C^l, t \in T \tag{3.67}$$

$$\sum_n i_{n,c,t} = 0, \forall c \in C^l, t \in T \tag{3.68}$$

$$-F_l^{RateC} \leq \sum_n PTDF_{n,l}^{C} i_{n,c,t} \leq F_l^{RateC}, \forall l: l \neq c, c \in C^l, t \in T \tag{3.69}$$

$$\sum_n PTDF_{n,l}^{C} i_{n,c,t} = 0, \forall l: l = c, c \in C^l, t \in T \tag{3.70}$$

Analogous to the extensive-form *N*-1 reliable unit commitment formulation in Section 3.2, C^g is the set of generator contingencies and C^l is the set of transmission element (i.e., transmission line or transformer) contingencies excluding the radial transmission lines. In its minimalistic form, contingency analysis basically involves executing a dc power flow analysis for each potential outage. The resulting power flows on transmission lines are restricted to lie within the emergency line ratings (rate C) indicated by constraints (3.66) and (3.69), for generator and transmission element contingencies, respectively. Furthermore, in the above formulation, slack variables $LS^{+}_{n,c,t}$ and $LS^{-}_{n,c,t}$ represent the load shedding and load surplus variables respectively. Consequently, the objective (3.56) is to minimize the load shed or the over-generation, in the event of an outage, subject to the physical network constraints of the system.

The primary motive is to continue serving demand reliably while maintaining the system frequency within a tolerable range of 60 Hz (or 50 Hz, depending on country/region). In this case, slack variables are introduced in constraints (3.64) and (3.67), which model the net injection at every node for the generator and transmission element contingencies respectively, to ensure the *feasibility* of the contingency analysis problem. The slack variables provide an indirect insinuation of the potential security violations in the post-contingency state. In addition, c^{LS} in the objective function represents the penalty cost to relax the constraints (3.64) and (3.67). In this dissertation, c^{LS} is an approximate value, which is assumed to range from $1000/MWh to $13000/MWh and can be interpreted as the value of lost load (VOLL). The VOLL can be construed as a rough approximation of the cost to correct the unreliable solution out of the market after contingency analysis is conducted.

Constraints (3.65) and (3.68) guarantee system-wide energy balance between the demand and the supply, for generator and transmission element contingencies, respectively. Constraint (3.60) forces the post-contingency dispatch decision for a generator to equal zero if it is the contingency and (3.70) forces the post-contingency flow on a transmission element to equal zero if it is the contingency. Constraints (3.57)-(3.59) and (3.61)-(3.63) model the post-contingency ramping and generation restrictions on generators, for generator and transmission element contingencies, respectively.

CHAPTER 4.

ENHANCING SYSTEM SECURITY VIA OUT-OF-MARKET CORRECTION PROCEDURES

Electric power grid is one of the most complex engineered systems in the 21st century. Several challenges, including unexpected system element failure and resource uncertainty, exist for an efficient and reliable operation of a power system. While algorithmic performance and computation hardware have advanced significantly, model approximations and simplifications are still used in commitment and dispatch models. Operators must, therefore, seek to adjust and correct unreliable solutions outside of the market engine. Such operator-initiated actions are referred to as out-of-market corrections (OMC) in this dissertation. Two OMC models are proposed, in this chapter [70], to mimic and optimize the process that operators take to adjust unreliable solutions. The OMC models estimate the operating costs incurred to move an unreliable solution to a reliable solution. The proposed models are used to evaluate the reliability of the system and are compared with the traditional value-of-lost-load approach. The case study is conducted using the IEEE 118-bus system.

4.1. Introduction

Electric power grids are among the most complex engineered systems. Market operators coordinate and manage resources in the system to ensure a reliable and efficient operation. Energy and ancillary service markets are the primary mechanisms that operators utilize to determine the least-cost operation of system resources.

Scheduling of generation resources is determined and managed through a suite of software tools, which includes SCUC and SCED. These tools identify the least-cost combination of generation resources to meet electricity demand and ensure system reliability. Due to the complexity of power systems, several challenges exist to operate the system both efficiently and reliably. First, scheduling models (i.e., commitment and dispatch models) incorporate a linear approximation of ac power flow. A full ac representation of transmission network cannot be included in scheduling models explicitly due to modeling complexity. In addition, present-day reliability assessment models only include a subset of critical contingencies. Second, power system operation faces uncertainties, such as renewable uncertainty and unexpected system element failures. Future uncertainties must be accounted for when making unit commitment and dispatch decisions. However, not all types of uncertainties can be adequately represented in scheduling models. Additional actions are needed to address the uncertainties that are not inherently captured by the scheduling models. Third, approximations are used in scheduling models that include, but are not limited to, the use of cutoffs for PTDFs, nom-ograms, proxy voltage limits, transmission interface flow limits, proxy reserve rules, etc. These approximate rules are used to represent complex physical limits of the system while keeping the added modeling and computational complexity at minimum. However, such approximate rules do not guarantee that the actual limits and requirements will be satisfied. Additional operational procedures are needed to mitigate and correct any issues that are introduced by model approximations and inaccuracies [71].

To address the above challenges and maintain a reliable and continuous supply of electricity, a multi-stage scheduling process is adopted by operators. Commitment and dispatch of generation is determined through a sequence of processes and reviewed and adjusted (by operators) continuously till the actual operational stage. The objective of these operator-initiated adjustments (or corrections) is to resolve reliability issues that cannot be internally accounted for by scheduling models. Thus, such adjustments are made after the fact (i.e., outside of the market) as and when required to account for modeling inaccuracies. The terms used for such adjustments varies between ISOs, e.g., exceptional dispatches in CAISO or out-of-merit energy/capacity in ERCOT [72], [73]. Inadequate reserves can force operators to turn on additional generators or hold back flexible resources in local areas to compensate for deliverability issues, e.g., MISO manually disqualifies reserves when such deliverability issues occur so that reserve requirements must be met by resources at more favorable locations, [74]-[76]. MISO refers to this process as reserve disqualification. Reserve downflags belong to a suite of potential uneconomic adjustments. ISO-NE partially controls the locations of reserves by specifying reserve downflags that explicitly disallow locations from contributing towards the reserve requirement [75], [76]. Reserve downflags are currently determined largely on a manual basis. Such actions, which are made outside of the optimization engine, are costly, distort price signals [22], and can cause a market separation between the forward market (day-ahead) and the spot market (real-time).

The additional corrections that are made outside of the market auction model are referred to as OMCs in this dissertation. Previously, OMCs have been investigated in [77] and [78], where heuristic OMC procedures are formulated to iteratively correct unreliable market solutions. Two approximate OMC model formulations, which are further used in the subsequent sections, are proposed in this dissertation. The proposed models mimic the

OMC actions adopted by operators to correct unreliable generation schedules to obtain *N*-1 reliability. To simplify the complex process adopted by industry while capturing the key features of OMC, the proposed models are formulated as two-stage stochastic programs. The proposed models provide an estimation of the operating cost incurred during the adjustment process to move an unreliable solution to a reliable solution. The proposed approach is applied to adjust unreliable SCUC solutions and assess (quantify) the security violations in the system. Finally, the proposed models are compared with the traditional value of lost load (VOLL) approach, wherein system security violations are assessed using a pre-determined penalty price, i.e., the VOLL.

This chapter is organized as follows. Section 4.2 discusses the proposed OMC models, including the model formulation and model description. The proposed models are implemented and validated on a modified IEEE 118-bus test case and the numerical results are presented in Section 4.3. Finally, Section 4.4 concludes the chapter.

4.2. Proposed Out-of-Market Correction Model Formulations and Description

In this subsection, two OMC model formulations are proposed to optimize and mimic operator-initiated interventions (rather than depending upon an operator's engineering judgment/experience) that aim to correct unreliable SCUC solutions. The need for OMC can be attributed to various issues, which include, but are not limited to, insufficient reactive power support, undeliverable backup capacity (reserve), model approximations, the deterministic structure of market auction models, and unexpected system element failure that results in an unreliable solution due to the embedded inaccuracies and relaxations within an auction model. The focus of the chapter is to design an OMC model that produces a (*G*-1 reliable) solution that can withstand any single generator contingency without causing any security violations (e.g., load shedding, flow limit violation, etc.). While the proposed OMC models are designed to ensure N-1 reliability against generator contingencies, the extension of the model to accommodate transmission contingencies is trivial.

4.2.1. Overview of Day-Ahead Scheduling and Value of Lost Load Approach

The overall day-ahead (DA) scheduling process begins with preparing the inputs, preprocessing (i.e., collecting offers and bids, and building topology), and then running the DA SCUC model. The market auction solution is subsequently assessed for deliverability, by performing contingency analysis, to satisfy NERC's N-1 mandate. Flagged security violations at this stage are then subject to reliability unit commitment or operator's review for manual adjustments via an iterative process until the operator is satisfied with the final solution or the time is exhausted [79].

Security violations are generally included in optimization programs, e.g., contingency analysis, to relax equality/inequality constraints and ensure that a (relaxed) solution can be obtained. In academia, one common approach to evaluate the cost of system security violations is to use VOLL [80]-[82]. Typically, a VOLL is projected based on the potential consumer impacts associated with unserved energy. The system-wide security violations are determined and a predefined VOLL is used to associate a cost with the security violations. However, such an approach is not consistent with existing industry practices; since any potential vulnerability in the market auction solution is corrected through the scheduling process. Also, the results are subject to the choice of VOLL. While the VOLL approach offers an approximate way to evaluate the cost of system security violations, the proposed OMC models provide a more objective assessment of the cost to correct the unreliable solution. Note that OMC costs are eventually passed on as uplift payments to customers and the end goal of ISOs is to maximize social welfare.

4.2.2. Out-of-Market Correction Model 1

The OMC models are formulated as two-stage stochastic programs, wherein the first and the second stage represent the base case and the post-contingency states for generator contingencies, respectively. The scheduled unit commitment status, scheduled real power production, and scheduled reserve describe the unreliable solution obtained from the deterministic DA SCUC model. The complete formulation of the first OMC model, also referred to as OMC-1, is detailed below [70].

Minimize: $\sum_{g,t} \rho^{BC} c_g(P_{gt}) + c_g^{NL} u_{gt} + c_g^{SU} v_{gt} + c_g^{SD} w_{gt} + c_g^{res} r_{gt} +$

$$\sum_{g,c,t} \rho^{c} c_g(P_{g,c,t}) + \sum_{g,t} M\delta_{gt} \quad (4.1)$$

Subject to:

Base-case modeling of generation:

$$P_g^{min} u_{gt} \leq P_{gt}, \forall g \in G, t \in T \quad (4.1)$$

$$P_{gt} + r_{gt} \leq P_g^{max} u_{gt}, \forall g \in G, t \in T \quad (4.2)$$

$$0 \leq r_{gt} \leq R_g^{10} u_{gt},\ \forall g \in G, t \in T \quad (4.3)$$

$$P_{gt} - P_{g,t-1} \leq R_g^{60} u_{g,t-1} + R_g^{SU}(1 - u_{g,t-1}), \forall g \in G, t \geq 2 \quad (4.4)$$

$$P_{g,t-1} - P_{gt} \leq R_g^{60} u_{gt} + R_g^{SD}\left(1 - u_{gt}\right), \forall g \in G, t \geq 2 \quad (4.5)$$

$$P_{g1} - P_{g,T} \leq R_g^{60} u_{g,T} + R_g^{SU}\left(1 - u_{g,T}\right), \forall g \in G \quad (4.6)$$

$$P_{g,T} - P_{g1} \leq R_g^{60} u_{g,1} + R_g^{SD}\left(1 - u_{g1}\right), \forall g \in G \quad (4.7)$$

$$\sum_{q=t-UT_g+1}^{t} v_{g,q} \leq u_{gt}, \forall g \in G, t \geq UT_g \quad (4.8)$$

$$\sum_{q=T+t-UT_g+1}^{T} v_{g,q} + \sum_{q=1}^{t} v_{g,q} \le u_{gt}, \forall g \in G, t \le UT_g - 1 \tag{4.9}$$

$$\sum_{q=t-DT_g+1}^{t} w_{g,q} \le 1 - u_{gt}, \forall g \in G, t \ge DT_g \tag{4.10}$$

$$\sum_{q=T+t-DT_g+1}^{T} w_{g,q} + \sum_{q=1}^{t} w_{g,q} \le 1 - u_{gt}, \forall g \in G, t \le DT_g - 1 \tag{4.11}$$

$$v_{gt} \ge u_{gt} - u_{g,t-1}, \forall g \in G, t \ge 2 \tag{4.12}$$

$$w_{gt} \ge u_{g,t-1} - u_{gt}, \forall g \in G, t \ge 2 \tag{4.13}$$

$$v_{g1} \ge u_{g1} - u_{g,T}, \forall g \in G \tag{4.14}$$

$$w_{g1} \ge u_{g,T} - u_{g1}, \forall g \in G \tag{4.15}$$

$$0 \le v_{gt} \le 1, \forall g \in G, t \in T \tag{4.16}$$

$$0 \le w_{gt} \le 1, \forall g \in G, t \in T \tag{4.17}$$

$$u_{gt} \in \{0,1\}, \forall g \in G, t \in T \tag{4.18}$$

Base-case modeling of power flow:

$$\sum_{g \in G^n} P_{gt} - D_{nt} = P_{n,t}^{inj}, \forall n \in N, t \in T \tag{4.19}$$

$$\sum_n P_{n,t}^{inj} = 0, \forall\, t \in T \tag{4.20}$$

$$-F_l^{RateA} \le \sum_n PTDF_{n,l}^{BC} P_{n,t}^{inj} \le F_l^{RateA}, \forall l \in L, t \in T \tag{4.21}$$

Limitations on adjustments made during the OMC process:

$$\delta_{gt} \in \{0,1\}, \forall g \in G, t \in T \tag{4.22}$$

$$u_{gt} = \overline{u_{gt}}, \forall \overline{u_{gt}} = 1, g\colon g \ne c, t \in T \tag{4.23}$$

$$u_{gt} = \overline{u_{gt}}, \forall g \in G_s, g\colon g \ne c, t \in T \tag{4.24}$$

$$u_{gt} = \delta_{gt}, \forall \overline{u_{gt}} = 0, g\colon g \ne c, t \in T \tag{4.25}$$

$$u_{gt} \ge \overline{u_{gt}}, \forall g \in G_f, g\colon g \ne c, t \in T \tag{4.26}$$

OMC heuristic that allows deviation of DDP of online units (i.e., when $\delta_{gt} = 1$):

$$P_g^{min}\delta_{gt} + \overline{P_{gt}}(1-\delta_{gt}) \leq P_{gt}, \forall \overline{u_{gt}} = 1, g: g \neq c, t \in T \tag{4.27}$$

$$P_{gt} \leq \overline{P_{gt}}(1-\delta_{gt}) + P_g^{max}\delta_{gt}, \forall \overline{u_{gt}} = 1, g: g \neq c, t \in T \tag{4.28}$$

OMC heuristic that allows for the commitment of additional units (i.e., when $\delta_{gt} = 1$), which were originally offline in the market model:

$$P_g^{min}\delta_{gt} \leq P_{gt}, \forall \overline{u_{gt}} = 0, g: g \neq c, t \in T \tag{4.29}$$

$$P_{gt} \leq P_g^{max}\delta_{gt}, \forall \overline{u_{gt}} = 0, g: g \neq c, t \in T \tag{4.30}$$

Post-contingency ramping restriction on generation and modeling of generator contingencies:

$$P_{g,c,t} = 0, \forall g: g = c, c \in C^g, t \tag{4.31}$$

$$P_{gt} - P_{g,c,t} \leq R_g^{10} u_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.32}$$

$$P_{g,c,t} - P_{gt} \leq R_g^{10} u_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.33}$$

$$P_{gt} - P_{g,c,t} \leq r_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.34}$$

$$P_{g,c,t} - P_{gt} \leq r_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.35}$$

OMC heuristic that allows deviation of DDP of online units:

$$P_g^{min}\delta_{gt} + (\overline{P_{gt}} - \overline{r_{gt}})(1-\delta_{gt}) \leq P_{g,c,t}, \forall \overline{u_{gt}} = 1, g: g \neq c, c \in C^g, t \in T \tag{4.36}$$

$$P_{g,c,t} \leq (\overline{P_{gt}} + \overline{r_{gt}})(1-\delta_{gt}) + P_g^{max}\delta_{gt}, \forall \overline{u_{gt}} = 1, g: g \neq c, c \in C^g, t \in T \tag{4.37}$$

OMC heuristic that allows commitment of originally offline units:

$$P_g^{min}\delta_{gt} \leq P_{g,c,t}, \forall \overline{u_{gt}} = 0, g: g \neq c, c \in C^g, t \in T \tag{4.38}$$

$$P_{g,c,t} \leq P_g^{max}\delta_{gt}, \forall \overline{u_{gt}} = 0, g: g \neq c, c \in C^g, t \in T \tag{4.39}$$

Post-contingency modeling of power flow:

$$\sum_{g \in G^n} P_{g,c,t} - D_{nt} = P_{n,c,t}^{inj}, \forall n \in N, c \in C^g, t \in T \tag{4.40}$$

$$\sum_{n} P_{n,c,t}^{inj} = 0, \forall c \in C^{g}, t \in T \tag{4.41}$$

$$-F_{l}^{RateC} \leq \sum_{n} PTDF_{n,l}^{BC} \; P_{n,c,t}^{inj} \leq F_{l}^{RateC}, \forall l \in L, c \in C^{g}, t \in T. \tag{4.42}$$

The objective, (4.1), is to minimize the expected total system costs over a wide range of uncertain generator contingencies and the penalty cost to deviate from the DA SCUC solution. This includes the first stage costs, i.e., base case operating costs, no-load, startup, shutdown and reserve costs, the second stage costs, i.e. post-contingency re-scheduling costs, and the penalty cost to modify the DA SCUC solution using an OMC action. Constraint (4.2) and (4.3) represent the generator output limits and (4.4) describes the ramp rate restriction for ten-minute spinning reserve. Note that, in this work, contingency reserve is modeled by spinning reserve, which is subsequently used to mitigate contingencies in the system. The hourly ramp rate constraints are described in (4.5)-(4.8). The minimum up and down time constraints are shown in (4.9)-(4.12) [69]. Startup and shutdown decisions, the unit commitment decision, and the relationship between them are described in (4.13)-(4.19). Constraint (4.20) models the power injection at each bus, whereas (4.21) guarantees energy balance between demand and supply at the system level. Constraint (4.22) describes the dc power flow and the flow limit for each line (i.e., thermal or stability limit).

In order to be consistent with contemporary market management practices, that restrict the changes made during the OMC process, the proposed OMC procedures disallow de-committing units that were originally committed in the DA SCUC market model. This is evident from constraint (4.24) that fixes the commitment statuses of the online units from the DA SCUC model. In addition, the OMC procedure also fixes the commitment statuses of the slow start units, i.e., units that have a startup time that is greater than a particular pre-defined threshold (usually one or two hours), described by constraint (4.25). Here, set G_s can be redefined to include units that have a minimum downtime that is greater than a specific threshold.

Although the aforementioned formulation disallows de-committing online units, it does allow for the commitment of additional units (i.e., $\delta_{gt} = 1$) that were originally offline in the DA SCUC model, at an extremely high penalty cost 'M', in order to ensure the reliability of the SCUC solution against the loss of any single generating element. This condition is described by constraint (4.26), whereas constraint (4.27) restricts the additional units that can be turned on through an OMC action to a predefined set of fast start units (or units with a minimum downtime threshold that is less than a specific value). Note that if an offline unit were to be turned on in the OMC process, the subsequent base-case and post-contingency dispatch decisions are still bounded by its capacity limits, which is evident from (4.30)-(4.31) and (4.39)-(4.40), respectively.

Furthermore, the aforementioned OMC procedure also allows for a deviation (or modification) of the desired dispatch points (DDPs) from their formerly scheduled dispatch levels, in order to ensure the reliability of the market solution, at cost 'M'. Analogously, the base-case and post-contingency dispatch decisions for the unit are bounded by its capacity limits in (4.28)-(4.29) and (4.37)-(4.38), respectively. For a unit that has its DDP or commitment status adjusted by an OMC action, the ramping restrictions are still respected through constraints (4.33)-(4.36). Constraint (4.32) forces the post-contingency dispatch schedule for a generator to equal zero if it is the contingency and constraints (4.41)-(4.43) together model the post-contingency power flows. Lastly, note that an OMC action, i.e., the modification of a unit's DDP or a change in its commitment status, is heavily penalized through the $M\delta_{gt}$ term in the objective function. Here, δ_{gt} is a binary variable, (4.23), analogous to the unit commitment variable u_{gt}. If the OMC algorithm chooses to make an adjustment to a unit's DDP or its status, then δ_{gt} takes on a value of one.

4.2.3. Out-of-Market Correction Model 2

The complete formulation of the second OMC model, i.e., OMC-2, is detailed below.

Minimize: $\sum_{g,t} \rho^{BC} c_g(P_{gt}) + c_g^{NL} u_{gt} + c_g^{SU} v_{gt} + c_g^{SD} w_{gt} + c_g^{res} r_{gt} +$

$$\sum_{g,c,t} \rho^{c} c_g(P_{g,c,t}) + \sum_{g,t} M\delta_{gt} + M^{DDP}\delta_{gt}^{DDP} + M^{RES}\delta_{gt}^{RES} \quad (4.44)$$

Subject to:

The base-case modeling of generation and power flow is similar to the first OMC algorithm presented above in Section 4.2.2.

Limitations on the changes made during the OMC process:

$$\delta_{gt} \in \{0,1\}, \forall g \in G, t \in T \quad (4.43)$$

$$0 \le \delta_{gt}^{DDP} \le \infty, \forall g \in G, t \in T \quad (4.44)$$

$$0 \le \delta_{gt}^{RES} \le \infty, \forall g \in G, t \in T \quad (4.45)$$

$$u_{gt} = \overline{u_{gt}}, \forall \overline{u_{gt}} = 1, g\colon g \ne c, t \in T \quad (4.46)$$

$$u_{gt} = \overline{u_{gt}}, \forall g \in G_s, g\colon g \ne c, t \in T \quad (4.47)$$

$$u_{gt} = \delta_{gt}, \forall \overline{u_{gt}} = 0, g\colon g \ne c, t \in T \quad (4.48)$$

$$u_{gt} \ge \overline{u_{gt}}, \forall g \in G_f, g\colon g \ne c, t \in T \quad (4.49)$$

OMC heuristic that allows deviation of DDP of the online units:

$$\delta_{gt} = 0, \forall \overline{u_{gt}} = 1, g\colon g \ne c, t \in T \quad (4.50)$$

$$\delta_{gt}^{DDP} \ge P_{gt} - \overline{P_{gt}}, \forall \overline{u_{gt}} = 1, g\colon g \ne c, t \in T \quad (4.51)$$

$$\delta_{gt}^{DDP} \geq \overline{P_{gt}} - P_{gt}, \forall \overline{u_{gt}} = 1, g: g \neq c, t \in T \tag{4.52}$$

$$\delta_{gt}^{RES} \geq r_{gt} - \overline{r_{gt}}, \forall \overline{u_{gt}} = 1, g: g \neq c, t \in T \tag{4.53}$$

$$\delta_{gt}^{RES} \geq \overline{r_{gt}} - r_{gt}, \forall \overline{u_{gt}} = 1, g: g \neq c, t \in T \tag{4.54}$$

OMC heuristic that allows for the commitment of additional units (i.e., when $\delta_{gt} = 1$), which were originally offline in the market model:

$$P_g^{min} \delta_{gt} \leq P_{gt}, \forall \overline{u_{gt}} = 0, g: g \neq c, t \in T \tag{4.55}$$

$$P_{gt} \leq P_g^{max} \delta_{gt}, \forall \overline{u_{gt}} = 0, g: g \neq c, t \in T \tag{4.56}$$

Post-contingency ramping restriction on generation and modeling of generator contingencies:

$$P_{g,c,t} = 0, \forall g: g = c, c \in C^g, t \in T \tag{4.57}$$

$$P_{gt} - P_{g,c,t} \leq R_g^{10} u_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.58}$$

$$P_{g,c,t} - P_{gt} \leq R_g^{10} u_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.59}$$

$$P_{gt} - P_{g,c,t} \leq r_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.60}$$

$$P_{g,c,t} - P_{gt} \leq r_{gt}, \forall g: g \neq c, c \in C^g, t \in T \tag{4.61}$$

OMC heuristic that allows deviation of DDP of the online units:

$$P_g^{min} u_{gt} \leq P_{g,c,t}, \forall \overline{u_{gt}} = 1, g: g \neq c, c \in C^g, t \in T \tag{4.62}$$

$$P_{g,c,t} \leq P_g^{max} u_{gt}, \forall \overline{u_{gt}} = 1, g: g \neq c, c \in C^g, t \in T \tag{4.63}$$

OMC heuristic that allows (i.e., $\delta_{gt} = 1$) commitment of originally offline units:

$$P_g^{min} \delta_{gt} \leq P_{g,c,t}, \forall \overline{u_{gt}} = 0, g: g \neq c, c \in C^g, t \in T \tag{4.64}$$

$$P_{g,c,t} \leq P_g^{max} \delta_{gt}, \forall \overline{u_{gt}} = 0, g: g \neq c, c \in C^g, t \in T \tag{4.65}$$

Post-contingency modeling of power flow:

$$\sum_{g \in G^n} P_{g,c,t} - D_{nt} = P_{n,c,t}^{inj}, \forall n \in N, c \in C^g, t \in T \tag{4.66}$$

$$\sum_n P_{n,c,t}^{inj} = 0, \forall c \in C^g, t \in T \tag{4.67}$$

$$-F_l^{RateC} \leq \sum_n PTDF_{n,l}^{BC}\, P_{n,c,t}^{inj} \leq F_l^{RateC}, \forall l \in L, c \in C^g, t \in T. \tag{4.68}$$

The two algorithms differ with respect to their computational performance. In order to reduce the computational burden of the first OMC procedure, two continuous variables, i.e., δ_{gt}^{DDP} and δ_{gt}^{RES} defined by (4.46)-(4.47), are introduced to model the OMC action of adjusting the DDP of a formerly committed unit while forcing the originally defined binary variable δ_{gt} for the corresponding online unit to equal zero in (4.52). In the case of units that were formerly committed in the day-ahead market auction model, the OMC process is to minimize the deviation from the DA SCUC solution. Therefore, the $M^{DDP}\delta_{gt}^{DDP}$ term in the objective function along with (4.53)-(4.54) penalizes the adjustments in DDPs and the $M^{RES}\delta_{gt}^{RES}$ term in the objective function along with (4.55)-(4.56) penalizes the deviations in procured reserves, for the formerly committed units. Inclusion of binary variables typically complicates an optimization problem, i.e., increases its solution time; consequently, this algorithm restricts the use of the binary variables δ_{gt} to model the OMC action of turning on additional units that were previously offline to enable secure operations. The post-contingency dispatch decision for a formerly committed unit is bounded by its capacity limits in (4.64)-(4.65). The remainder of the constraints bear the same explanation as the previously presented OMC algorithm.

