

Ensuring the Reliable Operation of the Power Grid: State-Based and Distributed Approaches to Scheduling Energy and Contingency Reserves

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Jose Fernando Prada

B.Sc., Electrical Engineering, National University of Colombia
M.Sc., Technology and Policy, Massachusetts Institute of Technology
M.Sc., Electrical Engineering, Massachusetts Institute of Technology

Carnegie Mellon University
Pittsburgh, PA

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Abstract

Keeping a contingency reserve in power systems is necessary to preserve the security of real-time operations. This work studies two different approaches to the optimal allocation of energy and reserves in the day-ahead generation scheduling process.

Part I presents a stochastic security-constrained unit commitment model to co-optimize energy and the locational reserves required to respond to a set of uncertain generation contingencies, using a novel state-based formulation. The model is applied in an offer-based electricity market to allocate contingency reserves throughout the power grid, in order to comply with the $N-1$ security criterion under transmission congestion.

The objective is to minimize expected dispatch and reserve costs, together with post contingency corrective redispatch costs, modeling the probability of generation failure and associated post contingency states. The characteristics of the scheduling problem are exploited to formulate a computationally efficient method, consistent with established operational practices.

We simulated the distribution of locational contingency reserves on the IEEE RTS96 system and compared the results with the conventional deterministic method. We found that assigning locational spinning reserves can guarantee an $N-1$ secure dispatch accounting for transmission congestion at a reasonable extra cost. The simulations also showed little value of allocating downward reserves but sizable operating savings from co-optimizing locational nonspinning reserves. Overall, the results indicate the computational tractability of the proposed method.

Part II presents a distributed generation scheduling model to optimally allocate energy and spinning reserves among competing generators in a day-ahead market. The model is based on the coordination between individual generators and a market entity.

The proposed method uses forecasting, augmented pricing and locational signals to induce efficient commitment of generators based on firm posted prices. It is price-based but does not rely on multiple iterations, minimizes information exchange and simplifies the market clearing process.

Simulations of the distributed method performed on a six-bus test system showed that, using an appropriate set of prices, it is possible to emulate the results of a conventional centralized solution, without need of providing make-whole payments to generators. Likewise, they showed that the distributed method can accommodate transactions with different products and complex security constraints.

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Abbreviations and Acronyms

AC	Alternating Current
CAISO	California Independent System Operator, California ISO
CCUC	Contingency-Constrained Unit Commitment
DC	Direct Current
ED	Economic Dispatch
EENS	Expected Energy not Served, Expected Energy not Supplied
ELNS	Expected Load not Served, Expected Load not Supplied
ENS	Energy not Served, Energy not Supplied
IO	Interval Optimization
ISO	Independent System Operator
ISO NE	Independent System Operator New England, ISO New England
LAUC	Look Ahead Unit Commitment
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
LR	Lagrangian Relaxation
MC	Market Coordinator
MIP	Mixed Integer Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non Linear Programming
MISO	Midcontinent Independent System Operator
MW	Megawatt
MWh	Megawatt-hour
$N-1$	“en” minus one
$N-1-1$	“en” minus one minus one
$N-k$	“en” minus “key”
NERC	North American Electric Reliability Corporation
NYISO	New York Independent System Operator, New York ISO
OPF	Optimal Power Flow
PBUC	Price Based Unit Commitment
PJM	Pennsylvania New Jersey Maryland Interconnection

RTO	Regional Transmission Organization
RUC	Reliability Unit Commitment
SCED	Security-Constrained Economic Dispatch
SCUC	Security-Constrained Unit Commitment
SP	Stochastic Programming
SDP	Stochastic Dynamic Programming
SUC	Stochastic Unit Commitment
UC	Unit Commitment
VoLL	Value of Lost Load
WECC	Western Electricity Coordinating Council
\$	Dollar
h	Hour

Nomenclature

The main symbols used in the dissertation are defined below, others are defined in the text.