4.3. Analysis and Numerical Results

The performance of the proposed OMC models is tested on a modified IEEE 118-bus test system, which has 54 generators, 186 transmission assets, and 99 loads [83]. The system is modified by decreasing: the normal rates of transmission assets to induce congestion; and the system load to 85% of the original load. The IEEE reliability test system (1996) is employed to define the hourly load profile for the demand data [83]. A winter weekday and a summer weekday are used to represent the first and the second sample test day, respectively. All simulations are run on a computer with an Intel® Xeon® CPU X5687 @ 3.60 GHz, 48 GB RAM, and solved using CPLEX v12.6. The relative MIP gap is set to 0.2% and the time limit is set to 1200 seconds.

The testing process includes: 1) solving the DA SCUC model, and 2) performing contingency analysis to identify the potential security violations. For the OMC approach, the proposed OMC models are solved to pull the unreliable SCUC solution to a G-1 reliable solution and estimate the corresponding incurred costs. Note that, the reliability of the OMC solution is validated by performing another contingency analysis after the fact. For the VOLL approach, a predefined VOLL is used to estimate the violation costs for the identified security violations. The contingency analysis in step 2 and the OMC models are run for 100 different realizations of net load scenarios to account for changing system operating conditions. Net load scenarios are used to represent the uncertainty introduced by stochastic resources, e.g., wind, solar, and demand. The error in the net load at each bus is assumed to follow a Gaussian distribution with zero mean and the variance is such that the resultant uncertainty is ~7%. To test for the robustness of the proposed OMC models, the overall process is evaluated on an additional test day. An extensive form stochastic unit commitment model is also run to provide an additional benchmark. The solution obtained from the extensive form is guaranteed to be G-1 reliable since generator contingencies are represented explicitly.

Table 4.1 summarizes the numerical results, averaged across net load scenarios, for the two proposed OMC models and the extensive form (Extsv.), for two sample test days. The discussions that follow are with respect to the first test day, however, the results are consistent for the second test day. The extensive form provides the best solution (i.e., closest to the optimal solution) as expected. The two OMC models differ with respect to their computational performance. Although the relative MIP gap was set to 0.2%, OMC-1 converges to a sub-optimal solution, i.e., 4.11% average MIP gap, in comparison to OMC-2 owing to the time limit of 1200 seconds. Consequently, the OMC cost is higher for OMC-1 since the algorithm has converged to a less economical solution in the set solution timeframe. This result can vary depending upon the time availability. The exclusion of binary variables to model the OMC action of deviating from the scheduled DDP and the scheduled reserve improves the computational tractability of OMC-2, thus, the average solution time for OMC-2 is reduced to ~71 seconds. Note that five (three) originally offline units are committed in OMC-2 (OMC-1) to ensure *G*-1 reliability. The OMC cost does not include the penalty cost to deviate from the DA SCUC solution.

Table 4.1 also includes the average results from contingency analysis: expected sum of security violations (E[viol.]), the number of contingencies and periods with non-zero violations (#viol.), the maximum reported violation (Max. viol.), and the actual sum of security violations (Σviol.), over the course of the day. The results for the worst-case net load scenario realization from the first test day are as follows: For contingency analysis, the E[viol.] is 10.98 MWh, the #viol. is 128, the Max. viol. is 267 MW and the Σviol. is 12,455 MWh. For OMC-1 (OMC-2), the cost is $0.39 M ($0.34 M), the solve time is 1235 s (619 s), the # of online units is 40 (43) and the MIP gap is 5.23% (0.20%). Analogously, the worst-case results for the second test day are as follows: For contingency analysis, the E[viol.] is 9.23 MWh, the #viol. is 121, the Max. viol. is 229 MW and the ∑ viol. is 10,546 MWh. For OMC-1 (OMC-2), the cost is $0.34 M ($0.31 M), the solve time is 1204 s (80 s), the # of online units is 38 (41) and the MIP gap is 4.52% (0.20%).

TABLE 4.1. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FOR THE OMC AND THE EXTENSIVE FORM MODELS

	Test Day 1			**Test Day 2**		
Model	**OMC-1**	**OMC-2**	**Extsv.**	**OMC-1**	**OMC-2**	**Extsv.**
Final Cost ($M)	1.50	1.46	1.30	1.51	1.45	1.31
DA SCUC Solution						
Cost ($M)	1.26		1.30	1.28		1.31
Time (s)	3.62		29	4.97		31.20
#Online Units	37		38	36		38
Contingency Analysis						
E[viol] (MWh)	6.01		0	4.85		0
#viol.	79		0	74		0
Max. viol. (MW)	207		0	172		0
∑ viol. (MWh)	6,879		0	5,555		0
Out-of-Market Correction (*G*-1 Reliable Solution)						
Cost ($M)	0.24	0.20	-	0.23	0.17	-
Time (s)	1209	71.05	-	1185	59.09	-
#Online Units	40	42	-	38	40	-
MIP Gap (%)	4.11	0.19	0.16	5.34	0.20	0.17

Table 4.2 summarizes the average results for the VOLL approach. The expected sum of security violations (E[viol.]), shown in Table 4.1, is multiplied by a predefined penalty price (or VOLL) to obtain the expected security violation costs. It is evident from Table 4.2 that, for five different values of VOLL ranging from $1,000/MWh to $13,000/MWh [84], the expected average final cost (i.e., the sum of the average DA SCUC cost and the expected average cost of security violations) to obtain a *G*-1 reliable solution for the VOLL approach can vary from $1.26 million to $1.33 million subject to the choice of VOLL. The expected average cost of security violations is directly related to the predefined VOLL. Different choices of VOLL can lead to different security violation costs and

potentially even different conclusions. Therefore, the OMC models provide a more appropriate and objective means to quantify the cost of security violations.

TABLE 4.2. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FOR THE VOLL APPROACH

VOLL ($/MWh)	**1,000**	**4,000**	**7,000**	**10,000**	**13,000**
Day 1: Final Cost ($M)	1.26	1.28	1.30	1.32	1.33
Day 2: Final Cost ($M)	1.28	1.29	1.31	1.32	1.34

4.4. Conclusions

This chapter proposes two OMC formulations to optimize the OMC actions that are usually adopted by operators rather than depending upon their engineering judgment/experience. Besides, with increasing penetration levels of stochastic resources and corresponding SCUC solutions that are harder to correct, operators will be forced to make many more expensive discretionary changes to obtain a reliable solution. An indirect benefit of the OMC models can result from reducing the amount of time spent by operators in making the numerous manual adjustments to obtain N-1 reliability. The OMC costs can potentially increase in the absence of such OMC models that seek to obtain economically efficient solutions, consequently, potentially increasing uplift payments.

CHAPTER 5.

A DATA-DRIVEN RESERVE RESPONSE SET POLICY FOR POWER SYSTEMS WITH STOCHASTIC RESOURCES

5.1. Overview of the Data-Driven Reserve Policy

5.1.1. Introduction

This chapter focuses on creating new dynamic reserve policies for contingency-based reserves (specifically, spinning reserves) and ramping products that are needed to compensate for resource uncertainty. The objective is to create reserve response set policies that specify a set of generators that will respond given a specific event while considering resource uncertainty and network limitations. The main incentive is to allocate reserves at appropriate locations that face fewer deliverability issues. The proposed approach aims to model the predicted effects of nodal reserve deployment on critical transmission lines post-contingency, thereby, appropriately allocating reserves at potentially deliverable locations.

In addition, the proposed approach uses a data-mining algorithm to identify potentially responsive locations and define reserve response factors that aim to cover a specified uncertainty range. The key idea is to use data analytics-based algorithms to design and develop cohesive reserve policies that approximately encapsulate the wealth of knowledge that is available regarding other possible realizations of uncertain scenarios in order to improve reserve-scheduling decisions. Besides, the application of data-mining techniques to analyze engineering problems, such as those encountered in power systems, is not new [85]-[87].

5.2. Data-Driven Reserve Response Set Model Formulation

This subsection discusses the form and implementation of the proposed data-driven reserve response set model, including the reserve response factors and the post-contingency transmission constraint. The proposed reserve model utilizes a *data-driven* approach that combines advanced reserve policies with Monte Carlo simulations to address the impacts of stochastic resources and improve the deliverability of reserves in the post-contingency state [88]. The main motivation is to complement the existing efforts by industry to effectively control and appropriately schedule reserve with minimal added computational burden while maintaining its robustness and scalability for large-scale power systems.

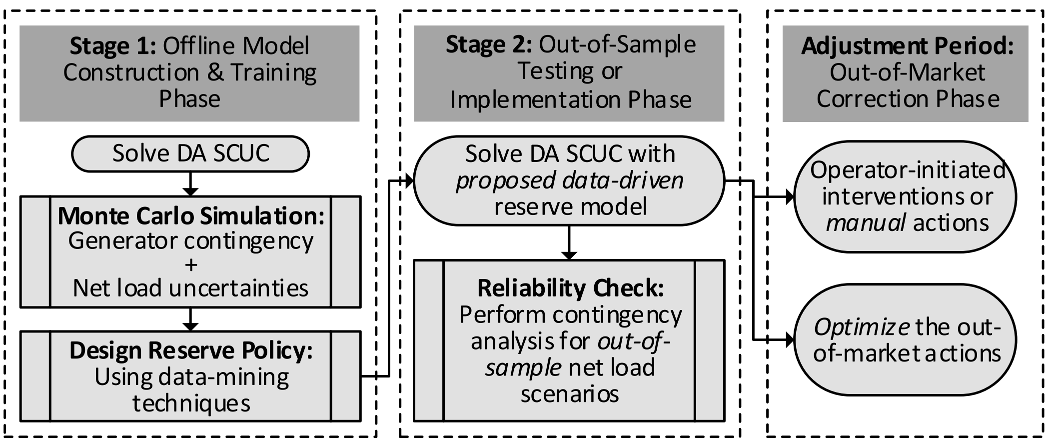


Fig. 5.1. Process flowchart for the proposed data-driven reserve response-set model.

Fig. 5.1 details the process employed by the proposed approach. The overall process includes two stages: 1) the *offline* model construction and training/analysis phase, and 2) the *out-of-sample* testing/implementation phase.

5.2.1. Offline Training Phase

In the training phase, first, a SCUC model that incorporates a zonal reserve model, which accounts for reserve sharing, is solved. The problem formulation is detailed below.

$$\text{Minimize:} \sum_{g,t}\left(\left[\sum_j C_{gj}\left(P_{gtj}\right)\right] + C_g^{NL}u_{gt} + C_g^{SU}v_{gt} + C_g^{SD}w_{gt} + C_g^{res}r_{gt}\right) \tag{5.1}$$

Subject to:

$$i_{nt} = \sum_{g\in G^n}\left(P_{gt}\right) - D_{nt}, \forall n \in N, t \in T \tag{5.2}$$

$$\sum_n i_{nt} = 0, \forall t \in T \tag{5.3}$$

$$F_{lt} = \sum_n PTDF_{n,l}\, i_{nt}, \forall l \in L, t \in T \tag{5.4}$$

$$-F_l^{RateA} \leq F_{lt} \leq F_l^{RateA}, \forall l \in L, t \in T \tag{5.5}$$

$$0 \leq P_{gtj} \leq P_{gj}^{max}u_{gt}, \forall g \in G, t \in T, j \in J \tag{5.6}$$

$$P_{gt} = \sum_j P_{gtj}, \forall g \in G, t \in T \tag{5.7}$$

$$0 \leq r_{gt} \leq R_g^{10}u_{gt}, \forall g \in G, t \in T \tag{5.8}$$

$$P_g^{min}u_{gt} \leq P_{gt}, \forall g \in G, t \in T \tag{5.9}$$

$$P_{gt} + r_{gt} \leq P_g^{max}u_{gt}, \forall g \in G, t \in T \tag{5.10}$$

$$P_{gt} - P_{g,t-1} \leq R_g^{60}u_{g,t-1} + R_g^{SU}v_{gt}, \forall g \in G, t \in T \tag{5.11}$$

$$P_{g,t-1} - P_{gt} \leq R_g^{60}u_{gt} + R_g^{SD}w_{gt}, \forall g \in G, t \in T \tag{5.12}$$

$$\sum_{q=t-UT_g+1}^{t} v_{gq} \leq u_{gt}, \forall g \in G, t \in \left\{UT_g, \dots, T\right\} \tag{5.13}$$

$$\sum_{q=t-DT_g+1}^{t} w_{gq} \leq 1 - u_{gt}, \forall g \in G, t \in \left\{DT_g, \dots, T\right\} \tag{5.14}$$

$$v_{gt} - w_{gt} = u_{gt} - u_{g,t-1}, \forall g \in G, t \in T \tag{5.15}$$

$$u_{gt} \in \{0,1\}, \forall g \in G, t \in T \tag{5.16}$$

$$0 \leq v_{gt} \leq 1, \forall g \in G, t \in T \tag{5.17}$$

$$0 \leq w_{gt} \leq 1, \forall g \in G, t \in T \tag{5.18}$$

Zonal reserve model with reserve sharing:

$$\sum_{k \in Z} \tilde{r}_{kt}^{c} \geq P_{ct} + r_{ct}, \forall c \in C^{g}, t \in T \tag{5.19}$$

$$\tilde{r}_{kt}^{c} \leq \sum_{g \in G^{k}} r_{gt}, \forall c \in C^{g}, k \in Z, t \in T \tag{5.20}$$

$$\tilde{r}_{kt}^{c} \leq F_{l_{k-z(c)}}^{RateC} \pm F_{lt_{k-z(c)}}, \forall c \in C^{g}, k \in Z, t \in T. \tag{5.21}$$

The objective (5.1) is to minimize the total system costs, including operational, no-load, startup, shutdown and reserve costs. It is pertinent to note that minimizing total system costs is equivalent to maximizing social welfare (or market surplus) since the demand is assumed to be perfectly inelastic. The power injected at each node is modeled using (5.2), whereas (5.3) ensures system-wide power balance between generation and demand. The dc power flow on a transmission asset, represented by (5.4), is restricted by its normal rating (rate A) in (5.5). The size of the piecewise segments (of generators) is bounded by constraint (5.6). The real power output of a generator is described by (5.7) and is equal to the sum total of its piecewise segments. Reserve scheduled from a specific generator is bounded by its 10-minute ramp rate in (5.8), and the minimum and maximum limitations on the real power scheduled from a generating resource are enforced in (5.9) and (5.10), respectively. Additional ramp rate limitations, including hourly, startup, and shutdown ramp rates, are imposed in (5.11) and (5.12), and the minimum up and down time requirements are modeled in (5.13) and (5.14), respectively. The relationship between the unit commitment, startup and shutdown variables is defined in (5.15). Constraint (5.16) restricts the unit commitment variable to be a binary, whereas (5.17) and (5.18) model the startup and shutdown variables as continuous. Constraints (5.19) –

(5.21) describe the zonal reserve model that accounts for reserve sharing. It is pertinent to note that, in order to avoid overestimating the reserve requirement and costs for the system, a liberal reserve sharing policy is used, i.e., the reserve sharing limit is set to equal the ATC $(\alpha = 1)$ of the inter-zonal link in (5.21).

Second, in order to assess the security of the day-ahead (DA) SCUC solution, i.e., scheduled unit commitment status, scheduled reserve, and scheduled real power production from generating resources, and to investigate the deliverability of reserves in the event of an uncertain realization in the post-contingency state, contingency analysis is performed for multiple net load scenarios (or Monte Carlo simulations are leveraged to generate hypothetical data). It is pertinent to note that, the results from Monte Carlo simulations can be replaced with historical data, if available. Here, 100 different realizations of net load scenarios are used for each of the modeled outages in contingency analysis. The contingency analysis problem formulation for a specific net load scenario is described below. Here, D_{nst} in (5.23) represents the load at node n for the corresponding realized *training* net load scenario s in period t.

Minimize: $\sum_{n,c,t} LS^{+}_{nct} + LS^{-}_{nct}$ (5.22)

Subject to:

$i_{nct} = \sum_{g \in G^n}\left(P_{gct}\right) - D_{nst} + LS^{+}_{nct} - LS^{-}_{nct}, \forall n \in N, c \in C^g, t \in T$ (5.23)

$\sum_n i_{nct} = 0, \forall c \in C^g, t \in T$ (5.24)

$F_{lct} = \sum_n PTDF_{n,l}\, i_{nct}, \forall l \in L, c \in C^g, t \in T$ (5.25)

$-F_l^{RateC} \leq F_{lct} \leq F_l^{RateC}, \forall l \in L, c \in C^g, t \in T$ (5.26)

$P_{gct} = 0, \forall g: g = c, c \in C^g, t \in T$ (5.27)

$\overline{P_{gt}} - \overline{r_{gt}} \leq P_{gct}, \forall g: g \neq c, c \in C^g, t \in T$ (5.28)

$$P_{gct} \leq \overline{P_{gt}} + \overline{r_{gt}}, \forall g: g \neq c, c \in C^g, t \in T \tag{5.29}$$

$$P_g^{min}\overline{u_{gt}} \leq P_{gct} \leq P_g^{max}\overline{u_{gt}}, \forall g: g \neq c, c \in C^g, t \in T \tag{5.30}$$

$$LS_{nct}^{+}, LS_{nct}^{-} \geq 0, \forall n \in N, c \in C^g, t \in T. \tag{5.31}$$

The objective (5.22) is to minimize the post-contingency security violations, which are denoted by slack variables LS_{nct}^{+} and LS_{nct}^{-}. Here, LS_{nct}^{+} and LS_{nct}^{-} represent the load shedding and load surplus variables respectively, and are included in the post-contingency power balance constraints, represented by (5.23), to ensure the feasibility of the problem. Constraint (5.24) ensures system-wide power balance in the post-contingency state, whereas (5.25) models the post-contingency dc power flows on transmission assets. The post-contingency power flows are restricted by the corresponding thermal (emergency) limits in (5.26). Generator contingencies are modeled using (5.27), whereas the deviation between the pre- and post-contingency real power production is restricted by the scheduled reserve obtained from DA SCUC solution in constraints (5.28) and (5.29). The post-contingency real power production is bounded by the resource's minimum and maximum output limits in (5.30). The slack variables are constrained to be non-negative in (5.31).

Third, the results from the offline stochastic simulations, which includes performing contingency analysis for the training set of net load scenarios, are then used in a data-mining algorithm for knowledge discovery. The contingency analysis results from *each* training net load scenario contribute to a training *record* (or an *instance/event*) in the data-mining algorithm. Each training record includes *indicators* (or *attributes*) X and a *target* value Y. Since the system state deviates considerably in the post-contingency state, it is crucial to identify the prime locations and amounts of activated reserves in addition to recording the deviations in line flows due to the deployed reserves from the pre-contingency state. Therefore, the central goal of the data-mining model is to estimate a regression function $f(X,\beta)$ (which is linear to avoid introducing nonlinearities) that approximates the post-contingency critical line flows due to nodal reserve deployment (Y) in the various combined critical generator contingency and net load scenarios. Here, X represents the independent variables, Y represents the dependent variable, and β represents the unknown parameters, i.e., $Y \approx f(X,\beta)$. Consequently, for a specific training record, the default choice for the indicators (or attributes) is the amounts of activated/deployed reserves from each of the responsive generators, and for the target variable is the corresponding post-contingency line flow due to the deployed reserves. The data-mining algorithm is run for each period t, each critical generator contingency c, and each critical transmission path l. For each run, the data records are obtained from the different net load scenarios. The target variable is expected to have a floating point or a continuous value instead of an integer or a categorical value.

The data-mining technique employed in this work is support vector machines for regression and function estimation (or *support vector regression*) and it considers only linear kernels [89]. Also, the algorithm is implemented using WEKA, an open source software which consists of a collection of machine learning algorithms for data-mining tasks [90]. The end goal is to model the predicted effects of nodal reserve deployment on critical transmission lines and improve the deliverability of deployed reserves post-contingency.

It is pertinent to note that, the data-mining model is built only for a subset of critical generator contingencies (G^c) and critical transmission paths (L^c). Here, set G^c includes the larger generating units because the loss of a larger unit has a higher chance of resulting in more severe security/reliability issues in contrast to the loss of a smaller unit due to the increased quantity of deployed reserves (to compensate for the corresponding loss) and the larger deviations in the flows on critical paths. However, this is system-dependent; hence, G^c can be extended to include the smaller units as well. Also, set L^c includes paths that are regularly congested in the pre- and post-contingency states, which can potentially cause reserve deliverability issues. Note that, critical paths can be pre-determined based on historical data and offline studies [22]. In addition, discerning a suitable size for these sets involves a trade-off between model accuracy and model complexity.

The data-mining model results in reserve response factors ($\beta^c_{g,l,t}$), analogous to the unknown parameters or regression coefficients resulting from a linear regression model, which are subsequently used in the implementation phase. $\beta^c_{g,l,t}$ can be interpreted as a factor that contains three pieces of information. One piece is the PTDF, which measures the impact of power injection from generator g's location on critical path l. Second, since support vector regression is performed using data from different net load scenarios for t, c, and l, the resultant coefficients represent the expected value across the different net load scenarios. The last piece includes information on the set of responsive generators that were activated to provide reserve under critical generator contingency c for the different net load scenarios. In addition, this information also includes the portion of reserve that is activated/deployed from the corresponding set of generators. To summarize, $\beta^c_{g,l,t}$

can be interpreted as a factor that defines the average influence (or impact) of a responsive generator g (due to its activated reserve) on a selected pre-defined critical path l for a given set of net load scenarios in period t and under contingency c; thus, indirectly capturing the embedded uncertainty in the training set of net load scenarios in an approximate sense. In other words, this factor can be viewed as a weighted PTDF, wherein the weights are the coefficients resulting from the previously mentioned support vector regression algorithm.

5.2.2. Out-of-Sample Testing Phase

In the testing phase, a SCUC model that incorporates the data-driven reserve response model, detailed below, is solved.

$$\text{Minimize:} \sum_{g,t}\left(\left[\sum_j C_{gj}\left(P_{gtj}\right)\right] + C_g^{NL}u_{gt} + C_g^{SU}v_{gt} + C_g^{SD}w_{gt} + C_g^{res}r_{gt}\right) \tag{5.32}$$

Subject to:

Constraints (5.2)–(5.18) (5.33)

Data-driven reserve response set model:

$$\sum_g r_{gt} \geq \eta\% \sum_n D_{nt}, \forall t \in T \tag{5.34}$$

$$\sum_{k\in Z} \tilde{r}_{kt}^c \geq P_{ct} + r_{ct}, \forall c \in C^g, t \in T \tag{5.35}$$

$$\tilde{r}_{kt}^c \leq \sum_{g\in G^k} r_{gt}, \forall c \in C^g, k \in Z, t \in T \tag{5.36}$$

$$\tilde{r}_{kt}^c \leq F_{l_{k-z(c)}}^{RateC} \pm F_{lt_{k-z(c)}}, \forall c \in C^{g^{ncrt}}, k \in Z, t \in T \tag{5.37}$$

$$-F_l^{RateC} \leq F_{lt} - P_{ct}PTDF_{n(c),l} + \sum_{g:g\neq c} r_{gt}\overline{\beta_{g,l,t}^c} \leq F_l^{RateC}, \forall c \in C^{g^{crt}}, l \in L^{crt}, t \in T. \tag{5.38}$$

The objective (5.32) is to minimize the total system costs analogous to (5.1). Here, $\tilde{r}_{kt}^c$ describes reserve in zone k that is categorized as deliverable for critical contingency c

in time t and $\overline{\beta_{g,l,t}^{c}}$ denote the reserve response factors that are obtained from the *offline* training phase. Equation (5.34) represents a myopic reserve policy. Constraint (5.35) is the contingency-based reserve policy, which requires there to be sufficient reserve to compensate for the loss of generation and reserve that was initially provided by the underlying critical generator outage. Constraint (5.36) ensures that $\tilde{r}_{kt}^{c}$ is no greater than the total amount of reserve that is held within zone k. Note that (5.35) and (5.36) together are equivalent to the myopic reserve policy described in (2.1). Constraint (5.37) limits the amount of reserve that can be shared between zone k and the contingency zone $z(c)$, for the set of non-critical generator contingencies $C^{g^{ncrt}}$, to the ATC of the corresponding inter-zonal link. Constraint (5.38) restricts the post-contingency transmission flows for the critical line set L^{crt}. Here, the first, second and the third component model the pre-contingency critical line flow, the effect of the critical generator outage and the effects (using the reserve response factors obtained from the first stage) of the reserves that are activated in response to the underlying critical generator contingency on the corresponding critical line flow, respectively. In other words, (5.38) models the post-contingency flow deviations for critical transmission paths *explicitly*.

Finally, the modified DA SCUC model, described by (5.32)–(5.38), is followed by a reliability check (akin to existing industry practices) or contingency analysis to assess the security of the DA market SCUC solution against generator contingencies combined with net load scenarios and to investigate the deliverability of scheduled reserves. The problem formulation is presented in (5.22)–(5.31). It is pertinent to note that, a *distinct* set of out-of-sample net load scenarios are used in the reliability check stage of the testing phase. Therefore, in this case, D_{nst} in (5.23) represents the load at node n for the corresponding realized *out-of-sample* net load scenario s in period t.

5.2.3. Analogous Approaches

Today, system operators use an analogous approach (i.e., line outage distribution factors, LODFs) to formulate transmission line contingencies in the DA SCUC model [91]. In this case, the post-contingency flow on a specific line l is represented as the sum of the pre-contingency flow on line l and the portion of the flow that is redistributed from the corresponding line outage c. Thus, line contingencies are represented explicitly without any second-stage recourse decisions. MISO uses post-zonal reserve-deployment transmission constraints analogous to (4.6) to determine their zonal reserve requirements [22]. Furthermore, existing RTCA tools use analogous participation factors for generator contingencies to estimate the post-contingency operating states [92]. Future work should investigate the potential of using inertia-based participation factors to improve the allocation of reserves.

5.2.4. Out-of-Market Corrections Phase

The solutions obtained from contemporary market SCUC models are not *N*-1 reliable due to the approximations, inaccuracies, and relaxations embedded in the model, thereby, resulting in more severe security violations. In order to overcome this issue, system operators adjust the market solution ex-post (i.e., after the market has cleared) to make it more reliable for the forecasted system conditions. Usually, a VOLL is estimated to approximate the value that consumers attribute to the security of electricity supply. Additionally, the VOLL is typically used to penalize the security violations; however, such results are subjective. Furthermore, the VOLL approach is not consistent with existing industry practices.

To obtain a more accurate estimation of the cost to repair an infeasible or unreliable solution, the overall process is extended to include an out-of-market correction (OMC) phase. The motive is to replicate the OMC procedures that are generally adopted by market operators to obtain results that are more objective. Furthermore, to be consistent with existing market rules that limit the changes made during the OMC process, the OMC formulation adopted in this work does not allow for de-commitment of units that were originally committed in the DA market model. It is pertinent to note that, the final solution from the overall process is N-1 reliable. Thus, a fair comparison can be made with other benchmark approaches by comparing valid solutions, obtained from the original DA SCUC solution plus the OMC adjustment phase, that guarantees the same level of reliability (i.e., N-1 reliability).

5.3. Polish 2383-Bus Test Case: Results and Analysis

The proposed approach is implemented and tested on a modified 2383-bus Polish test system and the simulation results are presented in this subsection.

5.3.1. Network Overview

The proposed approach is implemented on an actual large-scale test system to evaluate its effectiveness in allocating reserves at appropriate locations and to measure its capability to scale up on a practical sized system. Furthermore, the evaluation process included taking the reserve response factors obtained from the offline training stage and testing them against multiple test days across different seasons to test for the robustness of the proposed approach against varying operating conditions. The test case under consideration is a *modified* 2383-bus Polish test system, which has 327 generators, 2896 lines, and 1826 loads [93]. It represents the Polish 400, 200 and 110 kV networks and is part of the 7500+ bus European Union for the Coordination of the Transmission of Electricity (UCTE) system.

The modifications made to the original test system include repartitioning the original six zones into three zones to design a test case with potential reserve allocation (deliverability) issues and highlight the drawbacks of traditional approaches, reducing the nominal line ratings to induce congestion, and increasing the emergency line capacities to equal 1.05–1.25 times the corresponding nominal line capacities. Note that zones are partially effective at imposing locational reserve requirements. However, deciding the appropriate number of zones and the corresponding reserve requirements remains a challenge. Additionally, the reliability transmission organization unit commitment test system developed by the FERC, for industry use to examine potential improvements to DA and real-time market efficiency through improved software and models, is used to define generator information including offer curves (including fixed costs), minimum up and down times, and ramp rates [94]. A piecewise linear cost function is used to represent the variable fuel costs. Also, the IEEE reliability test system (1996) is used to describe the hourly load profile for the demand data [83].

5.3.2. Dataset and Software Description

The generator capacity threshold for set $C^{g^{crt}}$ is 500 MW and it includes 13 critical generators. The number of credible generator candidates for zones one, two, and three are two, seven, and four, respectively. Set L^{crt} is pre-determined to include four, frequently congested links. Three out of the four links are inter-zonal links, whereas one link is an intra-zonal link. Set L^{crt} can be extended to include additional inter- or intra-zonal links after weighing the trade-off between model accuracy and model complexity. Net load scenarios are used to represent the uncertainty introduced by stochastic resources. Here, in order to approximate the uncertainty without overcomplicating the scenario generation process, the net load at each bus is assumed to follow a Gaussian distribution with zero mean. Also, the variance of the distribution was pre-defined such that the resultant uncertainty is ~7%. Distributions that are more accurate can be adopted in future work.

It is pertinent to note that, the percentage split for the dataset is 66.67% training data and 33.33% testing data. In other words, the number of randomly generated net load scenarios used in the training and test phases is 100 and 50, respectively. The relative MIP gap tolerance for the DA SCUC model is set to 0.05%. The OMC process and the extensive form stochastic program are terminated upon reaching an optimality gap of 0.25% (or after 1200 seconds) and 0.025% (or after 1800 seconds), respectively. Testing is performed using CPLEX v12.6 on an 8-core, 3.6 GHz machine with 48 GB installed memory, and a 64-bit operating system.

5.3.3. Results and Analysis

In this subsection, the performance of the proposed data-driven reserve response set model is compared against two sets of benchmark reserve policies, i.e., the myopic reserve policies described by (2.1)–(2.2) and the reserve-sharing model described by (2.3)–(2.6), and an extensive form stochastic UC model. The percentage (η) of the system-wide demand in (2.2), for the myopic reserve policy, is fixed to 7%. In addition, the reserve sharing policy (α) is varied to rate its performance over different levels of conservatism. It is pertinent to note that, the DA SCUC model with the reserve sharing policy is infeasible for values of α less than 0.85. The extensive form stochastic UC model is formulated as a two-stage stochastic program with an explicit representation of all critical generator contingencies in all periods. Note that, for this test system, only the subset of critical generator contingencies is included in the extensive form as the extensive form is insolvable when all generator contingencies are included explicitly; thus, the extensive form results in a solution that is guaranteed to be *N*-1 reliable with respect to the modeled critical generator contingencies.

Fig. 5.2 compares the policies with respect to the final cost for *N*-1 reliable solutions, the expected sum of security violations (E[viol]) obtained from contingency analysis, and the number of contingencies and time periods with non-zero violations (# viol) over the course of the day for the corresponding out-of-sample test scenarios. Here, the *size* of the bubbles is indicative of the # viol. Also, final cost refers to the *sum* total of the operating cost obtained from the DA SCUC model and the cost to repair the unreliable market solution obtained from the OMC phase. In this chapter, E[viol] and # viol are statistical measures that are used to approximately compare and evaluate the extent of reliability that can be attained with the different approaches. Note that, the smaller the E[viol] and the # viol, the more reliable the approach. It is evident that, the proposed approach has a general tendency to give more reliable solutions at reduced overall costs because it preemptively anticipates the post-contingency states in the different net load scenarios through the reserve response factors, thereby, allocating the reserves at potentially deliverable locations. Also, as expected, the myopic policy results in the least reliable solutions because it fails to distribute the reserves at appropriate locations.

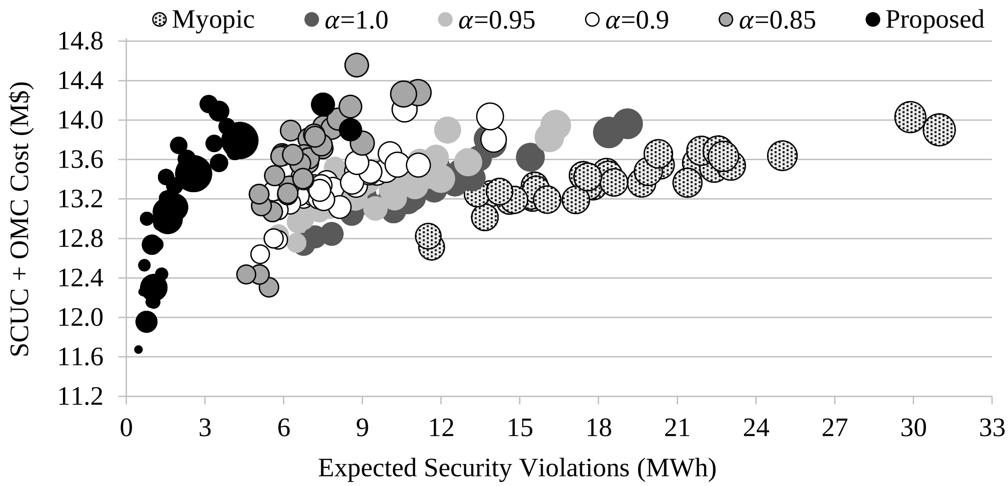


Fig. 5.2. Final costs for N-1 reliable solutions compared against the expected sum of security violations and the number of contingencies and times with non-zero violations (indicated by the *bubble size*) for DA SCUC solutions for the test scenarios.

Fig. 5.3 compares the policies with respect to two additional reliability metrics: the maximum reported security violation (Max viol) and the actual sum of security violations over the course of the day ($\sum$ viol) obtained from contingency analysis. Note that these security violations are eliminated during the OMC phase. It can be seen that the proposed approach has a general tendency to perform better than the other benchmark approaches with respect to both the metrics because the proposed policy effectively bounds the anticipated flows (for a range of net load scenarios) on the frequently congested lines to lie within the emergency limits. Effectively reducing the maximum reported security violation is particularly useful when the operator is interested in reducing the worst-case security violation.

Fig. 5.4 shows the hourly reserve schedules obtained from the DA SCUC solutions with differing reserve policies for generators over the course of a day. The distinction in the results can be attributed to the subtle differences in the distribution of the scheduled reserves across the system (and periods). For example, notice the subtle differences in the distribution of the scheduled reserves for the generating units (across the different time periods) that are highlighted within the dashed red rectangle in Fig. 5.4. The proposed approach tends to schedule lesser amounts of reserves from critical generator locations that are behind bottlenecks in the highly-congested hours, thereby, resulting in lesser post-contingency violations. Analogously, more reserves are scheduled from generator locations that are behind uncongested lines, thereby, resulting in more appropriate allocation of reserve and better reserve deliverability. Thus, the proposed approach is successful in finding solutions that capture post-contingency congestion reasonably.

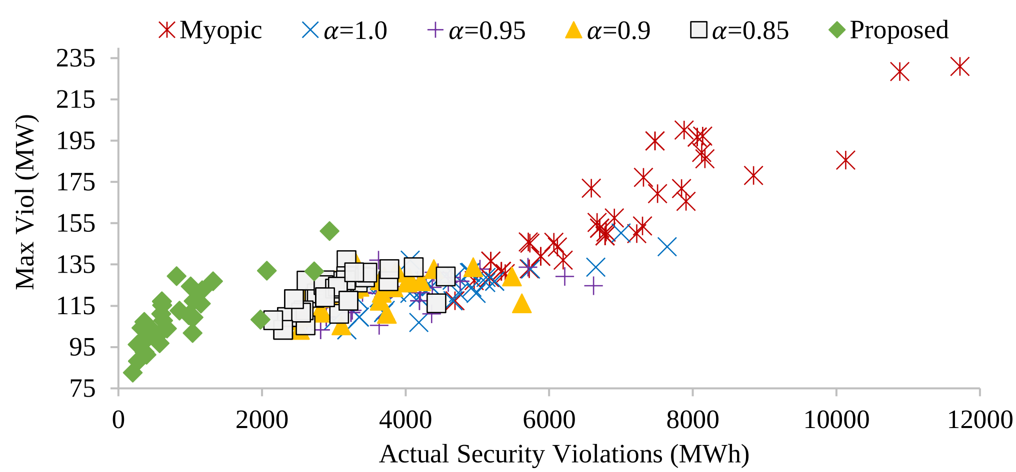


Fig. 5.3. Maximum-security violations compared against the actual sum of security violations for the DA SCUC solutions for the test scenarios.

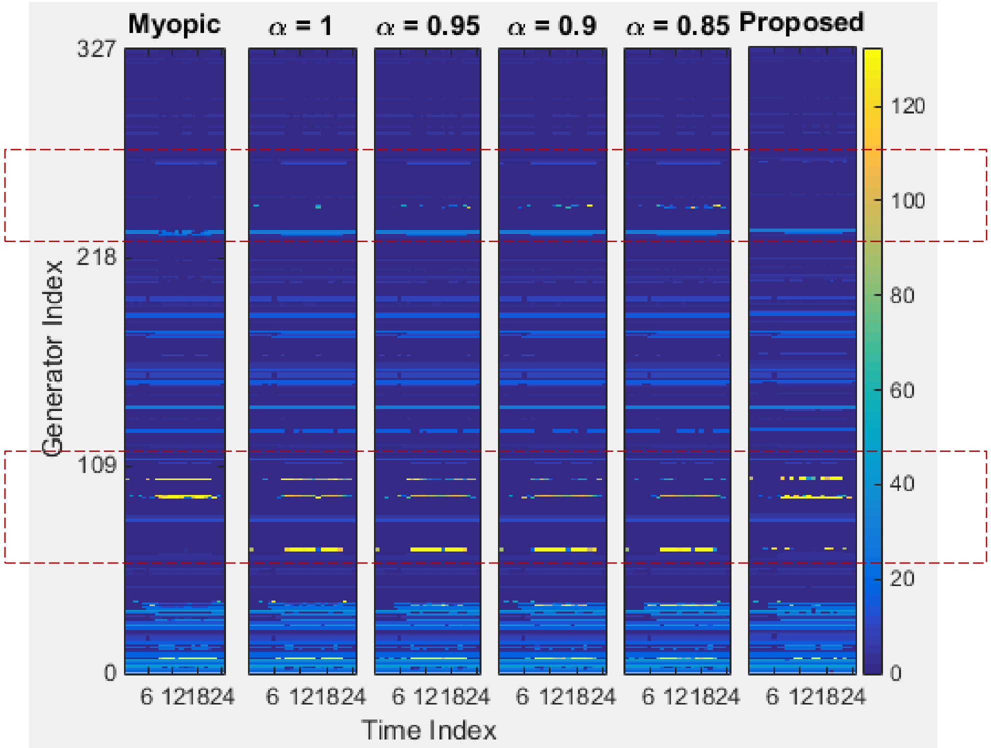
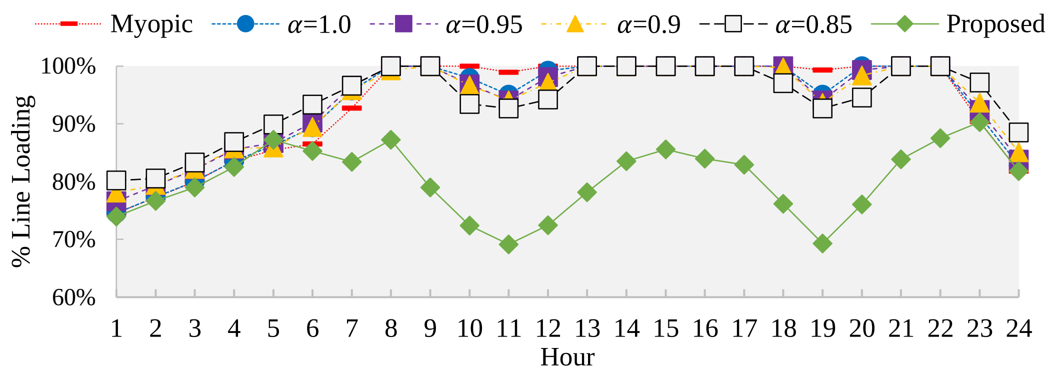
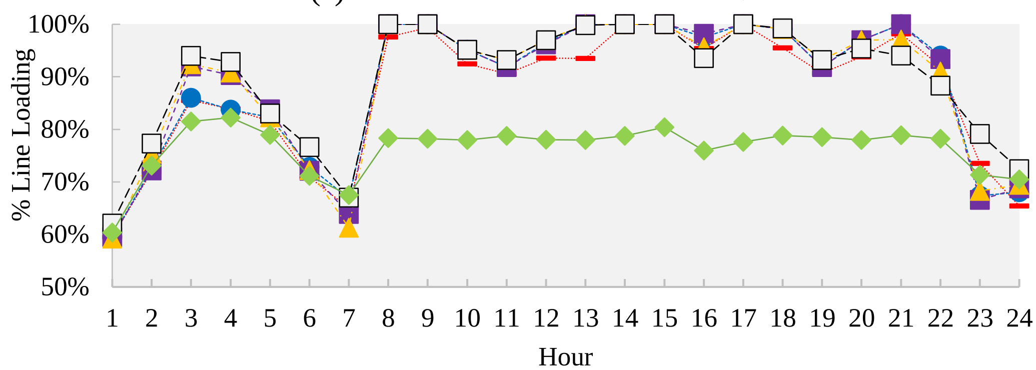


Fig. 5.4. Hourly ancillary service (i.e., spinning reserve) schedules from the DA SCUC solutions. The color bar scale is in MW.

Conversely, to satisfy network constraints, the proposed approach accounts for the impact of scheduled reserves from critical generator locations on bottlenecks by reducing the pre-contingency flows; consequently, minimizing the post-contingency violations due to the activation of reserves in the event of a critical generator contingency. This is evident from Fig. 5.5, which illustrates the *pre-contingency* flows (as a percentage of normal line capacity) on two critical bottlenecks (from set L^{crt}) for the different approaches.



(a) Critical *inter-zonal* bottleneck.



(b) Critical intra-zonal bottleneck.

Fig. 5.5. Critical line loading (pre-contingency) as a percentage of normal capacity for the DA SCUC solution.

Fig. 5.6(a) compares the average final costs (i.e., the cost *after* the OMC phase) for the different approaches. The extensive form provides the best solution (i.e., the solution that is closest to the lower bound or the optimal solution). Although the proposed model reports the highest SCUC cost, it is apparent that it requires the least number of uneconomic adjustments or OMCs (which translates into the lowest OMC cost), thereby, resulting in the lowest final cost. This is indicative of the fact that the proposed model tends to result in a solution that is more probable to be closer to an *N*-1 reliable solution obtained from the extensive form stochastic program, consequently, requiring fewer OMCs. This can be attributed to the explicit modeling of the post-contingency transmission constraints for a given set of critical generator contingencies and critical transmission paths, thereby, allocating the reserves appropriately while respecting the emergency network constraints. In addition, a more conservative reserve sharing policy (smaller α) tends to result in a more reliable solution, which is evident from Fig. 5.2, in comparison to a less conservative policy. However, the more conservative reserve sharing policy has an increased SCUC cost since it requires more reserve to be held within import-constrained regions. Fig. 5.6(b) demonstrates that the average percent cost savings obtained with the proposed approach *relative* to the benchmark approaches are in the range of 1%–3%. Fig. 5.6(c) compares the average computational time to solve the DA SCUC model for the different policies. The extensive form stochastic program results in an average solution time of 875 seconds. It is evident that, the proposed approach enhances the reliability of the system with minimal added computational burden. However, it is important to note that, the solution time is expected to increase with the size of the critical sets $C^{g^{crt}}$ and L^{crt}. Thus, determining the appropriate size for these sets is crucial.

The solution time for the *offline* training stage includes the computational time to solve the DA SCUC model (~157 s), Monte Carlo simulation (~3.85 hours for $c{\times}t{\times}s$ cases) and data-mining models (~320 s for a subset of critical cases). The average solution time to solve a Monte Carlo simulation is ~0.49 s and a data-mining model is ~0.58 s. Note that both the Monte Carlo simulation and the data-mining models can be parallelized since the analyses are independent of each other, thus, reducing the corresponding solve times drastically. Also, the DA SCUC model and the Monte Carlo simulation can be replaced with historical data, if available.

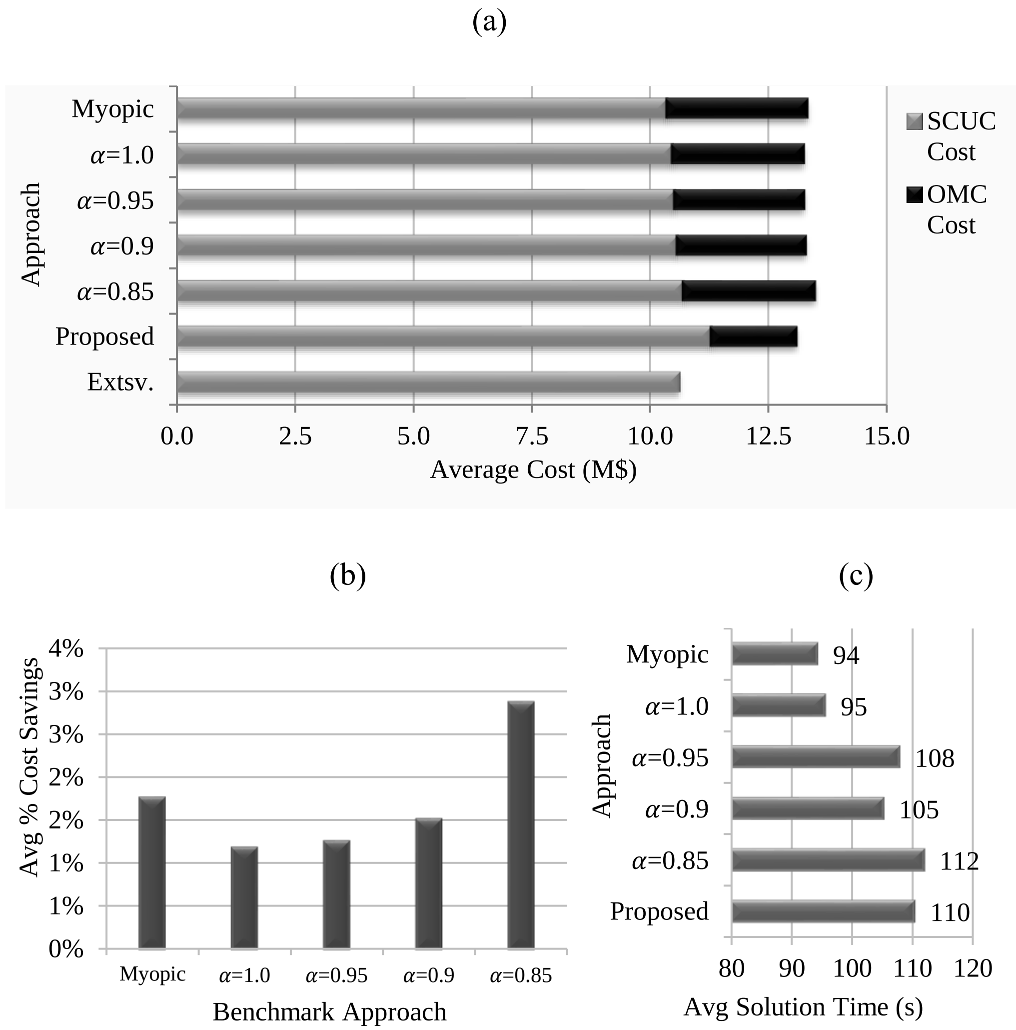


Fig. 5.6. Comparative performance (*averaged* across the test scenarios) of the proposed approach. (a) Final costs. (b) Percent cost savings. (c) Computational time to solve the DA SCUC.

Security violations aid in gauging reliability but do not necessarily result in generation/load curtailment. Normally, system operators mitigate such violations either by rerunning the SCUC model with additional restrictive constraints or by correcting the unreliable solution after the fact using prior operating experience or engineering judgment. Fig. 5.7 compares the average number of units that are turned on, in addition to the units that are previously committed from the DA SCUC run, to obtain an N-1 reliable solution.

It is evident that the proposed approach requires the least number of OMCs or out-of-merit adjustments on average. However, it is important to note that fewer adjustments do not necessarily translate into lower OMC costs. For instance, the reserve sharing policy with α equal to 1.0 requires 41 additional commitments to repair the corresponding unreliable solution in comparison to the 43 additional commitments required by the policy with α equal to 0.9. Although the policy with α equal to 1.0 requires fewer OMCs, the corresponding cost to repair the unreliable solution (i.e., the OMC cost) is $61,094 higher, which is evident from Fig. 5.6(a). Here, the OMC cost is higher for α equal to 1.0 owing to the inability (or infeasibility) to move from the corresponding unreliable solution to an *N*-1 reliable solution using the same set of cost-effective OMC actions that are used for the DA SCUC solution obtained with the reserve sharing policy equal 0.9.

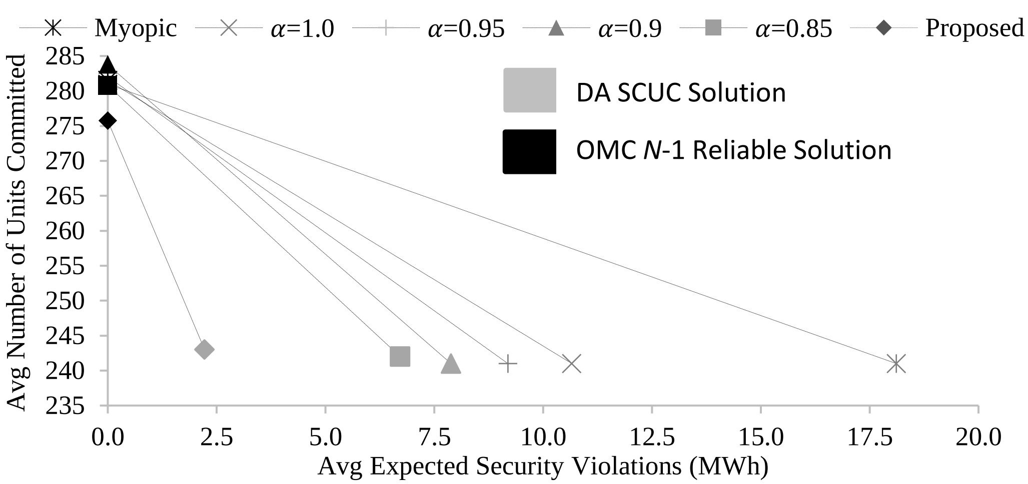


Fig. 5.7. The number of online units compared against the expected sum of security violations (*averaged* across the test scenarios) for the DA SCUC and *N*-1 reliable solutions.

The OMC results are further elaborated in Fig. 5.8, which compares the number of units that are committed in the final *N*-1 reliable solutions (for the corresponding realizations of net load scenarios) for the different approaches. The number of units that are committed in the final reliable solutions for the proposed approach are generally lower than the benchmark approaches implying their proximity to the corresponding *N*-1 reliable solutions. Thus, it is safe to conclude that, since the proposed approach tends to give an *N*-1 reliable solution with fewer commitments, it is more likely to result in lower final costs. Besides, it is important to note that, in this work, we use an OMC formulation to mimic (and *optimize*) the OMC procedures that are usually adopted by market operators [70]. However, in actual practice, such procedures are left to the discretion of operators. Thus, it can be assumed that in the absence of such OMC formulations, which seek to obtain *economically efficient* solutions, the OMC costs can possibly increase, consequently, potentially increasing cost savings. The performance of the proposed approach was also compared against a separate set of myopic reserve policies, obtained by increasing the percentage (η) of the system-wide demand in (2.2); the numerical results were consistent.

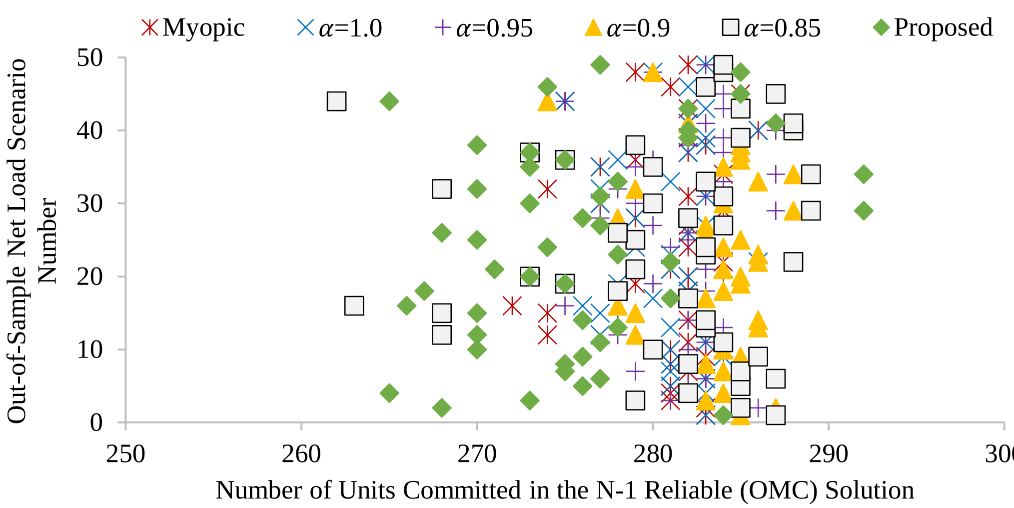


Fig. 5.8. The number of units committed in the final *N*-1 reliable solutions for the corresponding out-of-sample test scenarios.

The performance of the proposed approach was also evaluated against MISO's approach that considers post-contingency security constraints [22]. Table 5.1 summarizes the average results across out-of-sample net load scenarios from the first test day. The best results are *highlighted* for each metric. The proposed approach outperforms MISO's approach on an average basis in comparable solution times. Although MISO suggests enhancing their scheduling models by including post-generator contingency (zonal) security constraints, their approach does not address (local) congestion within a zone. It only accounts for the impact of deployed zonal reserve in the event of the largest generator outage per zone. Furthermore, MISO employs a zonal reserve model that imposes zonal reserve requirements and does not account for reserve sharing between zones when there is available transfer capability on critical inter-zonal paths, while the proposed approach overcomes the limitations of MISO's reserve model.

TABLE 5.1. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FROM THE FIRST TEST DAY FOR THE POLISH TEST SYSTEM

Approach	MISO [17]	Proposed
Final Cost (M$)	13.40	13.08
DA SCUC Solution		
Cost (M$)	10.45	11.28
Time (s)	84	110
# Online Units	241	243
Contingency Analysis		
E[viol] (MWh)	17.45	2.22
# viol	84	41
Max viol (MW)	193	108
∑viol (MWh)	6,373	795
OMC (*N*-1 Reliable Solution)		
Cost (M$)	2.95	1.80
# Online Units	283	276

5.3.4. Results and Analysis: Test for Robustness

The numerical results presented thus far were for out-of-sample net load scenarios from the first test day. To examine the robustness of the proposed approach against varying system operating conditions, the proposed approach was further evaluated on out-of-sample net load scenarios from multiple test days across different seasons. The numerical results for two additional test days are presented below; however, the results are consistent for other test days. The hourly system-wide net load profile for the *base* DA SCUC case for the three test days is shown in Fig. 5.9.

Tables 5.2 and 5.3 summarize the average results (across out-of-sample net load scenarios) for the two additional test days. The best results, excluding the results obtained from the extensive form stochastic UC model, are *highlighted* for each metric. The final cost represents the cost after the OMC phase, i.e., the sum of the DA SCUC cost and the OMC cost. The proposed approach consistently outperforms the two sets of benchmark reserve policies on an average basis by enhancing the reliability of the market solution at reduced final costs and out-of-merit adjustments in comparable solution times.

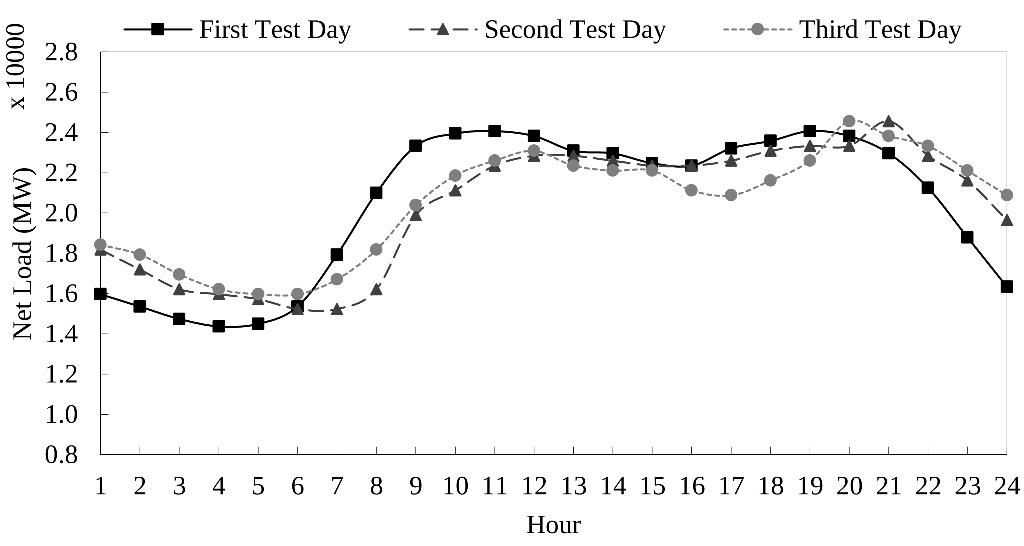


Fig. 5.9. Net load for each test day for the *base* DA SCUC case.

TABLE 5.2. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FROM THE SECOND TEST DAY FOR THE POLISH TEST SYSTEM

Approach	Myopic	α=1	α=0.95	α=0.9	α=0.85	Proposed	Extsv.
Final Cost (M$)	13.67	13.91	13.92	13.90	14.08	13.56	11.83
DA SCUC Solution							
Cost (M$)	10.63	10.85	11.04	11.29	12.15	11.96	11.83
Time (s)	96	113	109	108	112	121	815
# Online Units	244	244	245	249	268	249	263
Contingency Analysis							
E[viol] (MWh)	18	10.31	9.32	9.34	7.05	2.27	0
# viol	96	60	49	48	41	36	0
Max viol (MW)	163	138	135	153	127	105	0
$\sum$ viol (MWh)	6,575	4,022	3,554	3,377	2824	903	0
Out-of-Market Correction (*N*-1 Reliable Solution)							
Cost (M$)	3.04	3.06	2.88	2.61	1.93	1.60	-
# Online Units	292	292	290	288	290	285	-

TABLE 5.3. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FROM THE THIRD TEST DAY FOR THE POLISH TEST SYSTEM

Approach	Myopic	α=1	α=0.95	α=0.9	α=0.85	Proposed	Extsv.
Final Cost (M$)	13.76	13.87	13.85	13.83	14.13	13.62	11.43
DA SCUC Solution							
Cost (M$)	10.69	10.83	10.93	11.07	11.66	11.91	11.43
Time (s)	97	111	103	106	115	112	911
# Online Units	244	243	244	244	250	247	253
Contingency Analysis							
E[viol] (MWh)	20.51	11.86	9.91	8.63	7.37	1.84	0
# viol	100	68	60	51	45	43	0
Max viol (MW)	175	132	131	133	129	66	0
$\sum$ viol (MWh)	7,450	4,578	3,901	3,386	2,967	644	0
Out-of-Market Correction (*N*-1 Reliable Solution)							
Cost (M$)	3.07	3.04	2.92	2.76	2.47	1.71	-
# Online Units	289	288	288	288	286	282	-

5.4. Conclusions

The majority of the scheduling models use static reserve policies that pre-define the reserve quantity under the assumption that all reserves are deliverable. Such simple reserve policies that approximate *N*-1 result in either expensive market solutions or costly out-of-market adjustments when applied to constantly changing system operating conditions because they do not account for pre- and post-contingency congestion aptly. Besides, with increasing penetration levels of stochastic resources, the reserve deliverability issue will be further aggravated, and contemporary deterministic policies will become even less effective. This work presents a new approach to design cohesive reserve policies using data analytics-based algorithms to improve reserve scheduling decisions and allocation (or deliverability) in contemporary SCUC models. The proposed data-driven reserve response set policy includes post-contingency transmission constraints to account for post-generator contingency congestion and uncertainty more appropriately.

The proposed approach is successful in identifying solutions that reasonably capture congestion and reliability impacts while requiring fewer OMCs. The proposed approach lies in the space between existing techniques and other techniques (e.g., two-stage stochastic programs that have scalability issues and market pricing barriers) that face significant barriers to adoption. This research has shown that significant savings can still be obtained based on dynamic reserve policies that still scale well and can avoid market design barriers. Furthermore, well-designed scheduling policies can reduce the number of uneconomic adjustments necessary to correct unreliable market solutions while enhancing the reliability of the market solution. By doing so, market transparency and market pricing is improved since fewer discretionary adjustments outside of the market are needed, more of the required services are cleared through the market, which then results in more accurate price signals. The results from the Polish system demonstrate a consistent ability to improve market efficiency, maintain scalability, and enhance market transparency.

ISOs are required to be independent and pursue an objective that maximizes social welfare (or market surplus). The proposed approach enhances social welfare, which is the main deciding factor for adopting new technologies.

CHAPTER 6.

A RESERVE RESPONSE SET MODEL FOR SYSTEMS WITH STOCHASTIC RESOURCES

6.1. Background and Motivation

Security-constrained unit commitment (SCUC) is a classical problem used for day-ahead commitment, dispatch, and reserve scheduling. Even though SCUC models acquire reserves, *N*-1 reliability is not guaranteed. Furthermore, the uncertainty and variability associated with stochastic resources coupled with the constantly changing system operating conditions introduce new challenges to power systems. System operators must ensure there is sufficient generation capability and deliverability to respond to discrete disturbances (i.e., loss of any single non-radial transmission or generation element) or typical forms of uncertainty (for example, load, area-interchange, or renewables) by using certain proxy methods (or approximations) either through preventive or corrective actions.

This chapter presents an enhanced SCUC formulation that facilitates the integration of stochastic resources and accounts for reserve allocation and deliverability issues, in the event of generator contingency, through preventive (or pre-determined) biasing actions within the enhanced SCUC model. Reserves can then be allocated within the market auction model while accounting for post-generator contingency congestion. In the proposed formulation, the SCUC model is modified to incorporate a reserve response set model, which improves upon existing deterministic models (and industry practices to model credible generator contingencies, load uncertainty, and renewable uncertainty) and can potentially facilitate the transition to stochastic models. The proposed reserve model aims to predict the effects of nodal reserve deployment on critical transmission assets in the post-generator contingency state so as to improve the deliverability of reserves post-contingency. The proposed reserve policies are used as a means to predict reserve activation. The approach, thus, aims to acquire reserve at prime locations that face fewer reserve deliverability issues. Furthermore, an offline methodology is used to design the proxy reserve policies from historical data or the results of stochastic (or Monte Carlo) simulations that generate hypothetical data, thereby, shifting the computational burden to an offline stage. The proposed model has minimal added computational complexity compared to existing deterministic SCUC models. By having an offline study stage and explicitly representing post-contingency flows for *critical* system elements and contingencies, the proposed approach has tractable computational complexity for actual-size systems. The performance of the proposed approach is demonstrated on a 2383-bus system. The primary goal is to enhance power system flexibility to satisfy physical network constraints when the system state deviates from the forecast.

The remainder of this chapter is organized as follows. Section 6.2 describes the formulation and implementation of the proposed reserve response set model, including the post-contingency nodal reserve deployment constraint. The proposed approach is implemented and tested on the IEEE 118-bus and the 2383-bus Polish test systems and the numerical results are presented in Section 6.3 and Section 6.4, respectively. Finally, Section 6.5 concludes the chapter.

6.2. Reserve Response Set Model Formulation and Methodology

This subsection describes the formulation and implementation of the proposed reserve response set model, including the post-contingency nodal reserve deployment constraint [95]. The proposed reserve model utilizes a *policy-driven* approach. The goal is to alleviate the deliverability issues associated with reserve in the post-contingency state while maintaining scalability and computational tractability for large-scale power systems. A policy is a rule that governs a decision given the information available in a particular state [17]. Fig. 6.1 illustrates the overall methodology of the proposed approach, which consists of two primary phases: 1) the offline training phase and 2) the out-of-sample testing phase.

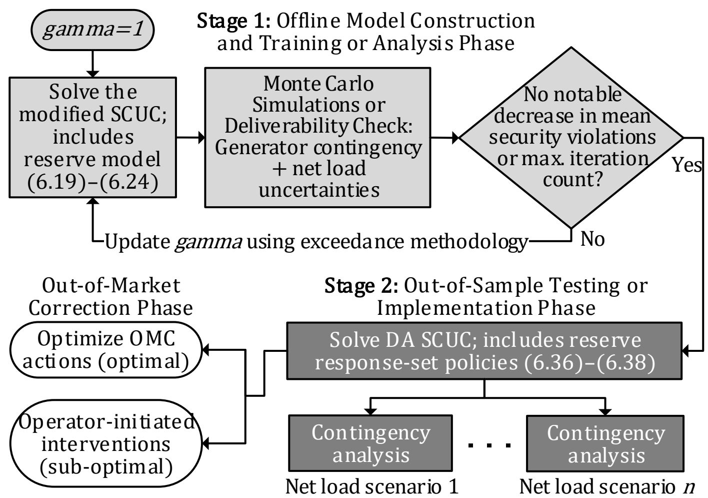


Fig. 6.1. The overall methodology of the proposed reserve response set model.

6.2.1. Offline Model Construction and Training or Analysis Phase

The first stage is the *offline* model construction and analysis phase, which utilizes a knowledge discovery process from historical data (or Monte Carlo simulations) analogous to contemporary data-mining techniques to allocate reserve. The objective is to identify the prime locations where reserves are deliverable post-contingency and determine the appropriate quantity of reserves that each generator should provide. First, a modified deterministic SCUC model, formulated as a MILP, that includes a response-set (for each of the modeled generator contingencies) reserve model is solved using CPLEX's MIP optimizer (dynamic search algorithm).

$$\text{Minimize:} \sum_{g,t} \left(\left[\sum_j C_{gj}\left(P_{gtj}\right) \right] + C_g^{NL} u_{gt} + C_g^{SU} v_{gt} + C_g^{SD} w_{gt} + C_g^{res} r_{gt} \right) \tag{6.1}$$

Subject to:

$$i_{nt} = \sum_{g \in G^n} \left(P_{gt}\right) - D_{nt}, \forall n \in N, t \in T \tag{6.2}$$

$$\sum_n i_{nt} = 0, \forall t \in T \tag{6.3}$$

$$F_{lt} = \sum_n PTDF_{n,l}\, i_{nt}, \forall l \in L, t \in T \tag{6.4}$$

$$-F_l^{RateA} \le F_{lt} \le F_l^{RateA}, \forall l \in L, t \in T \tag{6.5}$$

$$0 \le P_{gtj} \le P_{gj}^{max} u_{gt}, \forall g \in G, t \in T, j \in J \tag{6.6}$$

$$P_{gt} = \sum_j P_{gtj}, \forall g \in G, t \in T \tag{6.7}$$

$$0 \le r_{gt} \le R_g^{10} u_{gt}, \forall g \in G, t \in T \tag{6.8}$$

$$P_g^{min} u_{gt} \le P_{gt}, \forall g \in G, t \in T \tag{6.9}$$

$$P_{gt} + r_{gt} \le P_g^{max} u_{gt}, \forall g \in G, t \in T \tag{6.10}$$

$$P_{gt} - P_{g,t-1} \le R_g^{60} u_{g,t-1} + R_g^{SU} v_{gt}, \forall g \in G, t \in T \tag{6.11}$$

$$P_{g,t-1} - P_{gt} \le R_g^{60} u_{gt} + R_g^{SD} w_{gt}, \forall g \in G, t \in T \tag{6.12}$$

$$\sum_{q=t-UT_g+1}^{t} v_{gq} \le u_{gt}, \forall g \in G, t \in \left\{UT_g, \dots, T\right\} \tag{6.13}$$

$$\sum_{q=t-DT_g+1}^{t} w_{gq} \le 1 - u_{gt}, \forall g \in G, t \in \left\{DT_g, \dots, T\right\} \tag{6.14}$$

$$v_{gt} - w_{gt} = u_{gt} - u_{g,t-1}, \forall g \in G, t \in T \tag{6.15}$$

$$u_{gt} \in \{0,1\}, \forall g \in G, t \in T \tag{6.16}$$

$$0 \le v_{gt} \le 1, \forall g \in G, t \in T \tag{6.17}$$

$$0 \le w_{gt} \le 1, \forall g \in G, t \in T \tag{6.18}$$

Response-set (contingency-based) reserve model:

$$\sum_g r_{gt} \ge P_{gt} + r_{gt}, \forall g \in G, t \in T \tag{6.19}$$

$$\sum_g r_{gt} \geq \eta\% \sum_n D_{nt}, \forall t \in T \tag{6.20}$$

$$\sum_g r_{gt}^c \geq P_{ct} + r_{ct}, \forall c \in C^g, t \in T \tag{6.21}$$

$$r_{gt}^c \leq \Gamma_{gt}^c r_{gt}, \forall c \in C^g, g \in G, t \in T \tag{6.22}$$

$$-F_l^{RateC} \leq F_{lt} - P_{ct} PTDF_{n(c),l} + \sum_{g:g \neq c} PTDF_{n(g),l} r_{gt}^c \leq F_l^{RateC}, \forall c \in C^{g^{crt}}, l \in L^{crt}, t \in T \tag{6.23}$$

$$\Gamma_{gt}^c \in [0,1], \forall c \in C^g, g \in G, t \in T. \tag{6.24}$$

In the formulation, the objective (6.1) is to minimize the total system costs, which includes the operational, no-load, startup, shutdown and reserve costs. The demand is assumed to be perfectly inelastic; therefore, minimizing the total system costs is equivalent to maximizing the social welfare. Constraint (6.2) models the power injected at each node whereas (6.3) ensures system-wide power balance between generation and load. The dc power flow on each transmission asset, described by (6.4), is bounded by the corresponding normal rate (rate A) in (6.5). Constraint (6.6) imposes limits on the size of the piecewise segments. The real power produced by each generator, represented by (6.7), is restricted to be equal to the summation of its corresponding piecewise segments. The scheduled reserve is restricted by the 10-minute ramp rate in (6.8). Constraints (6.9) and (6.10) impose minimum and maximum restrictions on the real power scheduled from generator resources. Constraints (6.11) and (6.12) model the ramp rate restrictions, which includes the hourly, startup and shutdown ramp rates, and (6.13) and (6.14) model the minimum up and down time requirements. The relationship between the unit commitment, startup and shutdown variables is described in (6.15). The unit commitment variable is restricted to be a binary variable in (6.16), whereas the startup and shutdown variables are modeled as continuous variables in (6.17) and (6.18) respectively.

Since the system state changes post-contingency, it is critical to identify the appropriate quantity and prime locations of reserve and capture the deviation in line flows from the pre-contingency state. This is achieved by including the post-contingency line flow constraints for critical transmission paths that are frequently congested in the pre- and post-contingency states, which can then cause reserve deliverability issues. Critical paths can be pre-identified based on historical data, operational procedures, and offline studies [22]. The corresponding offline training phase contingency-based reserve model is described by (6.19)–(6.24). Constraints (6.19) and (6.20) represent the system-wide reserve policies similar to (2.1) and (2.2). In this case, η is fixed to equal the approximate level of uncertainty in the system-wide net load. Constraint (6.21) is the contingency-based reserve policy, which requires the total *deployed* reserves to be no less than the generation lost in the corresponding contingency event. Constraint (6.22) ensures that the activated reserve is no greater than a fraction (Γ_{gt}^{c}) of the scheduled reserve, (6.23) is post-contingency line flow constraint, and (6.24) bounds the reserve activation factor Γ_{gt}^{c} such that it can only take on values between zero and one. In (6.23), the first component captures the pre-contingency line flow, the second component models the deviation in line flow due to the corresponding critical generator contingency, and the third component reflects the impact of nodal reserve deployment on critical paths in the post-contingency state *explicitly*.

Second, a deliverability check (or contingency analysis) is conducted to inspect each generator's reserve deliverability for each combined generator contingency and net load scenario. A generator is said to be able to deliver its scheduled reserve $\overline{r_{gt}}$ if the reserve can be activated without violating any thermal (emergency) limits. Such an offline stochastic simulation methodology (Monte Carlo simulations) is created to generate hypothetical data, i.e., replace (missing) historical data. The scheduled unit commitment status, reserve, and real power production from each of the generating resources, obtained from the aforementioned modified SCUC, are provided as inputs to the Monte Carlo simulations. Furthermore, 100 different realizations of net load scenarios (in a particular generation contingency state) are utilized in this stage.

From literature [96], the usual practice in data-mining is to split the sampled dataset (in this case, net load scenarios) into training (60–80%) and testing (40–20%). The split proportion is also dependent on the size of the sampled dataset. The main rationale is to have a sufficient number of representative samples when building the model to better model the underlying distribution in the training stage. The size of the sampled dataset used in this dissertation was restricted to ~130-200 scenarios because obtaining a very large number of samples is either too expensive or time-consuming. However, this size can be modified based on time availability. It is expected that a larger sampled dataset can potentially result in better performance (or accuracy). Note that, the adopted design approach is still a considerable improvement over existing practices, which do not necessarily consider sufficient samples in designing their reserve policies. A split proportion of ~77% training data (100 net load scenarios) and ~23% testing data (30 net load scenarios) was maintained when validating the approach on the Polish test case; however, due to the relative ease to test a larger sample size (in the testing stage) for a smaller system, the dataset splitting proportion was fixed to 50–50% (100 net load scenarios each) for the IEEE 118-bus test case. Finding an optimal sample size and dataset splitting proportion is out of the scope of this research work.

The contingency analysis linear programming problem, detailed below, for each training net load scenario (where $s \in S^{TRN}$) is solved using CPLEX's optimizers based on simplex algorithms. Here, D_{nst} denotes the demand at bus n, for the corresponding realized training net load scenario s, in time t.

Minimize: $\sum_{n,c,t} LS_{nct}^{+} + LS_{nct}^{-}$ (6.25)

Subject to:

Post-contingency restrictions on generation (6.26)–(6.28) and modeling of generator contingencies (6.29):

$$-P_{gct} \leq \bar{r}_{gt} - \bar{P}_{gt}, \forall g: g \neq c, c \in C^{g}, t \in T \quad (6.26)$$

$$P_{gct} \leq \bar{r}_{gt} + \bar{P}_{gt}, \forall g: g \neq c, c \in C^{g}, t \in T \quad (6.27)$$

$$P_{g}^{min}\bar{u}_{gt} \leq P_{gct} \leq P_{g}^{max}\bar{u}_{gt}, \forall g: g \neq c, c \in C^{g}, t \in T \quad (6.28)$$

$$P_{gct} = 0, \forall g: g = c, c \in C^{g}, t \in T \quad (6.29)$$

Post-contingency modeling of real power flow:

$$i_{nct} = \sum_{g \in G^{n}}\left(P_{gct}\right) - D_{nst} + LS_{nct}^{+} - LS_{nct}^{-}, \forall n \in N, c \in C^{g}, t \in T \quad (6.30)$$

$$\sum_{n} i_{nct} = 0, \forall c \in C^{g}, t \in T \quad (6.31)$$

$$-F_{l}^{RateC} \leq \sum_{n} PTDF_{n,l}\, i_{nct} \leq F_{l}^{RateC}, \forall l \in L, c \in C^{g}, t \in T. \quad (6.32)$$

Slack variables LS_{nct}^{+} and LS_{nct}^{-} (i.e., load shedding and load surplus variables, respectively) give an indication of the post-contingency security violations and are included in the post-contingency power balance constraint (6.30) to ensure the feasibility of the contingency analysis problem. Note that the slack variables are restricted to be non-negative in the mathematical model. The objective (6.25) is to minimize the post-contingency security violations. The deviation between the pre- and post-contingency real power production is restricted by the scheduled reserve (from the modified SCUC model) in (6.26)–(6.27). Constraint (6.28) imposes bounds on the post-contingency real power production from generating resources, whereas (6.29) models the generator contingencies. Constraint (6.31) ensures system-wide power balance in the post-contingency state and (6.32) limits the post-contingency flows to lie within the emergency limits.

For each realized training net load scenario, i.e., $s \in S^{TRN}$, the reserve deliverability check stage (Monte Carlo simulations) results in the amount of reserve that is activated (or deployed) during each of the generator contingency states c, $r_{g,s,t}^{c}$. Also, the activated reserve in response to generator contingency c and during training net load scenario s is equal to the difference between the post-contingency real power production for the corresponding net load scenario and the scheduled real power production. Furthermore, for a specific generator contingency state c, the reserve deployed in the different training set of net load scenarios are then sorted in the descending order (analogous to the more familiar load duration curve analysis) following which a certain value of $r_{g,s,t}^{c}$ is chosen based on a pre-determined choice of *exceedance level*. This value of $r_{g,s,t}^{c}$ is then used in updating the parameter Γ_{gt}^{c} using (6.33). Exceedance level represents a measure of the fraction of times an event exceeds a pre-defined reference level [81]. Such an approach is adopted in present-day industry practices. For instance, CAISO uses the exceedance counting methodology (with values varying from 30% to 70%), in their generator deliverability studies, to assess the minimum amount of generation that a renewable resource can realistically produce and deliver in at least a certain percentage (exceedance level) of the studied hours [97]. Analogously, EPRI uses a similar approach to determine the flexibility requirements for a system with renewable generation integration [98]. An illustration of the exceedance level is presented in Fig. 6.2.

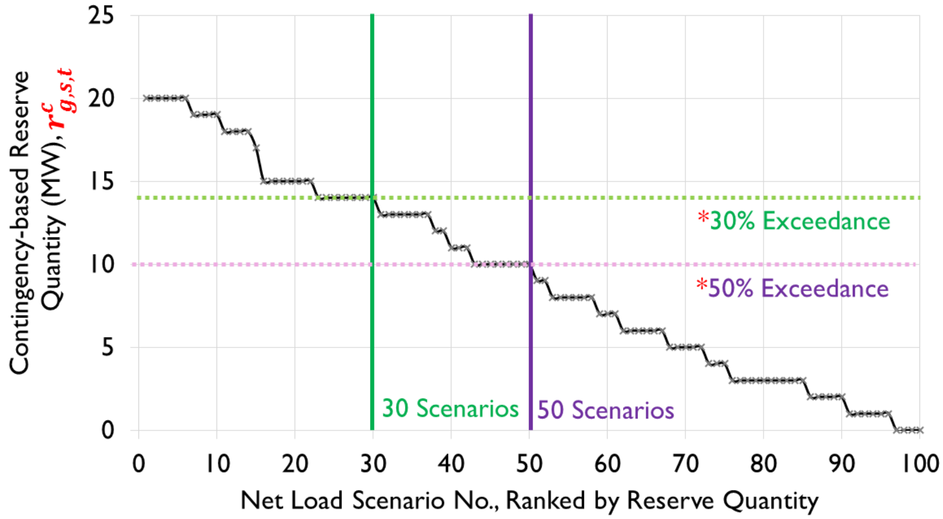


Fig. 6.2. Illustration of the exceedance level.

In Fig. 6.2, if a 50% exceedance level is chosen as a reference then $r^c_{g,s,t}$ will take on the value of 10 MW. This exceedance level implies that, for the 100 training net load scenarios included in the Monte Carlo simulations, 50% of the time the activated reserve in response to generator contingency c is larger than the chosen value of $r^c_{g,s,t}$, which is 10 MW in this case, in (6.33). Since the activated reserve for the training set of net load scenarios is sorted in the descending order, a lower choice of exceedance level results in a larger value of $r^c_{g,s,t}$ in (6.33) and a correspondingly larger Γ^c_{gt}. A larger value of Γ^c_{gt} implies that a larger fraction of reserve is deliverable from generator g in response to contingency c for a certain percentage (exceedance level) of the net load scenarios. Thus, a lower exceedance level represents a less conservative reserve policy, whereas, a higher exceedance level represents a more conservative reserve policy. In other words, the higher the exceedance level, the more conservative the reserve policy.

Updating Γ_{gt}^{c} based on a pre-defined exceedance level:

$$\Gamma_{gt}^{c} = \frac{r_{g,s,t}^{c}}{\overline{r_{gt}}}, \forall c \in C^{g}, g \in G, t \in T. \tag{6.33}$$

The deliverability of reserve provided by each generator is enhanced by iteratively updating the parameter Γ_{gt}^{c}, which defines the response set and is initially set to one, using (6.33) until a termination criterion is met. In other words, the offline training phase modified SCUC, which includes the response-set reserve model, is solved repeatedly until the updated Γ_{gt}^{c} does not further reduce the expected sum of post-contingency security violations significantly for the training set of net load scenarios on an average basis or until a maximum iteration count is reached; therefore, it is system-dependent. The maximum iteration count can be set based on time availability. The output of the first stage is the reserve activation factor, $\overline{\Gamma_{gt}^{c}}$.

To summarize, during the offline training phase, data generated from Monte Carlo simulations is analyzed to determine the quantity of reserves that are activated from each generator in addition to identifying the prime locations of the reserve. In other words, the offline process is used to determine a response set for each contingency. The response set is identified by using the parameter Γ_{gt}^{c}, which again aims to capture the deliverability of reserve at each location in each contingency.

6.2.2. Out-of-Sample Testing or Implementation Phase

The second stage is the out-of-sample testing or implementation phase, where the day-ahead (DA) SCUC model is modified to incorporate the reserve response-set policies described by (6.36)–(6.38) in comparison to (6.19)–(6.24) that were included in the training stage. The complete formulation of the modified deterministic DA SCUC model, formulated as a MILP and solved using CPLEX's dynamic search algorithm, is described by (6.34)–(6.38) detailed below.

$$\text{Minimize:} \sum_{g,t}\left(\left[\sum_j C_{gj}\left(P_{gtj}\right)\right] + C_g^{NL}u_{gt} + C_g^{SU}v_{gt} + C_g^{SD}w_{gt} + C_g^{res}r_{gt}\right) \tag{6.34}$$

Subject to:

Constraints (6.2)–(6.18) (6.35)

$$\sum_g r_{gt} \geq \eta\% \sum_n D_{nt}, \forall t \in T \tag{6.36}$$

$$\sum_g \overline{\Gamma_{gt}^c} r_{gt} \geq P_{ct} + r_{ct}, \forall c \in C^g, t \in T \tag{6.37}$$

$$-F_l^{RateC} \leq F_{lt} - P_{ct}PTDF_{n(c),l} + \sum_{g:g\neq c} PTDF_{n(g),l}\overline{\Gamma_{gt}^c} r_{gt} \leq F_l^{RateC}, \forall c \in C^{g^{crt}}, l \in L^{crt}, t \in T. \tag{6.38}$$

The objective is to minimize the total system costs, which includes the operational, no-load, startup, shutdown and reserve costs similar to (6.1). Constraint (6.36) is similar to (6.20) and (6.37) is equivalent to (6.21), which identifies a potential response set by incorporating the deliverability information (i.e., the quantity and prime locations) for each contingency event. The input parameter $\overline{\Gamma_{gt}^c}$, obtained from the first stage, reflects the quotient of scheduled reserve that is potentially deliverable in contingency state c. Constraint (6.38) is similar to (6.23), which ensures the deliverability of deployed reserves through set L^{crt}. Here, subsets $C^{g^{crt}}$ and L^{crt} (consistent for both training and testing stages) are pre-defined to include only the larger units and the routinely congested transmission assets (respectively) after weighing the trade-off between model accuracy and model complexity. However, they can be extended to include the less critical units and transmission assets as well. Again, the DA SCUC model is followed by contingency analysis (or deliverability check) to test its market solution against generator contingencies combined with *out-of-sample* net load scenarios, i.e., $s \in S^{OOS}$.

6.2.3. Out-of-Market Correction Stage

Existing market SCUC solutions do not guarantee *N*-1 reliability due to the changing system operating conditions, its deterministic structure, and model approximations, thereby, resulting in potential system security violations. Often, a value of lost load (VOLL) is assumed to estimate the cost of security violations; however, the results obtained using such an approach are sensitive to the choice of VOLL. Today, market operators adjust market solutions outside the market engine to create realistic, feasible solutions. Thus, contingency analysis is followed by an OMC phase to obtain the cost to move from an unreliable to a reliable solution. Such operator mediations are classified as exceptional dispatches in CAISO and reserve disqualifications in MISO [72], [22]. The analysis, in this work, aims to simulate (or optimize) the OMC procedures that are usually taken by system operators to more accurately (objectively) estimate the actual incurred costs for correcting security violations rather than taking an approach that is dependent on a subjective VOLL. The final solutions included in the results are *N*-1 reliable. In order to be consistent with existing market practices, the adopted OMC formulation does not allow de-committing units that were originally committed in the DA SCUC market model; however, it does allow for a modification of the dispatch schedules and the commitment of additional units at increased penalty costs in order to ensure reliable operations. It is pertinent to note that the OMC costs that are reported in this chapter do not include the aforementioned penalty costs to deviate from the DA SCUC solution.

6.3. IEEE 118-Bus Test Case

6.3.1. Network Overview

The proposed approach is implemented on a modified IEEE 118-bus test system to evaluate its effectiveness. The modified IEEE 118-bus test case has 54 generators, 186 lines, and 91 loads [83]. The modifications made to the original test system include: decreasing the line ratings to create congestion; and decreasing the system load to 90% of the original load. The system is partitioned into three zones using the zone partitioning method presented in [23].

6.3.2. Dataset and Software Description

Critical transmission asset set L^{crt} is pre-defined by conducting contingency analysis on a proposed SCUC solution with varying system operating conditions and by pre-identifying the frequently congested inter-zonal links in the post-contingency state; however, the critical transmission set can be extended to include intra-zonal links. In this case study, set L^{crt} includes one *routinely* congested (critical/credible) transmission asset and set $C^{g^{crt}}$ includes all generating elements that have a maximum real power generating capacity of greater than or equal to 350 MW, i.e. *five* generating units. Thus, a total of $1 \times 5 \times 24 = 120$ post-contingency transmission constraints are included, where 24 represents the number of time periods in the DA model. This work considers net load uncertainty. In other words, the uncertainty introduced by stochastic resources, such as wind, solar or load, is represented by *net* load scenarios. The net load at each bus is assumed to follow a Gaussian distribution with zero mean to approximate the uncertainty without overcomplicating the scenario generation process. The variance chosen was such that the resultant uncertainty is ~7%. More accurate distributions can be adopted in future work. Variable fuel costs are denoted by a piecewise linear cost function. The exceedance level is pre-set to 50% (neither too conservative nor overstated, after conducting a sensitivity analysis) in sync with existing industry practices. In addition, it is noticed that, for this case study, there is no significant reduction in the average security violations beyond three iterations, therefore, the number of iterations for updating Γ_{gt}^{c} is set to three. Additionally, 100 different net load scenarios are used in the out-of-sample testing phase. The relative MIP gap for the various optimization problems is set to 0.2%. The proposed algorithm is solved with CPLEX v12.6. All simulations are run on a computer with the following specifications: Intel® Xeon® CPU X5687 @ 3.60 GHz, 48 GB RAM, and 64-bit operating system.

6.3.3. Results and Analysis

The performance of the proposed approach is compared against the reserve sharing model defined by (2.3)-(2.6) and an extensive form stochastic UC model (abbreviated as "Exten. Form" or "Extsv." in the figures and tables) at a one-hour resolution. Varying reserve sharing policies are used for the reserve sharing model, with α ranging from 0.4 to 0.8. It is important to note that, the reserve sharing model is infeasible for α less than 0.4. The extensive form stochastic UC model is formulated as a two-stage stochastic program, where all generator contingencies are represented explicitly (in a probabilistic fashion) in all time periods. Thus, the solution obtained from the extensive form is guaranteed to be *N*-1 reliable with respect to generator contingencies.

The subsequent results are *averaged* across the out-of-sample net load test scenarios. Fig. 6.3 compares the final costs for the different approaches. Here, final cost refers to the cost *after* the OMC phase, therefore, it includes both the SCUC cost and the OMC cost. It is apparent that the extensive form stochastic UC reduces the need for OMCs, which can be attributed to the explicit modeling of the forecasted states and recourse decisions for the given set of generator contingencies. In addition, the stochastic program benchmark provides the best solution (i.e., the solution that is closest to the optimal solution or the lower bound) because it allocates reserves at deliverable locations by considering post-contingency states. Although the proposed model results in the highest SCUC cost in comparison to the reserve sharing models, it has the fewest uneconomic adjustments and therefore the lowest OMC cost, thereby, resulting in the lowest overall cost. The result also indicates that the proposed approach can obtain a solution that is closer to the *N*-1 reliable solution obtained from the extensive form, thereby decreasing the need for OMCs. By the market SCUC capturing reliability issues more adequately, prices are also a better reflection of the true marginal cost of providing reliable electricity.

Fig. 6.4(a) illustrates that the percent cost savings of the proposed approach *relative* to the different reserve sharing models is in the range of ~1%-5%. Fig. 6.4(b) compares the computational time to solve the DA SCUC for the different approaches. Although the proposed approach reported a relatively short solution time, this result can vary (within a reasonable range) depending upon the size of the critical sets $C^{g^{crt}}$ and L^{crt}. Owing to the relatively small size of the test system, the proposed model is not always expected to outperform the benchmark models with respect to the solution time. However, it can be concluded that, the proposed approach enhances the DA SCUC model with minimal added computational burden. In addition, it is important to note that, although the extensive-form was solvable within a short timeframe, this would not be the case for a practical sized power system such as MISO, whose network model includes over 45,000 buses and 1,400 generating resources [12]. Note that the solution time for the offline training stage is not time sensitive; thus, its solution time is not reported.

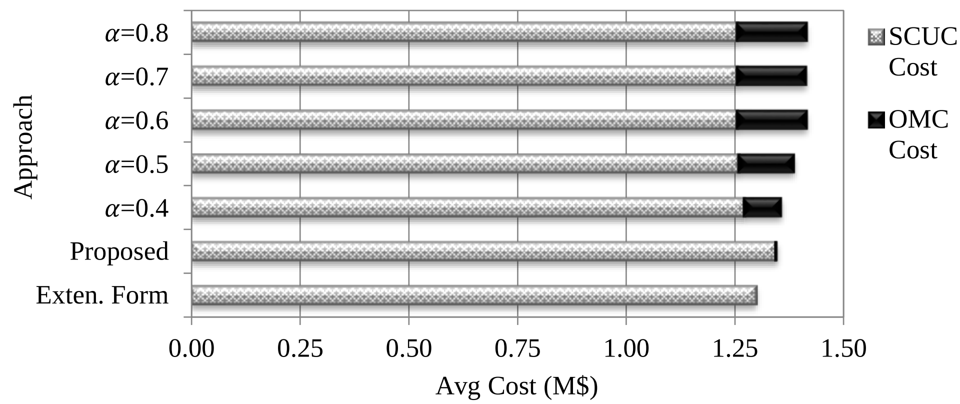


Fig. 6.3. Average final costs, including SCUC cost and OMC cost, comparison. Here, α signifies varying reserve sharing policies for the reserve sharing model and Exten. Form denotes the extensive-form stochastic UC model.

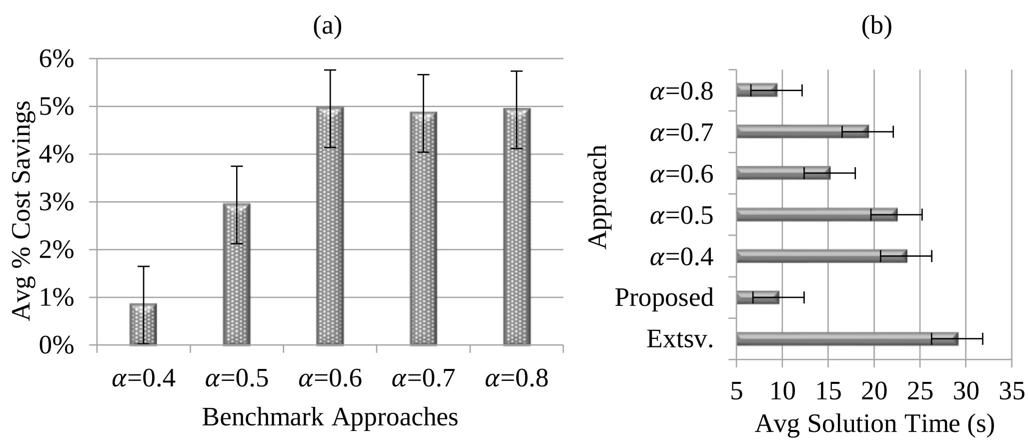


Fig. 6.4. Performance of the proposed approach in comparison to the reserve sharing model (with varying α sharing policies) and the extensive-form stochastic UC model (Extsv.). (a) Average percent cost savings with standard error for sample size $n = 100$. (b) Average computational time to solve the Extsv. and the DA SCUC model (for the reserve sharing α approach and the proposed approach) with standard error for sample size $n = 100$.

Fig. 6.5 presents a statistic that measures the relative performance ($RP\%$), which is defined as the percentage of the highest cost savings that the proposed approach can potentially achieve. The $RP\%$ metric is computed as follows:

$$RP\% = \frac{C_{BA} - C_{Prpsd}}{C_{BA} - C_{Extsv}} . 100\%. \tag{6.39}$$

In (6.39), the denominator represents the maximum potential cost savings that the proposed approach can achieve, i.e. final cost of the corresponding benchmark approach (C_{BA}) less the final cost of the extensive form stochastic program (C_{Extsv}). Also, C_{Prpsd} represents the final cost of the proposed approach. Finally, the expected variability in the estimated means of the percent cost savings, computational time to solve the DA SCUC problem, and the relative performance of the proposed approach is shown by error bars such as the standard error (SE, which describes the standard deviation of the mean). SE describes the uncertainty in the mean and is calculated by dividing the standard deviation by the square root of the number of samples (represented by n) that make up the mean. The lesser the original data values range above and below the mean, i.e., the narrower the SE bar, the more confidence one has in a specific value, i.e., the estimated mean.

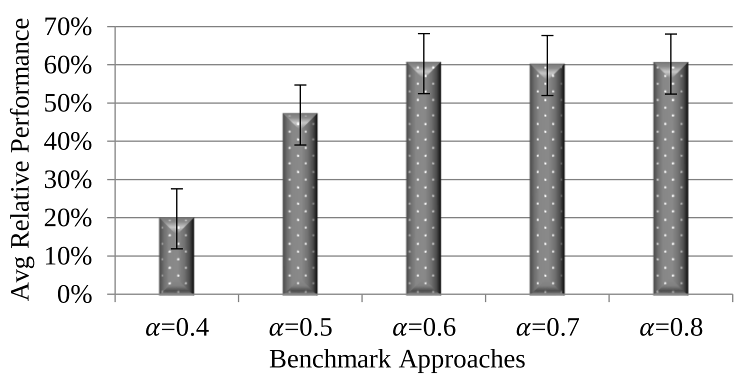


Fig. 6.5. Average relative performance ($RP\%$) of the proposed approach in comparison to the reserve sharing model (with varying α sharing policies) with standard error for sample size $n = 100$.

Fig. 6.6 compares the final costs for *N*-1 reliable solutions against the expected sum of security violations (or E[viol]) for the corresponding DA SCUC solutions for the out-of-sample net load test scenarios. Here, the bubble size is indicative of the number of cases, i.e. over all contingencies and time periods, with violations for the corresponding net load scenario, denoted by #violated cases. The proposed approach has the least #violated cases in addition to the lowest amount of E[viol] because it preemptively locates reserve in prime locations with better potential deliverability. Less conservative policies (large α) tend to result in higher E[viol], #violated cases, and final costs but lower SCUC costs because they require lesser reserve to be held within local regions.

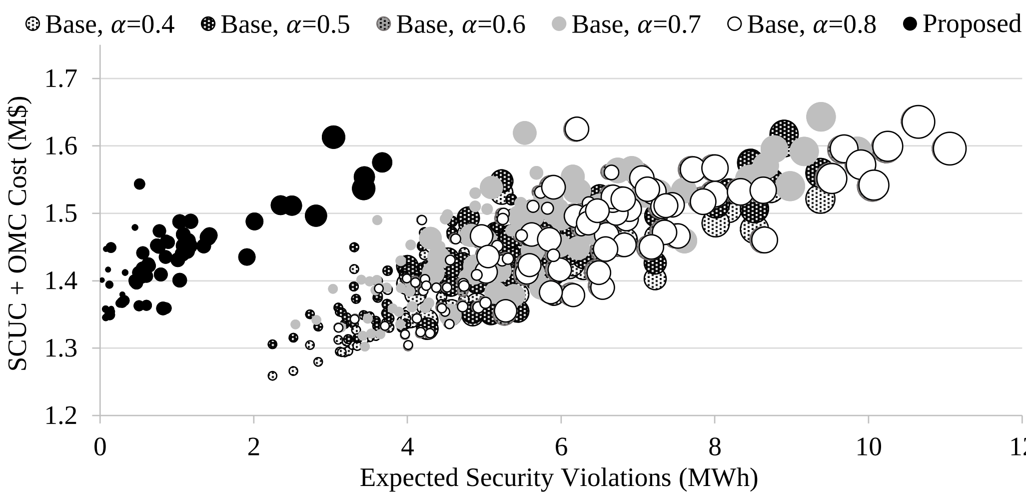


Fig. 6.6. Final costs for *N*-1 reliable solutions compared against the E[viol] for DA SCUC solutions for the test scenarios. The bubble size represents the number of cases ($\forall c, t$) with violations for the corresponding net load scenario.

6.3.4. Results and Analysis: Test for Robustness

Lastly, the testing process included taking the gamma obtained from the offline training stage and evaluating it against multiple test days across different seasons to test for its robustness against varying operating conditions. Table 6.1 summarizes the average results for one such test day. It can be seen that the performance of the proposed approach is consistent with the aforementioned results (i.e., in Section 6.3.3) for the first test day.

TABLE 6.1. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FROM THE SECOND TEST DAY FOR THE IEEE 118-BUS TEST SYSTEM

Approach	SCUC Cost	OMC Cost	Time (s)	RP%	E[viol] MW	#violated cases
α=0.8	$1,275,342	$129,397	15.5	46.5%	5.21	76
α=0.7	$1,275,305	$132,918	17.2	48.5%	5.34	76
α=0.6	$1,275,295	$108,771	12.5	30.6%	5.12	75
α=0.5	$1,276,481	$122,175	15.6	42.6%	5.09	75
α=0.4	$1,291,387	$91,612	25.8	29.5%	4.31	74
Proposed	$1,360,623	$2,172	3.6	-	0.66	35
Extsv.	$1,314,560	$0	31.2	-	0	0

6.4. 2383-Bus Polish Test Case

6.4.1. Network Overview

The proposed approach is also tested on an actual large-scale power system (i.e., a modified 2383-bus Polish test system) in order to evaluate its computational scalability. The modified test case has 327 generators, 2896 lines, and 1826 loads [93]. The modifications include: repartitioning the original six zones in the system into three zones; decreasing the line ratings to create congestion; and increasing the emergency line ratings to 1.05-1.25 times the corresponding nominal line ratings. In addition, demand information from the RTS96 dataset is used to define the hourly peak load profiles [83]. The test system developed by FERC, as a benchmark for industry evaluation of differing optimization problems, is used to define the detailed generator information including the piecewise linear cost coefficients, fixed costs, minimum up and down times, and ramp rates [94].

6.4.2. Dataset and Software Description

In this case study, set L^{crt} includes *four* routinely congested (critical/credible) transmission assets and set $C^{g^{crt}}$ includes 13 critical generator contingencies for units that have a $P_g^{max} \geq 500$ MW. Thus, a total of $4 \times 13 \times 24 = 1248$ post-contingency transmission constraints are included. Again, the uncertainty introduced by stochastic resources is represented by net load scenarios. It is assumed that the net load at each bus in the system follows a Gaussian distribution with zero mean. The variance of the Gaussian distribution was selected such that the resultant uncertainty is about 7%. Note that the distribution of the net load at each bus may not necessarily be Gaussian. The assumption of a Gaussian distribution in this case study is to approximate the net load without overcomplicating the scenario generation process. More accurate distributions can be adopted in future work. A piecewise linear cost function is used to represent the variable fuel costs. For this case study, since no notable reduction in average security violations is noticed beyond a single iteration, the number of iterations for updating Γ_{gt}^{c} is set to one. Owing to the large size of the system, only 30 different net load scenarios are used in the out-of-sample testing phase. The relative MIP gap for SCUC is set to 0.05%. The OMC and the extensive form stochastic UC problems are terminated after 1800 seconds or upon reaching an optimality gap of 0.025%; note that MISO uses a time limit of 1200 seconds for their DA SCUC model [12]. The proposed algorithm is written in Java and solved with CPLEX version 12.6. All simulations are run on a computer with the following specifications: Intel® Xeon® CPU X5687 @ 3.60 GHz, 48 GB RAM, and 64-bit operating system.

6.4.3. Results and Analysis

The performance of the proposed model is compared against the myopic policy and the reserve sharing model described in Chapter 2 and an extensive form stochastic UC model. In this case, the reserve sharing model is infeasible for α less than 0.85. It is noteworthy to emphasize that only a subset of credible generator contingencies, i.e., $C^{g^{crt}} \subseteq C^{g}$, consistent with the remainder of the benchmarks is modeled in the extensive form for this case study due to the insolvability of the extensive form with an explicit representation of all generator contingencies, C^{g}. Fig. 6.7(a) shows that the final cost is consistently lower with the proposed approach, which can be attributed to the more appropriate allocation of reserve at prime locations with better potential deliverability while respecting the critical network constraints post-contingency. In addition, the proposed approach requires fewer discretionary changes or uneconomic adjustments by market operators; it provides a solution that is more reliable as it is closer to the extensive form stochastic UC solution. Small values of α tend to have higher SCUC costs because they necessitate more reserve to be held within local regions. The reduced final cost for the proposed approach translates into increased percent savings relative to the benchmark approaches, which is apparent in Fig. 6.7(b). Fig. 6.7(c) illustrates that the computational complexity of the proposed approach is comparable to the benchmark reserve models. However, it is pertinent to note that, the solution time is dependent upon the size of the critical sets $C^{g^{crt}}$ and L^{crt}. Determining a suitable size for these sets involves a trade-off between model complexity and model accuracy. Finally, it is worth noting that, the average computational time to solve the extensive-form (Extsv., not shown in Fig. 6.7-c to enhance clarity) increased drastically to 757 seconds in this case (*as expected*) owing to the larger size of the Polish test system. The expected variability in the estimated means of the percent cost savings and the solution time to solve the DA SCUC problem for the different approaches is shown by the SE bars. The average $RP\%$ of the proposed approach in comparison to the benchmark approaches is in the range of ~26%-46%.

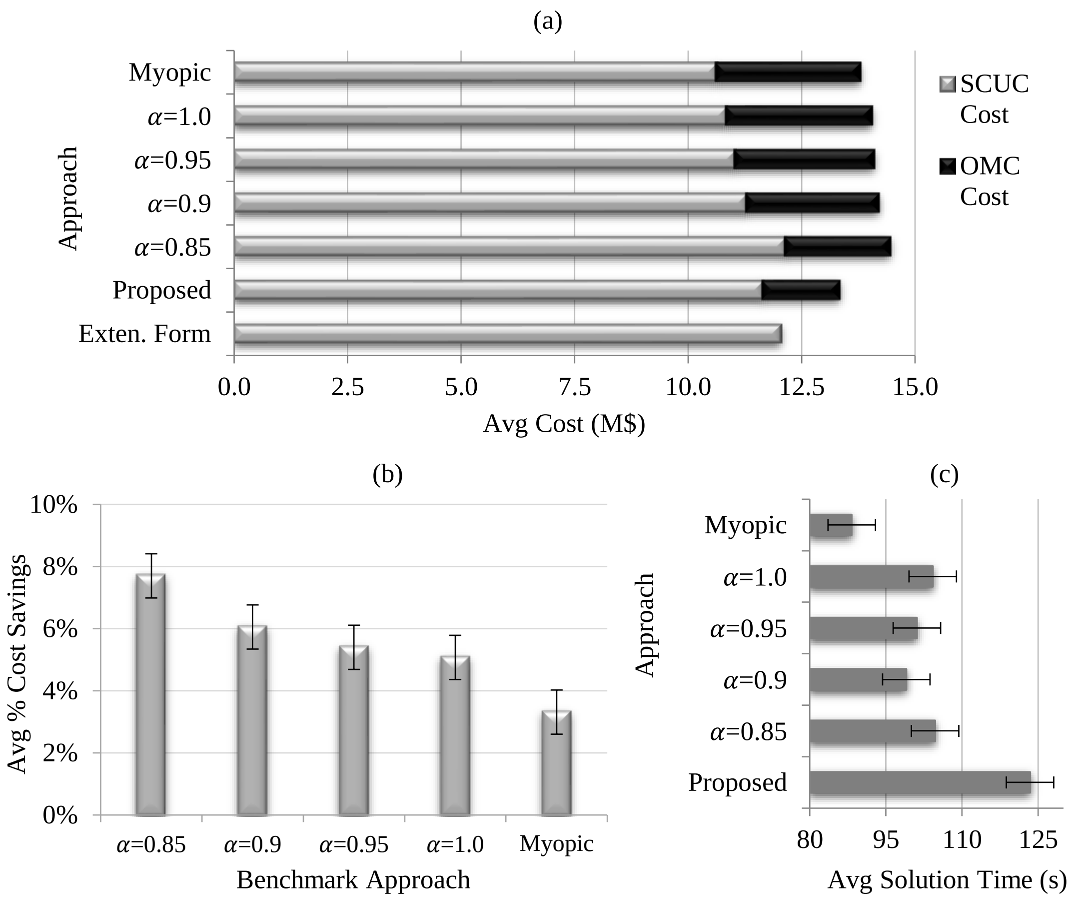


Fig. 6.7. Performance of the proposed approach in comparison to the myopic reserve model, the reserve sharing model (with varying α sharing policies), and the extensive-form stochastic UC model (Exten. Form). (a) Average final costs, including SCUC cost and OMC cost. (b) Average percent cost savings with standard error for sample size $n = 30$. (c) Average computational time to solve the DA SCUC with standard error for sample size $n = 30$.

Fig. 6.8 compares the final costs for N-1 reliable solutions against the E[viol] for the corresponding DA market SCUC solutions. Here, the bubble size represents #violated cases. Conservative policies (small α) tend to result in lower E[viol] (i.e. be more reliable) but at increased operating (i.e., SCUC) costs because they require more local reserve. As expected, the myopic policy is the most unreliable because it does not disperse the reserves across the system. It is evident that the proposed approach has the least #violated cases in addition to the lowest amount of E[viol] because it anticipates the influence of congestion on corrective actions by explicitly modeling the post-contingency transmission constraints. Consequently, for this case study, the proposed approach is the most reliable in comparison to the benchmark approaches.

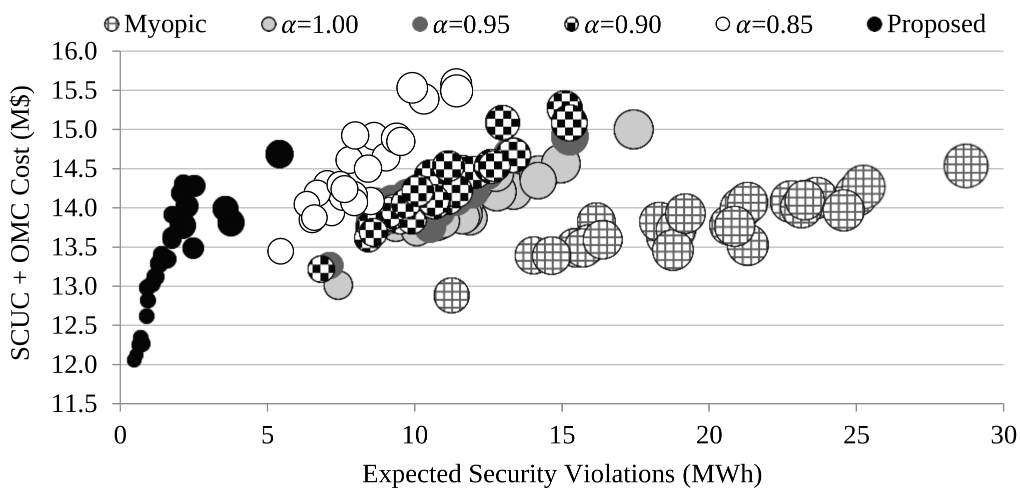


Fig. 6.8. Final costs for N-1 reliable solutions compared against the E[viol] for DA SCUC solutions for the test scenarios. The bubble size represents the number of cases ($\forall c, t$) with violations for the corresponding net load scenario.

6.4.4. Results and Analysis: Test for Robustness

The proposed approach was evaluated on net load scenarios from two additional test days to assess its robustness. Tables 6.2 and 6.3 summarize the average results over the two different test days. Analogous to the first test day, conservative reserve sharing policies tend to be more reliable but result in higher operating costs. It is evident that the proposed approach consistently outperforms (on an average basis) the benchmark reserve models on multiple test days by enhancing the reliability of the market solution in comparable solution times while also reducing the overall operational costs (or the final costs).

TABLE 6.2. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FROM THE SECOND TEST DAY FOR THE POLISH TEST SYSTEM

Approach	SCUC Cost	OMC Cost	Time (s)	E[viol] MW	#violated cases
Myopic	$10,477,236	$3,363,591	93	17.16	77
α=1.0	$10,629,829	$3,257,164	95	10.38	60
α=0.95	$10,748,834	$3,253,228	106	9.64	54
α=0.9	$10,944,167	$3,119,700	106	9.57	52
α=0.85	$11,705,694	$2,522,554	99	7.13	46
Proposed	$11,433,091	$2,079,107	119	1.62	20
Extsv.	$11,730,828	$0	860	0	0

TABLE 6.3. AVERAGE RESULTS ACROSS NET LOAD SCENARIOS FROM THE THIRD TEST DAY FOR THE POLISH TEST SYSTEM

Approach	SCUC Cost	OMC Cost	Time (s)	E[viol] MW	#violated cases
Myopic	$10,357,614	$3,077,257	88	19.93	86
α=1.0	$10,469,458	$2,880,663	96	11.78	67
α=0.95	$10,518,182	$2,828,948	116	10.27	61
α=0.9	$10,575,037	$2,862,207	95	8.83	57
α=0.85	$10,701,285	$3,026,199	111	7.32	52
Proposed	$11,013,072	$2,016,311	112	1.52	22
Extsv.	$10,718,310	$0	822	0	0

6.5. Conclusions

Model complexity involves a trade-off between simplicity and accuracy of the model. While complexity generally increases the accuracy of a model, it reduces its computational tractability and applicability. Smart, well-designed policies that address the allocation and deliverability issues associated with reserve can improve existing deterministic models and facilitate the transition to future stochastic programs. The proposed reserve response-set model enhances the reliability of the market solution with minimal added computational burden while also reducing the overall operational costs. Additionally, it requires fewer OMCs (or discretionary changes) by market operators. The proposed approach is more effective than existing deterministic models and more scalable than stochastic programs. The central philosophy of the proposed approach is to enhance reserve modeling to capture more requirements in market models in order to improve efficiency, enhance price signals, and maintain scalability and transparency.

CHAPTER 7.

GENERATOR CONTINGENCY MODELING IN ELECTRIC ENERGY MARKETS: DERIVATION OF PRICES VIA DUALITY THEORY

Traditional electric energy markets do not explicitly model generator contingencies. In an effort to improve the representation of resources and to enhance the modeling of uncertainty, existing markets are moving in the direction of including generator contingencies and remedial action schemes within market action models. This chapter contributes to the theoretical domain of electric energy market design; the market implications due to the explicit representation of generator contingencies are demonstrated by deriving the dual formulation associated to the market auction model. The derivation of the prices and the dual formulation are based on leveraging duality theory from linear optimization theory. This work paves the way forward for market reform as it demonstrates how to derive and analyze auction reformulations in order to streamline market reform associated to uncertainty modeling and modeling of corrective actions.

Recent literature suggests modifying the contemporary market auction models to include post-contingency transmission flow constraints for generator contingencies explicitly. These constraints aim to preemptively anticipate post-contingency congestion patterns in the event of a generator contingency. The enhanced formulations utilize predetermined factors, such as generation loss distribution factors (GDF), to predict the influence of recourse actions during critical generator contingencies. The primary goal is to acknowledge and enhance reserve deliverability in the post-generator contingency state. A primal (and the corresponding dual) formulation, which accounts for the proposed changes to the auction model, is provided to enable a theoretical analysis of the anticipated changes including, but not restricted to, the effect on market prices, settlements, and revenues. Furthermore, variations of the primal auction (and the corresponding dual) formulation are also provided to investigate the market implications of different reformulations to introduce corrective actions. A comparison to existing market structures is also included. By doing so, this research contributes to the market design realm by providing detailed analysis of impending changes, it provides insightful guidance in understanding the market implications, and it provides recommendations on necessary changes to ensure a fair and transparent market structure. In particular, the primary impact of the proposed changes includes the addition of a new congestion component within the traditional locational marginal price, which reflects the influence of congestion during the post-contingency states for the modeled critical generator contingencies.

7.1. Introduction

ISOs maintain a continuous, reliable, and economically efficient supply of electric energy with the assistance of energy management systems and market management systems. One key feature within the management systems is the determination of the generation dispatch and ancillary services schedule while respecting complex operational requirements and strict physical restrictions. The transmission planning standard (TPL-001-4), set by the NERC is an instance of one such requirement, which stipulates system performance requirements under both normal and emergency conditions [99]. Particularly, the system is required to recover from the loss of any single bulk element, e.g., a generator or a non-radial transmission element, without inconveniencing customers (involuntary load shedding). This rule is more commonly referred to as the *N*-1 reliability requirement and makes the underlying problem stochastic in nature. However, modeling such uncertain events within resource scheduling tools presents two practical barriers: (1) computational complexity of the resulting stochastic optimization problem and (2) market barriers primarily due to the complications associated with pricing in a stochastic market environment. Consequently, most of the contemporary power system operational frameworks rely on deterministic approaches and utilize numerous approximations to handle uncertainties to meet the N-1 mandate.

Today, ISOs model critical transmission contingencies in the market explicitly without utilizing second-stage recourse decision variables; post-contingency line flows are represented using shift factors, such as LODFs, for a subset of critical transmission contingencies. Decomposition techniques are leveraged to manage the complexity of the overall mathematical program by acknowledging only the constraints deemed to be critical. Such approaches enable an efficient handling of critical transmission contingencies within market management systems today.

Of course, the loss of a generating unit can also constrain the transmission system considerably. Generator contingencies are not modeled explicitly within state-of-the-art market auction models; instead, system or zonal operating reserve requirements are formed to ensure the system is reliable against generator contingencies. For instance, common industry practices, to approximate the N-1 mandate for generator contingencies, include simplistic policies that require a MW level of contingency reserve to be acquired somewhere in the system. However, such policies do not assure reliable operations (or ensure reserve deliverability) since they only capture a quantitative aspect. Moreover, such approximate, deterministic approaches require OMCs to adjust resource schedules to account for model inaccuracies. Consequently, there is a push in the industry to include an explicit representation of generator contingencies in the auction models within the market management systems.

Two-stage scenario-based stochastic programs are often proposed to improve operations by optimizing the system response, e.g., reserve activation, in the post-contingency states. However, recent industry movement to model generator contingencies suggests using pre-determined factors, such as generator loss distribution factors (GDFs) and zonal reserve deployment factors [31], [22], to approximate the system response to a generator contingency; such factors are analogous to the more familiar participation factors that are used today in real-time contingency analysis (RTCA) when simulating generator contingencies. CAISO recently proposed to update its market auction models to recognize the impact of generator contingencies and remedial action schemes (RAS) in the market, explicitly, without using second-stage recourse decision variables [31]. Furthermore, MISO augmented their market auction models by modeling the loss of the largest generator for each zone and the corresponding system response in the post-contingency state, explicitly, without using second-stage recourse decision variables [22]. MISO's approach approximates post-contingency congestion on critical transmission interfaces due to the deployed zonal reserves. Moreover, the system response is modeled via zonal aggregated sensitivity factors and pre-determined zonal reserve deployment factors. With the explicit modeling of generator contingencies within the market auction models, the industry is moving away from deterministic program formulations to a stochastic program structure. The anticipated impacts include market prices that better reflect the quality of service provided by generators in response to a generator contingency. The primary purpose of this chapter is to provide a theoretical analysis of the recent changes in market auction models while focusing on its influences on market clearing prices, i.e., locational marginal prices (LMPs). It investigates the impact that the explicit inclusion of generator contingencies will have on the market pricing structure using duality theory. Primal and dual formulations of market auction models, with and without explicit generator contingency modeling, derivation of the corresponding LMPs to demonstrate how the proposed changes affect market prices, settlements and revenues, are presented.

The remainder of the chapter is organized as follows. Section 7.2 introduces a theoretical analysis of a contemporary market auction model. Section 7.3 investigates the anticipated changes by providing an enhanced primal formulation for the market auction model and an economic interpretation of the corresponding dual problem, its variables, and its constraints. In addition, this section proposes a variation of the primal auction (and the corresponding dual) formulation to examine the market implications of a different reformulation to introduce corrective actions. Note that, in the following discussions, GDFs are used to model the corrective actions approximately without using a recourse decision variable. Finally, Section 7.4 concludes the chapter and summarizes potential future work.

7.2. Dual Problems of Electric Energy Market Formulations

7.2.1. Background on Duality Theory for Linear Optimization

In linear optimization, there is the primal problem, the problem at hand. In this case, the problem of interest is the direct current optimal power flow (DCOPF) problem or a security-constrained economic dispatch problem. Each primal problem then has a corresponding dual problem and together they form what is known in linear optimization theory as a primal-dual pair. The dual problem can be interpreted as an optimization problem that is searching for the tightest lower bound (when the primal is a minimization problem); it also provides the shadow prices (dual variables) corresponding to the constraints in the primal. Dual variables, based on linear optimization theory, can also be interpreted as the corresponding Lagrange multipliers for the constraints within the primal. From the perspective of an economist, they are interpreted as shadow prices. The constraints within the dual describe the relationships between the dual variables. Likewise, the primal variables are the corresponding shadow prices for the dual constraints.

The following example demonstrates the relationship between the primal-dual pair, where $\mathbf{a_i}$ is a row and $\mathbf{A_j}$ is a column from a given **A** matrix that captures the constraint set (which consists of M constraints: M_1 >= constraints, M_2 <= constraints, and M_3 = constraints) for the primal; each constraint has a scalar b_i. In addition, **c** is the cost vector and **X** is the vector of primal variables, where N_1, N_2, and N_3 denote the subset of non-negative, non-positive and unrestricted primal variables respectively. Also, **p** denotes the penalty (or shadow) price for violating the corresponding primal constraint. This primal-dual pair presentation can be found in a variety of textbooks, including [100].

Primal:	Dual:
Minimize: $\mathbf{c^T X}$	Maximize: $\mathbf{p^T b}$
Subject to:	Subject to:
$\mathbf{a_i^T X} \geq b_i, \quad i \in M_1$	$p_i \geq 0, \quad i \in M_1$
$\mathbf{a_i^T X} \leq b_i, \quad i \in M_2$	$p_i \leq 0, \quad i \in M_2$
$\mathbf{a_i^T X} = b_i, \quad i \in M_3$	p_i: free, $\quad i \in M_3$
$x_j \geq 0, \quad j \in N_1$	$\mathbf{p^T A_j} \leq c_j, \quad j \in N_1$

$x_j \leq 0, \qquad j \in N_2 \qquad\qquad \mathbf{p^T A_j} \geq c_j, \ \ j \in N_2$

x_j: free, $\qquad j \in N_3 \qquad\qquad \mathbf{p^T A_j} = c_j, \ \ j \in N_3.$

Prior work related to optimization problems for power systems derive the properties of the prices, which come from the dual formulation, based on applying Karush-Kuhn-Tucker (KKT) conditions and simplifying the equations [101], [102]. Note that the dual formulation is derived by creating a Lagrangian dual and then simplifying it into the form presented above. Leveraging the known properties for a primal-dual pair for linear optimization models is used in this chapter since it is more concise and straightforward than superfluous procedures that re-derive the dual from scratch.

7.2.2. The Dual Formulation for a Standard DCOPF Problem

This subsection provides an explicit formulation of the primal-dual pair for the DCOPF problem, which is a simplified representation of existing market formulations that generally come in the form of a SCUC or a SCED model. Most of the contemporary market models use a linearized DCOPF formulation that is based on PTDFs. A less commonly used DCOPF formulation is the *B*-θ formulation that relies on the susceptance of transmission assets (*B*) and the bus voltage angles (θ). The *B*-θ formulation requires declaring variables for all bus voltage angles in addition to incorporating dc power flows for all transmission assets although it is a known fact that few transmission assets may reach their transfer limits; by having to determine all line flows and bus voltage angle values, the *B*-θ formulation is doing much more work than necessary.

On the other hand, the PTDF-based formulation is easier to solve since it provides the option of ignoring the transmission assets that are inconsequential (*rarely* congested), thereby reducing modeling complexity. For instance, a large market environment may have over 10,000 transmission assets to monitor; to ensure *N*-1 for transmission contingencies, there would be 100M potential transmission asset variables to track. If the operator is concerned about only one line being congested or overloaded for the pre-contingency state and for each post-contingency state, then the *B*-*θ* formulation would require the calculation of all 100M flow variables. Conversely, with a PTDF formulation, only the flows for lines that may be congested would need to be determined, roughly 10,000 instead. A primal problem formulation for a standard PTDF-based DCOPF is detailed below.

$$\underset{P_n, D_n}{\text{Minimize:}} \sum_n c_n P_n \tag{7.1}$$

Subject to:

$$-P_n \geq -P_n^{max}, \forall n \in N \qquad (\alpha_n) \tag{7.2}$$

$$\sum_n PTDF_{k,n}^R (P_n - D_n) \geq -P_k^{max,a}, \forall k \in K \qquad (F_k^-) \tag{7.3}$$

$$-\sum_n PTDF_{k,n}^R (P_n - D_n) \geq -P_k^{max,a}, \forall k \in K \qquad (F_k^+) \tag{7.4}$$

$$\sum_n P_n - D_n = 0, \qquad (\delta) \tag{7.5}$$

$$D_n = \overline{D_n}, \forall n \in N \qquad (\lambda_n) \tag{7.6}$$

$$P_n \geq 0.$$

The objective, (7.1), is to minimize the linear operating costs, which is equivalent to maximizing the market surplus since the demand is assumed to be perfectly inelastic. Constraint (7.2) imposes an upper bound on the real power scheduled from a generating resource. Note that, for simplicity, the minimum real power generating capacity is assumed to be zero for all generating resources. The dc power flow on a transmission asset is constrained by its normal (thermal or stability) rating, i.e., rate A, in (7.3) and (7.4) respectively. Note that the dual variables of (7.3) and (7.4) are the flowgate marginal prices for those transmission assets or flowgates; these dual variables are used to calculate the congestion component of the LMP. Constraint (7.5) assures system-wide power balance between generation and demand; the dual variable of (7.5) captures the energy component of the LMP. Note that, in this formulation, the demand is treated as a variable following which it is fixed to equal a parameter in (7.6). The dual variable of (7.6) signifies the increase (or decrease) to the primal objective (7.1) if there is slightly more (or less) consumption by the demand at node n, which directly translates into the definition of the LMP. The corresponding dual problem formulation for the aforesaid primal problem is given below.

$$\underset{\alpha_n, F_k^-, F_k^+, \delta, \lambda_n}{\text{Maximize}} : -\sum_n P_n^{max} \alpha_n - \sum_k P_k^{max,a} (F_k^- + F_k^+) + \sum_n \overline{D_n} \, \lambda_n \tag{7.7}$$

Subject to:

$$-\alpha_n + \sum_k PTDF_{k,n}^R (F_k^- - F_k^+) + \delta \leq c_n, \forall n \in N \qquad (P_n) \tag{7.8}$$

$$\sum_k PTDF_{k,n}^R (F_k^+ - F_k^-) - \delta + \lambda_n = 0, \forall n \in N \qquad (D_n) \tag{7.9}$$

$$\alpha_n \geq 0, F_k^- \geq 0, F_k^+ \geq 0, \delta \text{ free}, \lambda_n \text{ free} .$$

At optimality, the dual objective (7.7) is equal to the primal objective (7.1) by strong duality. The first, second, and the third components of (7.7) denote the generation rent (short-term generation profit), the congestion rent, and the load payment, respectively. Since generation revenue is equal to generation cost plus generation rent, it can be proven that, at optimality, load payment is equal to generation revenue plus congestion rent. Constraints (7.8) and (7.9) represent the dual constraints corresponding to the generator production and the demand variables in the primal problem, respectively. Constraint (7.9) within the dual problem identifies λ_n as the LMP at node n. Thus, the LMP, defined by (7.9a), is equal to the sum of the marginal energy (δ) and the marginal congestion components. Note that, since the PTDF-based DCOPF formulation defined by (7.1)–(7.6) is assumed to be a lossless model, there is no loss component of the LMP for the work presented in this chapter. After identifying the equation that defines the LMP via (7.9), (7.8) reduces to (7.8a).

$$\lambda_n = \delta + \sum_k PTDF^R_{k,n}(F_k^- - F_k^+), \forall n \in N \qquad (D_n) \qquad (7.9a)$$

$$-\alpha_n + \lambda_n \leq c_n, \forall n \in N. \qquad (P_n) \qquad (7.8a)$$

The dual variable of (7.2), i.e., non-negative, signifies the marginal value of increasing a specific generator's maximum capacity. Three cases can potentially exist in this context, while remembering that the lower bounds of all generators are assumed to be zero for this simplified DCOPF problem: 1) if a generator is producing, but not at its maximum capacity (i.e., $\alpha_n = 0$ by complementary slackness), then the LMP at the node of the generator is equal to its marginal cost (by complementary slackness); 2) if a generator is not producing anything (i.e., $\alpha_n = 0$ by complementary slackness), then the LMP at its node is less than or equal to its marginal cost; and 3) if the generator is producing at its maximum capacity (i.e., $\alpha_n \geq 0$), then the LMP at its node is greater than (when $\alpha_n > 0$) or equal (when $\alpha_n = 0$) to its marginal cost (by complementary slackness). These results match with a simple economic interpretation of the shadow price for (2). Whenever you are not producing at your maximum capacity the short-term marginal benefit to increase your capacity beyond its existing capability is zero. When you are operating at your maximum capacity, the short-term marginal benefit to increase your capacity by 1 MW is equal to the difference between your LMP and your marginal cost; keep in mind that this explanation applies to the presented primal DCOPF formulation. If the presented formulation included other constraints that could restrict the generator's output, e.g., ramp rate limits, then the description would be more complex.

In general, note that if the DCOPF is formulated differently, the dual will not be the same and may result in different interpretations of that different dual. For example, if a variant DCOPF formulation were used by leveraging the B-θ structure, there would be an added dual variable known as the susceptance marginal price. The B-θ formulation explicitly models the separation of current through the grid based on an approximation of Kirchhoff's laws derived from the ac power flow (ACPF) formulation; this known equation, $p_k = b_k(\theta_n\text{-}\theta_m)$, would have a dual variable that reflects the marginal impact on the objective based on a marginal change in the susceptance of the line, i.e., a susceptance marginal price [103]. This susceptance marginal price does not show up in the PTDF formulation as the influence of a line's susceptance within the PTDF formulation is embedded within the pre-calculated PTDFs.

7.3. Recent Industry Movements to Model Generator Contingencies in Market

7.3.1. Primal Formulation for the Enhanced DCOPF Problem

To meet NERC's N-1 mandate more appropriately, recent literature suggests enhancing generator contingency modeling by ensuring post-contingency transmission security through an explicit representation of post-contingency congestion patterns for critical generator contingencies within the market auction models. The mathematical (primal) formulation for the enhanced DCOPF problem, motivated by the optimization problem proposed by CAISO in [31], is detailed below. Note that while the presented formulation below is related to CAISO's proposed formulation in [31], earlier portions of this thesis, which were proposed before [31], are very similar to CAISO's proposed change. For this chapter, the focus is on CAISO's proposed changes and extensions to this work can be made to analyze other attempts to introduce more advanced generator contingency modeling, renewable uncertainty, and corrective control actions.

$$\underset{P_n,P_n^c,D_n}{\text{Minimize:}} \sum_n c_n P_n \tag{7.10}$$

Subject to:

$$-P_n \geq -P_n^{max}, \forall n \in N \qquad (\alpha_n) \tag{7.11}$$

$$\sum_n PTDF_{k,n}^R (P_n - D_n) \geq -P_k^{max,a}, \forall k \in K \qquad (F_k^-) \tag{7.12}$$

$$-\sum_n PTDF_{k,n}^R (P_n - D_n) \geq -P_k^{max,a}, \forall k \in K \qquad (F_k^+) \tag{7.13}$$

$$P_n^c - P_n - GDF_{n'(c),n} P_{n'(c)} = 0, \forall n \in N, c \in C^{g^{crt}} \qquad (\beta_n^c) \tag{7.14}$$

$$\sum_n PTDF_{k,n}^R (P_n + GDF_{n'(c),n} P_{n'(c)} - D_n) \geq -P_k^{max,c}, \forall k \in K^{crt}, c \in C^{g^{crt}} \qquad (F_k^{c-}) \tag{7.15}$$

$$-\sum_n PTDF_{k,n}^R (P_n + GDF_{n'(c),n} P_{n'(c)} - D_n) \geq -P_k^{max,c}, \forall k \in K^{crt}, c \in C^{g^{crt}} \qquad (F_k^{c+}) \tag{7.16}$$

$$\sum_n P_n - D_n = 0, \qquad (\delta) \tag{7.17}$$

$$D_n = \overline{D_n}, \forall n \in N \qquad (\lambda_n) \tag{7.18}$$

$$P_n \geq 0, P_n^c \geq 0.$$

where:

$$GDF_{n'(c),n} = \begin{cases} -1, & n = n'(c) \\ 0, & n \neq n'(c) \wedge n \notin S^{FR} \\ \dfrac{u_n P_n^{max}}{\sum_{\substack{n \in S^{FR} \\ n \neq n'(c)}} u_n P_n^{max}}, & n \neq n'(c) \wedge n \in S^{FR} \end{cases}, \forall n \in N, c \in C^{g^{crt}}. \tag{7.19}$$

Note that, in this formulation, the generation loss is distributed across the system via GDFs and is presumed to be lossless in (7.14). Also, it is prorated based on the maximum online (frequency responsive) capacity, to approximate the actual system behavior, while ignoring capacity and ramp rate restrictions [31]. Equation (7.19) provides CAISO's definition for GDFs, which is proposed to estimate the effect of generation loss and the associated system response on critical transmission assets in the post-contingency state. The post-contingency dc power flow (under a critical generator outage) on a critical transmission asset is restricted by its emergency rating (rate C) in (7.15) and (7.16) respectively. The remainder of the formulation is consistent with the standard DCOPF formulation. Note that GDF is constructed to denote the outage of generation at a specific node, not to distinguish between the outage of a single generator at a node with multiple generators. Finally, note that CAISO's actual market model will be more complex than what is previously presented; that previously presented DCOPF does not include other modeling issues like transmission contingency modeling, reserve requirements, ramp rate limits, etc. The formulation is kept in a simpler manner to focus on the key proposed change, which is related to the inclusion of the generator contingency modeling with the use of the GDFs.

7.3.2. Dual Formulation for the Enhanced DCOPF Problem

The corresponding dual problem formulation is described below. Note that, while the following dual is derived based on the formulation in Section 7.3.1, other primal formulations are also possible, and the dual formulations will change as well.

$$\underset{\alpha_n, F_k^-, F_k^+, \beta_n^c, F_k^{c-}, F_k^{c+}, \delta, \lambda_n}{\text{Maximize}} : -\sum_n (P_n^{max}\alpha_n) - \sum_k \left(P_k^{max,a}(F_k^- + F_k^+)\right)$$

$$-\sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} \left(P_k^{max,c}(F_k^{c-} + F_k^{c+})\right) + \sum_n (\overline{D_n}\lambda_n) \tag{7.20}$$

Subject to:

$$-\alpha_n + \left(\sum_k PTDF_{k,n}^R (F_k^- - F_k^+)\right) - \left(\sum_{c\in C^{g^{crt}}} \beta_n^c + \bar{\gamma}_{n'(c),n} \sum_{s\in N} GDF_{n'(c),s}\beta_s^c\right)$$

$$+\left(\sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} (F_k^{c-} - F_k^{c+})\left(PTDF_{k,n}^R + \bar{\gamma}_{n'(c),n}\sum_{s\in N} PTDF_{k,s}^R GDF_{n'(c),s}\right)\right)$$

$$+\delta \le c_n, \forall n \in N \qquad (P_n) \tag{7.21}$$

$$\beta_n^c \le 0, \forall n \in N, c \in C^{g^{crt}} \qquad (P_n^c) \tag{7.22}$$

$$\sum_k PTDF_{k,n}^R (F_k^+ - F_k^-) + \sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} PTDF_{k,n}^R (F_k^{c+} - F_k^{c-}) - \delta + \lambda_n = 0, \forall n \in N$$

$$(D_n) \tag{7.23}$$

$\alpha_n \ge 0, F_k^- \ge 0, F_k^+ \ge 0, \beta_n^c$ free, $F_k^{c-} \ge 0, F_k^{c+} \ge 0, \delta$ free, λ_n free .

where:

$$\bar{\gamma}_{n'(c),n} = \begin{cases} 0, & n \ne n'(c) \\ 1, & n = n'(c) \end{cases}, \forall n \in N, c \in C^{g^{crt}}. \tag{7.24}$$

The dual objective now has an additional term, i.e., the third component in (7.20), which represents the post-contingency congestion rent resulting from generator contingency modeling. Constraints (7.21), (7.22), and (7.23) represent the dual constraints corresponding to the generator production, the generator production under contingency *c* and the demand variables in the enhanced primal problem, respectively. The primary impact that the proposed changes will have on market pricing is how it affects the LMPs. Constraint (7.23) within the dual problem identifies λ_n as the LMP at node *n*. Thus, the LMP, which is now defined by (7.23a), is equal to the sum of the marginal energy component, the marginal pre-contingency congestion component, and an additional marginal post-contingency congestion component that comes from the modeling of critical generator contingencies.

Note that, the enhanced primal problem defined by (7.10)–(7.18) differs from CAISO's primal problem in [31] with respect to the following aspects. 1) The demand is first treated as a variable following that is fixed to equal a parameter in (7.18) to enable the derivation of the LMP in a simpler manner. 2) The losses are ignored for simplification. 3) Transmission contingency security constraints are ignored to allow the derivation in this dissertation to focus on generator contingency modeling in a clear and concise manner. Furthermore, (7.23b) defines CAISO's proposed LMP definition [31]. It can be seen that CAISO's proposed LMP definition is consistent with (7.23a) for nodes that do not have critical generators (whose outages are modeled explicitly), i.e., $\gamma = 0$; however, there seems to be a discrepancy between the two LMP definitions for the nodes that do have critical generators i.e., $\gamma = 1$. More discussion is provided in the following sections, particularly, in Section 7.3.4.

$$\lambda_n = \delta + \sum_k PTDF_{k,n}^R (F_k^- - F_k^+) + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} PTDF_{k,n}^R (F_k^{c-} - F_k^{c+}), \forall n \in N \qquad (D_n) \quad (7.23a)$$

$$\lambda_n = \delta + \sum_k PTDF_{k,n}^R (F_k^- - F_k^+) + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(PTDF_{k,n}^R + \bar{\gamma}_{n'(c),n} \sum_{s \in N} PTDF_{k,s}^R GDF_{n'(c),s} \right) \right], \forall n \in N \qquad (D_n) \quad (7.23b)$$

7.3.3. Analyzing the Dual Formulation

To understand what is communicated by the dual problem presented in Section 7.3.2, first, start with the objective functions of the primal and the dual. Linear optimization theory includes strong duality, which guarantees that the objective of the primal problem equals the objective of the dual problem at optimality. Achieving strong duality means that there is no duality gap. Another way to interpret the strong duality relationship is through its expression of an exchange of money; payments and expenses resulting from the auction and the corresponding exchange of goods and services. There is the obvious piece from the objective of the primal problem, which is the total generation cost. The next obvious piece is the last term of the dual objective, which is the load payment, LMP times consumption. The second and third terms in the dual's objective represent the system-wide congestion rent; this is to be expected as it relates the flowgate marginal price to the line flow, once complementary slackness is applied; more description to come. The first term of the dual objective is the short-term generator profit for a generator at node n, summed over all nodes, or the system-wide generation rent.

Second, the system-wide generation rent is broken down for generators that are (and are not) contained in the critical generator contingency list, based on the proposed changes by CAISO, to analyze the subsequent impact on prices and revenues for generators. Recall first that GDF reflects the anticipated system response from a specific node in the network and the way it is structured in (7.19) assumes that there is only one unit at most at a node (easily modifiable). Second, note the formula to define the GDF is based purely on the generator's capacity relative to the rest of the fleet's capacity (for units that are frequency responsive). One obvious drawback of the proposed GDF is that it ignores the generator's capacity, the generator's ramp rate restrictions, and whether the ISO procured the necessary reserve product from the unit. As a result, this model assumes there is the capability to inject power at a node based on the definition of the GDF, not necessarily based on the actual ability for the generator to provide the needed reserve; for instance, a generator may be operating at its maximum capacity. The assumed GDF only accounts for capacity while not capturing the dispatch set point of the unit or whether the unit has been obligated to provide contingency reserve products (note that while the presented auction formulation does not include reserve procurement, the GDF itself does not reflect whatsoever on reserve and, as such, the impact of reserve is not captured anyway). Finally, the GDF shows up only in (7.14)–(7.16) and is multiplied by the MW dispatch variable for the generator that is modeled to be under outage (contingency generator). This translates into the post-contingency dispatch and congestion for a generator outage, in the primal problem, to being directly related to the dispatch variable for the contingency generator only. The only functional relationship between the change in a responsive generator's dispatch and a line's flow between the pre- and post-contingency state is driven by the primal variable for the simulated contingency generator and the GDF (a fixed input parameter). Consequently, this proposed formulation and the proposed GDF mask the response that is provided by the frequency responsive units for generator contingencies. Thus, γ reduces to zero for generators that are not located at the nodes of the generators included in the critical generator contingency list. This has further implications on the short-term generator profit for generators.

For generators that are not included in the critical list, substituting in the definition of γ from (7.24) and λ from (7.23a), (7.21) can be rewritten as (7.21a). It is then clearer to see the comparison between (7.8a) and (7.21a). Next, complementary slackness can be applied to the constraint-dual variable pairs in (7.21a), (7.11), (7.14), and (7.22) to create (7.25), (7.26), (7.27), and (7.28), respectively. Note that if complementary slackness is applied to (7.8a), it again allows for the determination of the short-term generator profit, i.e., the rent for a generator in the standard DCOPF problem, which is equal to the generator revenue (LMP times production) minus the generator cost. Equation (7.27) can be rewritten as (7.27a) using (7.28). Then based on (7.25) and (7.26), the generator rent for a unit that is not in the assumed critical list, its generator profit equation is listed by (7.29). Equation (7.29) can be rewritten as (7.29a) using (7.27a). This now provides an understanding on the generator revenue and generator profit that will be earned for generators that are not within the critical list. The generator rent obtained is, therefore, different from the standard DCOPF problem: (i) the LMP, denoted by λ_n, in the first term of (7.29a) now captures an additional congestion component that reflects congestion in the post-contingency operational state under a generator outage and (ii) the added last term in (7.29a), which is non-positive. Note that β is non-positive from (7.22). In addition, the last term in (7.29a) is zero if the generator does not respond to any outage in the critical list because then the GDF is zero in which case the generator rent is the same as the standard DCOPF (excepting the new LMP definition).

$$-\alpha_n + \lambda_n - \sum_{c \in C^{g^{crt}}} \beta_n^c \leq c_n, \qquad (P_n) \quad (7.21a)$$

$$-\alpha_n P_n + \lambda_n P_n - \sum_{c \in C^{g^{crt}}} \beta_n^c P_n = c_n P_n, \quad (7.25)$$

$$-P_n \alpha_n = -P_n^{max} \alpha_n, \forall n \in N \quad (7.26)$$

$$P_n^c \beta_n^c - P_n \beta_n^c - GDF_{n'(c),n} P_{n'(c)} \beta_n^c = 0, \forall n \in N, c \in C^{g^{crt}} \quad (7.27)$$

$$\beta_n^c P_n^c = 0, \forall n \in N, c \in C^{g^{crt}} \quad (7.28)$$

$$P_n \beta_n^c = -GDF_{n'(c),n} P_{n'(c)} \beta_n^c, \forall n \in N, c \in C^{g^{crt}} \tag{7.27a}$$

$$P_n^{max} \alpha_n = \lambda_n P_n - c_n P_n - \sum_{c \in C^{g^{crt}}} \beta_n^c P_n, \tag{7.29}$$

$$P_n^{max} \alpha_n = \lambda_n P_n - c_n P_n + \sum_{c \in C^{g^{crt}}} GDF_{n'(c),n} P_{n'(c)} \beta_n^c. \tag{7.29a}$$

For the critical generators, substituting in the definition of γ from (7.24) and λ from (7.23a), (7.21) can be rewritten as (7.21b). Analogously, applying complementary slackness to the constraint-dual variable pair in (7.21b) and based on (7.26) and (7.27a), the generator rent for a unit that is in the assumed critical list, its short-term generator profit is listed by (7.30).

$$\begin{aligned} &\alpha_n + \lambda_n - \left(\sum_{c \in C^{g^{crt}}} \beta_n^c + \sum_{s \in N} GDF_{n'(c),s} \beta_s^c\right) \\ &\quad + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(\sum_{s \in N} PTDF_{k,s}^R GDF_{n'(c),s} \right) \right] \leq c_n, \qquad (P_n) \end{aligned} \tag{7.21b}$$

$$\begin{aligned} P_n^{max} \alpha_n &= \lambda_n P_n - c_n P_n + \left(\sum_{c \in C^{g^{crt}}} GDF_{n'(c),n} P_{n'(c)} \beta_n^c - \sum_{s \in N} GDF_{n'(c),s} \beta_s^c P_s \right) \\ &\quad + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(\sum_{s \in N} PTDF_{k,s}^R GDF_{n'(c),s} P_s \right) \right] \end{aligned} \tag{7.30}$$

Note that there is a resemblance in the last term (with GDFs: in square brackets) of (7.30) and the last term in CAISO's definition of LMP in (7.23b), which indicates that they could potentially be accounting for this extra term's payment to the critical generators via the LMP. However, it is important to bear in mind that such modifications can have associated implications, for instance, in financial transmission rights (FTR) markets. Furthermore, some of the other terms that are now present in (7.29a) and (7.30), which are components of the short-term generator profit for the non-critical and the critical generators respectively, are not accounted for in their proposed payment structure. Thus, Section 7.3.4 proposes a variation of the primal auction (and the corresponding dual) formulation presented in Section 7.3.1 to examine the market implications of a different reformulation to introduce corrective actions via the proposed GDFs and to investigate CAISO's newly proposed payment structure in greater detail.

It is pertinent to note that the auction formulations, presented in this chapter, neglect various other constraints, most importantly the minimum production limit on a generator has been assumed to be zero for now, there are no ramping restrictions, inter-temporal restrictions, or reserve products in the formulations. The important piece of information is to compare the modified DCOPF with the inclusion of the GDF for generator contingencies with the simpler DCOPF that lacks such security criteria. However, the difference can be extracted and related to the case where there is a more complicated SCED market model that is expanded to include generator contingencies with this GDF factor that approximates reserve deployment.

7.3.4. A Different Reformulation of the Primal Problem

This section proposes a variation of the primal auction formulation presented in Section 7.3.1 to examine the associated market implications of a different reformulation to introduce corrective actions (or GDFs). While this primal is different than the primal in Section 7.3.1, the two (linear programs) primal problems are still equivalent transformations of the other mathematical program. Based on duality theory, when two primal problems are equivalent, the dual programs must also be equivalent transformations of each other. The mathematical reformulation of the primal problem is detailed below.

$$\underset{P_n, D_n}{\text{Minimize:}} \sum_n c_n P_n \tag{7.31}$$

Subject to:

$$-P_n \geq -P_n^{max}, \forall n \in N \qquad (\alpha_n) \qquad (7.32)$$

$$\sum_n PTDF_{k,n}^R (P_n - D_n) \geq -P_k^{max,a}, \forall k \in K \qquad (F_k^-) \qquad (7.33)$$

$$-\sum_n PTDF_{k,n}^R (P_n - D_n) \geq -P_k^{max,a}, \forall k \in K \qquad (F_k^+) \qquad (7.34)$$

$$\sum_n PTDF_{k,n}^R (P_n + GDF_{n'(c),n} P_{n'(c)} - D_n) \geq -P_k^{max,c}, \forall k \in K^{crt}, c \in C^{g^{crt}}$$

$$(F_k^{c-}) \qquad (7.35)$$

$$-\sum_n PTDF_{k,n}^R \left(P_n + GDF_{n'(c),n} P_{n'(c)} - D_n\right) \geq -P_k^{max,c}, \forall k \in K^{crt}, c \in C^{g^{crt}}$$

$$(F_k^{c+}) \qquad (7.36)$$

$$\sum_n P_n - D_n = 0, \qquad (\delta) \qquad (7.37)$$

$$D_n = \overline{D_n}, \forall n \in N \qquad (\lambda_n) \qquad (7.38)$$

$$P_n \geq 0.$$

where:

$$GDF_{n'(c),n} = \begin{cases} -1, & n = n'(c) \\ 0, & n \neq n'(c) \wedge n \notin S^{FR} \\ \dfrac{u_n P_n^{max}}{\sum_{\substack{n \in S^{FR} \\ n \neq n'(c)}} u_n P_n^{max}}, & n \neq n'(c) \wedge n \in S^{FR} \end{cases}, \forall n \in N, c \in C^{g^{crt}}. \qquad (7.39)$$

Note that this primal reformulation does not include a separate primal variable (and a corresponding equality constraint) to model the post-contingency dispatch set point for a generating resource under a specific generator contingency. In this case, the primal variables include only the generator production variable and the demand variable respectively. The rest of the primal reformulation is consistent with the primal formulation presented in Section 7.3.1.

The corresponding dual problem formulation for the aforesaid primal reformulation is described below.

$$\underset{\alpha_n, F_k^-, F_k^+, F_k^{c-}, F_k^{c+}, \delta, \lambda_n}{\text{Maximize}} : -\sum_n (P_n^{max}\alpha_n) - \sum_k \left(P_k^{max,a}(F_k^- + F_k^+)\right)$$

$$-\sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} \left(P_k^{max,c}(F_k^{c-} + F_k^{c+})\right) + \sum_n (\overline{D_n}\lambda_n) \tag{7.40}$$

Subject to:

$$-\alpha_n + \sum_k PTDF_{k,n}^R (F_k^- - F_k^+)$$

$$+\left(\sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} (F_k^{c-} - F_k^{c+})\left(PTDF_{k,n}^R + \bar{\gamma}_{n'(c),n}\sum_{s\in N} PTDF_{k,s}^R GDF_{n'(c),s}\right)\right)$$

$$+\delta \le c_n, \forall n \in N \qquad (P_n) \quad (7.\ 41)$$

$$\sum_k PTDF_{k,n}^R (F_K^+ - F_k^-) + \sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} PTDF_{k,n}^R (F_K^{c+} - F_k^{c-}) - \delta + \lambda_n = 0, \forall n \in N$$

$$(D_n) \quad (7.42)$$

$\alpha_n \ge 0, F_k^- \ge 0, F_k^+ \ge 0, F_k^{c-} \ge 0, F_k^{c+} \ge 0, \delta$ free, λ_n free .

where:

$$\bar{\gamma}_{n'(c),n} = \begin{cases} 0, & n \ne n'(c) \\ 1, & n = n'(c) \end{cases}, \forall n \in N, c \in C^{g^{crt}}. \tag{7.43}$$

In addition,

$$\lambda_n = \delta + \sum_k PTDF_{k,n}^R (F_k^- - F_k^+) + \sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} PTDF_{k,n}^R (F_k^{c-} - F_k^{c+}), \forall n \in N.$$

$$(D_n) \quad (7.42a)$$

The dual objective, (7.40), is consistent with (7.20). Constraints (7.41) and (7.42) represent the dual constraints corresponding to the generator production and the demand variables in the primal reformulation respectively. Constraint (7.42) within the dual problem identifies λ_n as the LMP at node n, which is further defined in (7.42a) and is equal to the sum of the marginal energy component, the marginal pre-contingency congestion component, and the marginal post-contingency congestion component that comes from the modeling of critical generator contingencies. Note that (7.42a) is consistent with the LMP definition in (7.23a) for the enhanced primal formulation.

The discussion that follows analyzes the corresponding impact on the rent and the revenue for generators that are and are not included in the assumed set of critical generator contingencies. To assist in understanding what is communicated within the aforesaid dual formulation in terms of the impact on prices and revenue for generators, it is helpful to go back to (7.35) and (7.36). It is noteworthy to emphasize that the GDF shows up only in (7.35) and (7.36) and it is multiplied by the MW dispatch variable for the generator that is lost. What this translates to is that the post-contingency congestion for a generator contingency is only directly related, in the primal reformulation, to the generator that is lost (i.e., its dispatch variable). For example, assume that generator 1 is lost, which is located at bus 1. Assume that generator 2 is anticipated to completely pick up this entire loss of supply from generator 1 (so the ISO sets the GDF = 1 for generator 2) and generator 2 is at bus 2. Even though generator 2 is the unit anticipated to provide the needed injection, the functional form in (7.35) and (7.36) relate the *change* in the injection at bus 2 to be determined by the GDF (a fixed input parameter) and the output of generator 1. The GDF is basically masking the response that is provided by generator 2 for generator 1's drop in supply. This is the reason that γ reduces to zero in (7.41) for generators that are not located at the nodes of the generators contained within the critical generator contingency list.

More importantly, the post-contingency congestion and the component of the LMPs that are reflective of this post-contingency state are driven by the cost of the generator that is lost; it is not driven by the cost that is associated to the generators that would actually respond. From a power engineering perspective, capturing the costs of the units responding does not fully matter in regard to ensuring a secure system; the primal problem captures the change in injection for the buses that are anticipated to have an increase in production when responding to the outage. From a cost perspective, it definitely has an impact as the cost is only related to the generator that is lost and not the units that respond. For instance, suppose that the only generator contingency that is explicitly modeled is a large, baseload unit like a nuclear unit. Such baseload units are often cheaper in regard to their marginal cost, $/MWh. On the other hand, the units that are likely to respond will be units that have fast ramping capabilities and are flexible; those are units that are generally more expensive. With this example it is clear that, at the very least, there is a high probability that the units that are chosen to be in the critical contingency list may be rather distinct in characteristics, *and costs*, than the units that are expected to respond. This is important since, *again*, the cost in the post-contingency state is not driven by the units responding but by the unit that is lost. At the same time, the model does not acknowledge any costs due to re-dispatch of generators in the post-contingency state. Only the pre-contingency costs are considered, which makes the impact of the post-contingency congestion a secondary influencing factor; the cost changes only by forcing a different pre-contingency dispatch set point that is secure rather than acknowledging the change in dispatch cost due to activation of reserve. Last, it is also equally important, if not more, to acknowledge the influence this has on the prices, via duality theory, that are then produced by this proposed reformulation by CAISO. This dissertation does not dive deeper into this potential problematic issue since that is a topic that will require much more research and investigation, as identified in the future work section in Chapter 8.

For those generators that are not in the critical list of generators, using the definition of γ from (7.43) and the LMP for that generator's location (λ_n) from (7.42a), (7.41) can be rewritten as (7.41a). There is now a one to one correspondence between (7.8a) of the standard DCOPF primal problem and (7.41a) with the exception that the LMP is now capturing an added, new congestion component reflecting congestion in the post-contingency operational state with the loss of a generator. Complementary slackness is then applied to the constraint-dual variable pair in (7.41a) to create (7.44). It is noteworthy to emphasize that (7.44) turns out to be identical to what would be obtained by applying complementary slackness to (7.8a), which again allows for the determination of the generator rent. Complementary slackness can also be applied to (7.32) to form (7.45). Then, based on (7.44) and (7.45), the generator rent for a generator that is not in the assumed critical generator contingency list is given by (7.46). The short-term generator profit (or generator rent) that will be earned by the non-critical generators is equal to the generator revenue less the generator cost. This generator rent term is basically identical to what is seen from the standard DCOPF formulation excepting that the LMP has an additional congestion component.

$$-\alpha_n + \lambda_n \leq c_n, \qquad (P_n) \qquad (7.41a)$$

$$-\alpha_n P_n + \lambda_n P_n = c_n P_n, \qquad (7.44)$$

$$-P_n \alpha_n = -P_n^{max} \alpha_n, \forall n \in N \qquad (7.45)$$

$$P_n^{max} \alpha_n = \lambda_n P_n - c_n P_n. \qquad (7.46)$$

For those generators that are included in the critical list of generators, using the definition of γ from (7.43) and the LMP for that generator's location (λ_n) from (7.42a), (7.41) can be rewritten as (7.41b). Complementary slackness is then applied to the constraint-dual variable pair in (7.41b) to create (7.47). Then based on (7.47) and (7.45), the generator rent for a generator that is contained within the assumed critical generator contingency list is given by (7.48).

$$-\alpha_n + \lambda_n + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(\sum_{s \in N} PTDF_{k,s}^R GDF_{n'(c),s} \right) \right] \le c_n, \qquad (P_n) \quad (7.41b)$$

$$-\alpha_n P_n + \lambda_n P_n + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(\sum_{s \in N} PTDF_{k,s}^R GDF_{n'(c),s} \right) \right] P_n = c_n P_n, \quad (7.47)$$

$$P_n^{max} \alpha_n = \lambda_n P_n - c_n P_n + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(\sum_{s \in N} PTDF_{k,s}^R GDF_{n'(c),s} P_s \right) \right]. \quad (7.48)$$

It is pertinent to note that the LMP defined in (7.42a) is consistent with CAISO's LMP definition in [31] for the nodes that do not have critical generators. Furthermore, CAISO's LMP definition for the nodes that do have critical generators, i.e., whose outages are modeled explicitly, is provided below in (7.23c). It is evident that there is a striking resemblance in the last term of the profit function (within square brackets) for the generators that are included in the critical contingency list in (7.48) and the last term of CAISO's LMP definition in (7.23c). This entails a detailed investigation into the net revenue stream for the generators that are contained within the assumed critical generator contingency list.

$$\lambda_n = \delta + \sum_k PTDF_{k,n}^R (F_k^- - F_k^+) + \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} PTDF_{k,n}^R (F_k^{c-} - F_k^{c+})$$

$$+ \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(\sum_{s \in N} PTDF_{k,s}^R GDF_{n'(c),s} \right) \right] \quad (7.23c)$$

There are a few key issues to consider here. First, note that despite the presence of the extra term in (7.48); (7.48) describes the profit that will be earned by the critical generators. In this specific primal reformulation of the DCOPF, described by (7.31)–(7.38), only a single linear operating cost component is considered for the production from the generator at node n. In addition, the generator production variable has no other restrictions other than a lower bound of zero and a real power maximum capacity restriction (upper bound). Analogous to the dual analysis provided for the standard DCOPF problem in Section 7.2.2, three cases can potentially exist for the generators in this primal reformulation with single linear cost coefficients and only lower and upper bounds. (1) If a generator is not producing at its maximum capacity, the short-term marginal benefit (profit) to increase its capacity beyond its existing capability is zero. (2) If it is operating at its maximum capacity, the short-term marginal benefit to increase its capacity by 1 MW is equal to the difference between what it is paid and its marginal cost. (3) If it is not producing anything, then what it is paid must be less than or equal to its marginal cost. Consequently, the penalty (shadow) price of (7.32), α, does completely capture the \$/MWh rate for the corresponding unit's profit or the marginal benefit of increasing its maximum capacity, which makes $\alpha_n P_n$ (or $\alpha_n P_n^{max}$ by complementary slackness) its profit function. Therefore, the net revenue stream for a generator should equal the sum of its profit and cost. Equation (7.48a) defines the revenue for the generators that are contained within the assumed critical list of generators.

$$P_n^{max}\alpha_n + c_n P_n = \lambda_n P_n + \sum_{\substack{k\in K^{crt},\\ c\in C^{g^{crt}}}} \left[(F_k^{c-} - F_k^{c+}) \left(\sum_{s\in N} PTDF_{k,s}^{R} GDF_{n'(c),s} P_s \right) \right]. \quad (7.48a)$$

Second, if the short-term generator profit for a generator at node n, summed over all nodes, is equal to the total generation profit, then by strong duality, at optimality the following relationship, i.e., (7.49), holds. In other words, at optimality, the objective of the primal reformulation must equal the objective of the dual problem, or the load payment is equal to the sum of the total generation cost, the total generation profit, and the total congestion rent.

$$\sum_n c_n P_n = -\sum_n P_n^{max} \alpha_n - \sum_k P_k^{max,a} (F_k^- + F_k^+) - \sum_{\substack{k \in K^{crt}, \\ c \in C^{g^{crt}}}} P_k^{max,c} (F_k^{c-} + F_k^{c+}) + \sum_n \overline{D_n} \lambda_n, \quad (7.49)$$

If $\alpha_n P_n^{max}$ is equal to the short-term generator profit for a generator then it implies that (7.48) describes the profit that will be earned by the critical generators, which means that a critical unit's revenue is not just the LMP at its location (λ_n) times the production, but its revenue also includes the added extra (last) term in (7.48).

On the contrary, if $\alpha_n P_n^{max}$ is not equal to the short-term generator profit and instead a critical unit is only paid the LMP at its location (λ_n) times the production, then its profit is equal to LMP at its location (λ_n) times the production less the cost. In this case, the short-term generator profit for a generator at node n, summed over all nodes, will not equal the term in the dual objective that is supposed to represent the total generation profit of the entire system. In other words, this would remove the added extra term from its revenue. Furthermore, since complementary slackness dictates that (7.48) should hold, which again is the short-term generator profit for a generator at node n summed over all nodes, will not equal the total generation profit of the entire system. To summarize, if $\alpha_n P_n^{max}$ does *not* denote the short-term generator profit for both the critical and the non-critical generators, it will result in an ISO that is *not* revenue neutral. The ISO will either have a revenue shortfall overall or surplus. This confirms and clarifies what the generators in the assumed critical list should be paid and explains the reasoning behind why CAISO is potentially including the added extra term in their definition of the LMP at the nodes of the critical generators in (7.23c). However, CAISO's definition of the LMP at the nodes of the critical generators is *not* consistent with the traditional definition of the LMP or the LMP that is identified by the corresponding dual formulation. Yes, the critical generators should now be paid this extra term but that does not imply you include the extra term in the LMP since this will have associated implications in the FTR markets (note that this LMP is further used to settle the FTR payments in the FTR markets). Also, note that, in (7.49), the load pays the LMP identified by the dual formulation. Further extension of this work is necessary to evaluate more advanced reformulations to enhance generator contingency modeling (an example is detailed in Section 7.4) and its corresponding effect on market prices, settlements, and revenues.

Third, it is necessary to understand the interpretation and the implications of the extra term in (7.48). If a critical generator is under an outage (or a contingency), the GDFs specify that the corresponding injections to compensate for the drop in its supply are defined based on its value for its locations. Essentially, the extra term in the profit function, (7.48), is what the critical generator is paid by the ISO to compensate for the loss of its production. Now, if the extra term is combined with the fact that the unit is being paid the LMP at its location for its production, what this translates into is that the corresponding critical generator is basically paying a congestion charge for the difference between injecting at its location and instead injecting at the locations identified by the GDFs. Thus, the combination of the extra term and its LMP component corresponding to the outage is basically a congestion transfer cost. Another way to interpret this is that, for that particular contingency scenario, the critical generator will inject at the locations that are identified by the GDFs instead of injecting at its own location. The LMP already compensates for the expected injection at its location. The extra term is the transfer due to injections based on the pre-defined rules of the GDF. Another way to interpret this would be that the generator that is lost has storage at each node identified by the GDF definition and is expected to compensate for its own contingency by injecting at those locations. The model still acknowledges that the generator is producing; it is just producing now magically at different locations. As such, the dual formulation suggests that the unit should be compensated exactly by that (invalid) assumption. The right way to make this work is to have the critical generator buy from the locations identified by the GDF instead or have some sort of a side contract with the generators at those locations. This section basically defines how this pricing structure would work if it is to follow the exact prescribed formulation proposed within the primal.

To assist in understanding the implications, it is helpful to go back to (7.35) and (7.36). Recall that the GDF shows up only in (7.35) and (7.36) and it is multiplied by the MW dispatch variable for the generator that is lost. This basically simulates the cost of a critical generator backing up its loss based on its costs at other locations. The fact that the equations are driven based on its dispatch variable and not the dispatch variables of the responding generators implies that this critical generator's cost influences the duals for this issue and not the cost of the responding generators. Thus, the responding generators do not affect the outcome for the generator that is lost. This is an important implication because this is sensitive to which generators are chosen to be included in the list of critical generator contingencies. The California ISO acknowledges this concern by stating that analogous to how transmission security constraints are selectively enforced in contemporary markets, the ISO will decide which generators are critical and need to be explicitly modeled based on engineering analysis and outage studies [31].

Finally, the definition of congestion rent is the flowgate marginal price times the flow on the line, summed over all lines. Congestion rent can be also identified by the difference in load payment and the generation revenue; it is easy to confirm that these two approaches provide the same value for the congestion rent as strong duality provides a formula where generation cost (the primal objective) is equal to the load payment minus the generation rent (short-term generation profit) minus the congestion rent at optimality. This can be more easily identified by applying strong duality to the simplified DCOPF and its dual, (7.1) and (7.7). For the more complicated primal reformulation auction model, presented in this section, that includes security constraints associated to generator contingencies, it becomes more complex; the congestion rent can be identified by taking (7.33)-(7.36) and applying complementary slackness. Thus, the system-wide congestion rent in this case is equal to the second and third terms in the dual's objective, (7.40); this is to be expected as it relates the flowgate marginal price to the line flow, once complementary slackness is applied.

7.4. Conclusions and Future Research

This chapter presents a comprehensive theoretical analysis of the recent industry movements, specifically, CAISO's efforts, to model generator contingencies in market models more appropriately. The main intention is to examine (and question) and complement the movement in the industry to enhance generator contingency modeling and to analyze the market impact of the policies that are proposed in this realm of research. It is noteworthy to emphasize that if the primal (DCOPF problem in this context) is formulated differently, the dual will not be the same and may result in different interpretations of that different dual. As this dissertation has demonstrated, this is why it is very important to perform a rigorous evaluation via duality theory to investigate the potential implications of the proposed market change.

Further extensions of the market auction formulation presented in Section 7.3.4 is essential to evaluate more advanced reformulations to enhance generator contingency modeling and its corresponding effect on market prices, settlements, and revenues. For instance, it is pertinent to analyze a market auction reformulation that enhances generator contingency modeling by incorporating an explicit representation of post-contingency *power balance* in addition to the previously mentioned post-contingency transmission (or network) security for critical generator contingencies. The post-contingency power balance constraints will help in assuring system-wide power balance between post-contingency generation and post-contingency demand. This essentially also provides an opportunity to model the expected post-contingency demand consumption under the different critical generator contingency states. However, the obvious setback with such an approach, i.e., the explicit inclusion of post-contingency power balance constraints, is the associated increase in the computational complexity of the corresponding problem. The anticipated impact that the corresponding change will have on market pricing is (again) how it affects the LMPs. This change will result in a LMP at a node for each of the modeled critical generator contingency states. In addition, it is also important to analyze the corresponding effect on the market settlements and revenues.

The explicit consideration of credible generator contingencies in general is expected to result in fewer ex-post or OMCs (or adjustments), which is technologically and economically beneficial. The explicit consideration of credible generator contingencies (and fewer ex-post adjustments) enable the market auction to optimize more of the market, which, in turn, results in improvements in market efficiency and improved price signals.

Future research should include implementing and testing the effectiveness of the proposed enhancements in improving the market surplus on a large-scale test system. Furthermore, to overcome the issues identified in this chapter, future work should examine the market implications of the generator contingency modeling approach proposed by MISO in [22] and identify a means to extend MISO’s approach to include both intra-zonal and inter-zonal transmission assets in addition to modeling more than one critical generator contingencies per reserve zone. The next steps should also investigate new means to introduce corrective actions via different reformulations and the associated market impacts.

CHAPTER 8.

CONCLUSIONS AND FUTURE RESEARCH TOPICS

8.1. Conclusions

Previous research has suggested stochastic programming approaches (or other similar approaches in this realm, e.g., robust optimization) to enhance scheduling models for many years. And yet the industry has not adopted what has been proposed. There is a clear gap that still exists that needs to be addressed. This dissertation's contribution primarily stems from trying to come up with innovative ways that achieve efficiency gains while not disrupting existing practices in order to increase the likelihood of industry movement. There are three issues that adequately reflect this work's contribution: 1) In March 2017, CAISO released a proposal to change their modeling of generator contingencies (and RAS) in a way that is very similar to what is proposed in this work. This industry example helps support the next two claims: 2) the proposed approaches are scalable (similar in complexity with what CAISO is proposing in [31]). 3) The proposed approaches can overcome market pricing barriers (again, very similar to what CAISO is pursuing).

The work done in this dissertation enhances generator contingency modeling without adding too much market complexity or computational complexity to the problem. Archival value and a contribution truly comes when a method can move industry. Work that artfully balances industrial barriers to adoption with advances in modeling and algorithms are the solution and this work is helping move the needle closer given the recent release from CAISO and how its pursuits align with the approaches proposed in Chapters 5 and 6. Furthermore, one of the main motivations for this work stemmed from communication with Dr. James E. Price from the Market Development and Analysis Department of CAISO in the United States; they were of the same opinion that enhanced reserve modeling and ramp products capture majority of the savings compared to a market design overhaul that implements two-stage stochastic programs. The goal of this dissertation is to align its efforts in a direction that would assist the industry. More specific contribution of this dissertation includes the following.

Currently, ISO MMS (SCUC and SCED models) ensure that for the loss of a credible non-radial transmission element, all remaining system elements remain within their emergency ratings. However, the loss of a credible generating element is not explicitly modeled within market auction models – as communicated by Dr. Eugene Litvinov of ISO-NE, industry has an efficient way to handle and decompose the modeling of transmission contingencies but they do not have an effective way to handle generator contingencies within market models. Instead, system or zonal reserve requirements are formed to ensure the system is reliable against credible generator contingencies. For example, common industry practices, to approximate the N-1 reliability criterion for generator contingencies, include simplistic policies that require a MW level of contingency reserve to be acquired somewhere in the system for any particular generator contingency. Such policies are formulaic rules that do not assure reliable operations (or ensure reserve deliverability) because they only capture a quantitative aspect; thus, there is a push to include an explicit representation of generator contingencies in market models. Since the existing market auction models do not satisfy the minimum stipulated N-1 contingency requirement adequately, this work (first) aims to improve upon such existing industry practices to handle the N-1 reliability criterion for generator contingencies more appropriately in addition to other typical forms of uncertainties such as load uncertainty and renewable uncertainty.

Mitigating uncertainty and maintaining system reliability is becoming progressively more difficult and more expensive in the wake of increasing levels of penetration of non-dispatchable stochastic resources. While operating conditions change, so should the reserve policies. Relying on static reserve policies will increase operational costs and degrade reliability as the integration of uncertain resources increases. Network flow patterns are becoming, and will continue to become, harder to predict. The weakness of the existing contemporary approaches in handling reserve deliverability warrants the investigation of alternatives. This dissertation has proposed enhanced reserve policies to improve the allocation and deliverability (i.e., feasibility of deployment) of reserves. The joint characterization of net load uncertainty and generator contingencies results in more effective scheduling and deployment of reserves. Existing approaches to respond to these challenges involve stochastic programming. It is possible that, in future, computational advancements would assist stochastic programs to address uncertainties more appropriately, thereby, outdating contemporary deterministic models. However, in the meantime, approaches based on proxy reserve requirements will continue to fill the gap between traditional deterministic and futuristic stochastic models.

For policy-driven approaches, one common characteristic is that such approaches almost always entail some approximations and attempt to utilize the knowledge that is gained offline during a prior stage in order to improve the complicated decision-making process in real-time, thereby, shifting the computational burden to an offline stage. As market structures change to improve the management of stochastic resources, advances in the design and development of ancillary services is needed. Currently, system operators and market designers are exploring new policy-driven approaches to accommodate stochastic resources. This dissertation aims to complement the existing efforts to effectively and efficiently allocate reserves across the system by incorporating enhanced reserve policies in the current operational procedures. The proposed enhanced reserve models are computationally scalable for actual-size systems and have minimal added computational complexity compared to existing deterministic reserve models that are more susceptible to infeasible reserve deployment.

In this dissertation, the effectiveness as well as the computational scalability was demonstrated on the Polish 2383-bus test system, which is an important contribution. The discussion that follows is with respect to the Polish test case. The average percent cost savings obtained with the approach proposed in Chapter 5 relative to the traditional reserve models are in the range of ~1.17%-2.86% for a sample test day. This translates into an average cost savings of $155,412-$385,198 correspondingly. Furthermore, the average percent cost savings of the approach proposed in Chapter 6 relative to the contemporary reserve models are in the range of ~3.3%-7.7% for a sample test day, which translates into an average cost savings of $456,860-$1,112,249 correspondingly. The average relative performance of the approach presented in Chapter 6, which is defined as the percentage of the highest cost savings that the proposed approach can potentially achieve, is in the range of ~26%-46% for the corresponding test day.

The proposed approaches are compatible with today's market structure and can be applied to address both intra- and inter-zonal congestion, whereas the existing zonal models cannot adequately represent and address intra-zonal congestion. The proposed framework accommodates different response sets for each contingency and period to reflect the changing system requirements and congestion patterns. The proposed reserve models can be viewed as a means to identify units that need to be disqualified from providing reserves, which will reduce the need for uneconomical OMC procedures.

In Chapter 4, two OMC procedures were developed to quantify the cost of security violations rather than using a purely subjective VOLL approach. In a typical VOLL approach, security violations are modeled as slack variables in the optimization model and are penalized using a set of pre-determined penalty prices (or VOLL). The main drawback of using such an approach is that the solution is sensitive to the choice of VOLL and may change if a different choice of VOLL is used. Also, the VOLL approach is not consistent with existing industry practices. The use of an OMC model provides a more appropriate and objective way to evaluate the cost to correct security violations. This is an important contribution of the dissertation since a more realistic approach is utilized to evaluate the system security violations.

Furthermore, due to the more appropriate consideration of credible generator contingencies and uncertainty introduced by stochastic resources, the approaches proposed in Chapters 5 and 6 results in a market SCUC solution that is closer to the desired N-1 SCUC solution and requires *fewer* ex-post or ISO discretionary adjustments, which is technologically and economically beneficial. For instance, for the Polish test case, the average OMC cost for a sample test day is reduced from \$2,960,410 for the myopic reserve policy to \$1,797,353 with the approach presented in Chapter 5. In addition, the average OMC cost for a sample test day is reduced from \$3,202,269 for the myopic reserve policy to \$1,686,938 with the approached proposed in Chapter 6. By having fewer ex-post or OMC adjustments, the proposed approaches are enabling the market auction to optimize more of the market. When more products and ancillary services are optimally handled within the market structure, you not only get an improvement in efficiency (and market surplus) but you also get improved price signals that are better reflections of actual system operational requirements. This translates into better market transparency (fairness) and reduced uplift payments. Right now all ISOs are being strongly encouraged by their stakeholders to limit as best as they can their out-of-market corrections.

To sum up the contributions, the proposed approaches offer augmentation with minimal added computational burden. They are designed to avoid practical (market, scalability) barriers while still capturing most of the potential cost savings. In addition, they require fewer OMCs, thereby improving market transparency and pricing. The proposed approaches are successful in finding solutions that capture post-contingency congestion reasonably. Furthermore, the proposed approaches are aligned with existing market structures and are least disruptive (avoidance of market overhaul); therefore, they would face fewer implementation barriers from stakeholders/market participants. Thus, this work can find potential benefits to ISOs, non-market entities, stakeholders and vendors. Finally, the work done in this dissertation should find potential applications in EMS, MMS, market settlement policies, SCUC, SCED, residual unit commitment, SFT and FTR auctions.

8.2. Future Research and Next Steps

To implement the reserve policies proposed in Chapters 5 and 6 in a practical setting, such as within modern day MMS, further research is needed. The subsequent subsections summarize the next research steps.

8.2.1. Impact of Reformulations on Financial Transmission Rights Markets

The financial transmission rights (FTR) revenue adequacy issue arises when there are discrepancies between the (convex) forward FTR allocation and auction models and the (convex) day-ahead market (DAM) model. Present-day DAM models produce a dispatch solution that respects network constraints, transmission flow constraints in specific, both in the pre- (or base) and post-transmission contingency cases. The congestion revenue right (CRR) process evaluates the simultaneous feasibility of the CRRs that are allocated and auctioned to confirm that the congestion rent that results from the corresponding dispatch solution is sufficient to compensate CRRs. Note that it is assumed that the DAM transmission topology is consistent with what is modeled within the FTR auction. In addition, for transmission contingencies, the transmission flow constraints included in the simultaneous feasibility test (SFT) are emergency ratings (rate C, post-transmission contingency) of transmission assets. The SFT for CRRs verifies that the scheduled injections (source/supply) and withdrawals (sink/consumption) corresponding to the CRRs produces flows that respect the transmission limitations (normal and emergency ratings) that are modeled in the pre- and post- transmission contingency cases in the FTR auction model. In other words, the FTR SFT maintains ***consistency*** and models the same set of transmission flow constraints that are included in the DAM model. Therefore, in the case of transmission contingencies, the congestion rent collected from the DAM model is sufficient to compensate the CRRs, thereby ensuring revenue adequacy.

There is speculation that the explicit modeling of generator contingencies can potentially lead to revenue inadequacy in the FTR markets. The key problem with respect to inconsistent modeling of generator contingencies between the FTR auction and the DAM is potentially the same as the inherent inconsistent modeling of transmission contingencies. No second-stage recourse variables are introduced in the proposed approaches analogous to the way transmission contingencies are handled; however, the difference lies in the fact that a transmission contingency does not need a re-dispatch (or a corrective action, by choice), whereas a generator contingency needs a re-dispatch (when modeled explicitly).

In the case of generator contingencies (the proposed cases), since the DAM model is enhanced to include the proposed post-generator contingency nodal reserve deployment transmission constraints, the DAM model accounts for the anticipated post-generator contingency effects on critical transmission paths by reserving transmission capacity (or reducing pre-contingency flows on the corresponding paths). However, to obtain a dispatch solution that is feasible for generator contingencies, the SFT for FTR auctions will also need to account for the anticipated post-generator contingency effects on critical transmission paths. This is possible by including the post-generator contingency transmission constraints (of the same form as the constraints used in the enhanced DAM model) in the FTR allocation and auction models as well. As a result, when auctioning and allocating CRRs (that can be injected at all locations and withdrawn at the load) to market participants, the FTR model will also reserve transmission capacity to account for the expected effects of generator contingencies. Thus, the only difference lies in the fact that the amount of CRRs cleared will now need to satisfy the proposed post-contingency nodal reserve deployment constraints. In other words, the CRRs will settle against the congestion in the DAM model analogous to what is done today. To conclude, the constraint set in the FTR allocation and auction models will need to be augmented to include the proposed post-generator contingency nodal reserve deployment transmission constraints (emergency limits, rate C); however, the objective function does not need to be modified. Therefore, the DAM model and the FTR model need to be aligned, i.e., consistently enforce the generator contingencies, for revenue adequacy.

It is noteworthy to emphasize that a similar revenue adequacy issue was raised by a few stakeholders in response to CAISO's recent proposal to change their modeling of generator contingencies [31]. Reference [31] includes comprehensive revenue adequacy results based on simulations on CAISO's MMS. In fact, in response to the stakeholders' concerns, CAISO has proposed to adjust their CRR auction and allocation process to include the corresponding post-generator contingency transmission constraints, analogous to the earlier suggestion of maintaining consistency in the treatment of network transfers between the FTR auction model and the DAM model to maintain revenue adequacy.

It is pertinent to note that, to avoid modeling complexity, many ISOs (including CAISO) currently use a *minimalistic* approach to handle transmission contingencies (or outages), wherein they simply apply a ***global scaling factor*** (*manually* based on operator's engineering judgment) to all the transmission assets (in all periods) that are included in the FTR auction model [104]. Such an approach of manually adjusting transmission path limits is also used to account for the effects of expected loop flows. Reference [104] details CAISO's current CRR allocation and auction process for handling transmission contingencies. Such a *simplistic conservative approach* is adopted to account for the potential de-rates (reduced transmission capacity) that may occur due to the differences (inconsistencies) in the way contingencies are modeled in the FTR auction model versus the DAM model. In other words, such an approach is a workaround to withhold the corresponding transmission capacity from being allocated or auctioned in the FTR markets, thereby attempting to avoid revenue inadequacy. This may not be the best (or the correct) way to handle (or resolve) this issue; however, the key point is that the state-of-the-art practices (or approximations) adopted in FTR auction models aren't as precise as they should be. Such an approach can also potentially cause revenue inadequacy in the FTR market, which is usually dealt with by de-rating each FTR holder's payment, implementing side payments (or wealth transfers), or by re-running a new auction to change the allocation of FTRs in the market. However, this does not serve the main purpose, which is to hedge against price risks. The right approach is to maintain *consistency* between the (convex) FTR auction model and the (convex) DAM model, and CAISO seems to be wanting to move in this direction as well.

Finally, if the corrective actions are structured in a manner that does not cause non-convexities and if the locational marginal prices are calculated appropriately, i.e., to include a marginal post-critical generator contingency congestion component, then revenue adequacy is guaranteed just as proposed by Hogan [105]. The proof of revenue adequacy for FTR markets, as proven by Hogan in [105], is driven based on the separating hyperplane theorem from convex optimization theory and the proof of revenue adequacy for point-to-point FTRs hold as long as the auctions are convex. FTR market auctions are not guaranteed to be revenue adequate today due to non-convexities. For instance, FTR auctions can result in revenue inadequacy when the day-ahead market transmission topology is different than what is modeled within the FTR auction. Another way to illustrate this example, if the allocations of FTRs from the auction were actually physically exercised, the solution would be feasible – if the topology changes, that is not guaranteed as the feasible space of injections changes.

Future research is needed to analyze the implications of the newly proposed market modifications, e.g., the modeling of corrective actions, on FTR markets, including the modifications to SFT, and revenue adequacy of FTR auctions.

8.2.2. Overall Market Evaluation and Implications

Modern day market structures have complemented the increased reliance on renewable energy resources with accompanying modifications in electric energy markets. These modifications include, but are not restricted to, new products, such as flexible ramping product [106], and market reformulations, such as contingency modeling enhancements [31], [107], to accommodate the variability and uncertainty introduced by stochastic resources and to represent contingencies in the presence of such resources more appropriately. Consequently, such market adjustments have an associated impact on market pricing and efficiency.

Chapter 7 investigates the market implications of the recently proposed and implemented market model enhancements, i.e., the inclusion of generator contingencies, by CAISO in [31]. This includes a thorough theoretical analysis, by leveraging duality theory from linear optimization, of the influence of the newly proposed changes by CAISO on market prices, settlements and revenues. It is pertinent to note that this work complements CAISO's efforts, which does not include the corresponding market assessment.

The enhancements to traditional SCUC and SCED formulations proposed in Chapters 5 and 6 also apply to vertically integrated (regulated) utilities. The value of the work is not limited to only market environments. However, since it is primarily the market environments that are initially moving in the direction of enhanced SCUC and SCED models, it is imperative to understand and address the market related issues. Further research is needed, analogous to the research in Chapter 7, to examine the market implications of the approaches presented in Chapters 5 and 6; particularly, a detailed investigation into the pricing mechanisms that correspond to the proposed market changes. The main impact that the proposed approaches will have on market pricing is how it affects the LMPs. Currently, LMPs already have a congestion component that comes from a critical transmission contingency. The LMPs will now have a congestion component that will result from a critical generator contingency. The proposed approaches are not intrusive to existing markets so that massive market redesigns are not necessary.

The next steps can also include an investigation on the system-wide price volatility. In addition, further research should also include a study of the impact of the proposed changes (reserve models) on ancillary services prices and analyze the associated impacts on market participants. Furthermore, since Chapter 5 and 6 enhance the DAM SCUC by better capturing post-contingency congestion, it will naturally lead to more accurate prices for ancillary services. Those generators that are valued more are expected to get paid (relative to competition) a better price since the proposed approaches, in Chapters 5 and 6, are providing another factor of system conditions that affect actual operations (but are not currently acknowledged in market auctions). The ancillary service pricing structure should aim to reward locations that provide a higher quality of reserves, thereby, reflecting the value of service provided by resources at critical locations where backup capacity is actually needed.

It is pertinent to note that the main deciding factor for implementing innovative technologies is whether the proposed approach enhances social welfare (also referred to as market surplus). ISOs are mandated to be independent and pursue an objective that maximizes social welfare so, while interesting, individual impacts on market participants (or a subgroup) is not the main driver, instead, one should show that it has a sizeable impact on the main driver, social welfare, which was done in Chapters 5 and 6. Implementation of smart, well-defined reserve policies in grid technologies, which enhances the social welfare, will be both vital and beneficial in future market structures. However, further research is needed for a comprehensive economic assessment, such as the impact of the proposed changes on generator rent, generator revenue, load payment, congestion rent, uplift/make-whole payments and incentives for participants.

Further work necessary to conduct a comprehensive investigation of the market implications is also not limited to how the proposed approaches affect prices but also how the proposed formulations relate to stochastic programs and clearing a market in a stochastic environment.

8.2.3. Investigate Techniques to Determine Generator Participation Factors

Future research should examine identifying more systematic and suitable ways to determine participation factors and response sets for each modeled contingency event to enhance market efficiency, maintain fair and accurate prices, and maintain a transparent market environment. The primary goal is to develop and evaluate reserve procurement policies that can be applied to day-ahead or real-time deterministic operations in order to accommodate stochastic operations. Further research should examine the potential use of inertia and/or synchronizing power coefficients based participation factors, potentially in combination with data-mining algorithms. Furthermore, generator response sets that are determined based on the generators' proximity (i.e., electrical distance) to the uncertain realization should be investigated.

Lastly, with the state-of-the-art computational advancements, the scope of solving advanced stochastic look-ahead commitment and dispatch models (via decomposition approaches, e.g., progressive hedging) to determine reserve procurement strategies, including generator participation factors and deployment factors, should be explored. Assuming that the corresponding stochastic program can be solved within required timeframes, future research is needed to translate the output of the corresponding stochastic programs to design and develop appropriate reserve procurement strategies that can be potentially utilized in a deterministic market environment.

The proposed future changes should be accompanied with a corresponding investigation of the market implications of the various proposed techniques to determine the participation factors and different reformulations to introduce corrective actions.

8.2.4. Identifying Critical Power Systems Elements

The computational performance of the approaches presented in this dissertation is dependent upon the size of the critical subsets that include the critical generator contingencies and the critical transmission assets respectively. The solution time of the enhanced SCUC model is expected to increase with an increase in the size of the critical subsets; thus, future work is needed to address the computational performance. The sizes of these subsets were defined after discussing common industry practices associated to the number of critical post-contingency constraints that are modeled as well as weighing a trade-off between model accuracy and model complexity. Note that such a practice to limit the number of transmission assets that are modeled with the post-contingency transmission constraints is also adopted by MISO in [22], where only *ten* frequently congested lines (designated as IROL constraints or critical SOL constraints) were chosen for enforcing the post-contingency zonal deployment constraints.

Market operators typically have an approximate notion of the critical transmission assets and contingencies that generally result in deliverability issues for their system [108], [109]. Therefore, the subset of critical transmission assets can vary from system to system. Furthermore, the utilization of such approximations is already evident in existing industry practices. The removal of inconsequential lines, which regularly have flows that are less than their normal rates, from the full network model in order to enhance the solvability of SCUC and SCED models, is a common industry practice.

Analogously, determining which contingencies to protect against is also a relevant issue. Market operators employ well-established practices (or offline procedures) to decide which contingencies are the most critical. There are three choices that exist. a) Not include any contingency scenarios (inefficient and doesn't meet NERC's N-1 mandate). b) Model the exhaustive list of contingencies (ideal choice but impractical with existing computational capabilities). c) Scenario reduction (what's being done today). For instance, it is apparent via communication with a leading software vendor of the MMS (ALSTOM, who was also recently purchased by General Electric) and other ISOs that their tools within MMS only consider a subset of contingencies. While the selection process is not perfectly transparent, it takes a holistic view of criticality/credibility that includes engineering studies/simulations/assessment of "what-if" tests, analyzing past events/trends and operator's engineering judgment/experience/expertise. For instance, the industry has significant experience in tracking generator reliability through the NERC generator availability data system [108]. It is pertinent to note that existing practices aren't perfect, but the proposed approaches can add on top of those practices (option c) instead of redefining them. Further research is needed in this realm to help identify and explore more appropriate means of defining critical transmission assets and generator and transmission contingencies.

8.2.5. Hybrid Approach of Policy Functions Combined with Stochastic Programming

The development and integration of proxy reserve policies within stochastic programming algorithms, such as progressive hedging and Benders' decompositions, may enhance the convergence and scalability of such programs by using a hybrid approach of policy functions combined with stochastic programming [34].

In particular, future research should focus on the scope of incorporating the proposed dynamic reserve policies within stochastic programs, e.g., stochastic unit commitment, to improve its performance. Such an approach can reduce the number of initial scenarios that are needed in stochastic programs by improving the offline mechanism to produce the reserve policies. Furthermore, since the embedded enhanced reserve policies do not increase the number of variables, such an approach has a tendency to reduce the size of the master problem. In addition, the hybrid approach has the potential of reducing the overall problem size and the number of iterations to achieve convergence, which will improve the computational performance while maintaining similar solution qualities. Additional research is necessary to further develop and test this hybrid concept.

8.2.6. Reserve Bidding

Contemporary market auction models incorporate numerous approximations to model discrete disturbances, such as generator and transmission contingencies, and continuous disturbances, such as demand and renewable uncertainty. Existing deterministic market structures inadequately reflect what resource is actually the best to provide reserve. For instance, the approach of reserve zones generalizes every generator in a specific zone as to having the same deliverability of reserve but that is not the actual case (industry example: MISO and their reserve disqualification process after closing their DAM). The generators that provide a reserve product that can be deployed when needed (a higher quality of service) should be better compensated for the corresponding service.

One common argument is that the reserve bid should incorporate the risk premium of carrying the reserve for deployment. Such an argument is flawed because the deterministic auction models to begin with do not capture the congestion patterns in the event of an uncertain realization appropriately. This inherently leads to inaccurate prices for energy and ancillary services.

Further research is needed to provide an insight whether an adjusted reserve bid can capture the value of providing reserve. Future work is necessary to demonstrate that a strategic reserve bid does not adequately capture the value of security in comparison to when contingencies are modeled explicitly.

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