PART I

Symbol	Description (units)
<i>Indices and Sets</i>	
i	Index of available generation units
j	Index of generation units able to provide reserves
k	Index of single generation contingencies
l	Index of single transmission line contingencies
m, n	Index of electrical nodes of transmission network
t	Index of time periods (hours)
I	Set of available generation units, running from 1 to I
$I^{(k)}$	Set of available generation units under contingency k
I_n	Set of available generation units connected to node n
J	Set of generation units able to provide reserves, running from 1 to J ($J \leq I$)
$J^{(k)}$	Set of generation units available to provide reserves under contingency k (subset of $I^{(k)}$)
K	Set of selected generation contingencies, running from 0 (no contingency) to K
L	Set of selected transmission line contingencies, running from 0 (no contingency) to L
M_n	Set of electrical nodes directly connected to node n
N	Set of electrical nodes of the transmission network, running from 1 to N
T	Set of (hourly) time periods, running from 1 to T
<i>Variables and Parameters</i>	
$\theta_{nt}^{(k)}$	Voltage phase angle at node n in period t under contingency k (rad)
$g_{it}^{(k)}$	Power output of unit i in period t under contingency k (MW)
r_{it}^{NS}	Nonspinning reserve of unit i in period t (MW)
r_{it}^{SP}	Spinning reserve of unit i in period t (MW)
$u_{it}^{(k)}$	Binary variable $\{0,1\}$, 1 when unit i is committed in period t under contingency k and 0 otherwise

Symbol	Description (units)
$v_{it}^{(k)}$	Binary variable $\{0,1\}$, 1 when unit i is started up in period t under contingency k and 0 otherwise
$w_{it}^{(k)}$	Binary variable $\{0,1\}$, 1 when unit i is shut down in period t under contingency k and 0 otherwise
$p_t^{(k)}$	Conditional probability that contingency k occurs in period t given that no contingency has occurred before
g_i^{\min}	Minimum power output of unit i (MW)
g_i^{\max}	Maximum power output of unit i (MW)
$r_{it}^{sp_max}$	Maximum spinning reserve limit of unit i in period t (MW)
$r_{it}^{ns_max}$	Maximum nonspinning reserve limit of unit i in period t (MW)
$\Delta\theta^{\max}$	Maximum voltage phase angle difference between adjacent nodes (rad)
RD_i	Maximum inter-period ramp-down limit of unit i (MW)
RU_i	Maximum inter-period ramp-up limit of unit i (MW)
RD^{10}_j	Maximum 10-minute ramp-down limit of unit j (MW)
RU^{10}_j	Maximum 10-minute ramp-up limit of unit j (MW)
SD_i	Maximum shut-down ramp limit of unit i (MW)
SU_i	Maximum start-up ramp limit of unit i (MW)
DT_i	Minimum down time of unit i (hours)
UT_i	Minimum up time of unit i (hours)
D_{nt}	Electrical demand at node n in period t (MW)
$B_{nm}^{(l)}$	Electrical susceptance of transmission line between nodes n and m in contingency l (S)
FN_{nm}^{\max}	Continuous power rating of transmission line between nodes n and m (MW)
FE_{nm}^{\max}	One-period (1-hour) emergency power rating of transmission line between nodes n and m (MW)
<i>Functions</i>	
$SC_{it}()$	Startup cost of generation unit i in period t (\$/h)
$GC_{it}()$	No load and variable production cost of generation unit i in period t (\$/h)
$RC^{sp}_{it}()$	Spinning reserve cost of generation unit i in period t (\$/h)
$RC^{ns}_{it}()$	Nonspinning reserve cost of generation unit i in period t (\$/h)

When not specified, variables and parameters (e.g. u_{it}) correspond to a system condition without contingencies ($k = 0$).

PART II

Symbol	Description (units)
<i>Indices and Sets</i>	
i	Index of available generation units
m	Index of electrical nodes connected to node n
n	Index of electrical nodes of transmission network
t	Index of time periods (hours)
I	Set of available generation units, running from 1 to I
I_n	Set of generation units connected to node n
N	Set of electrical nodes of the transmission network, running from 1 to N
T	Set of (hourly) time periods, running from 1 to T
M_n	Set of electrical nodes directly connected to node n
<i>Variables and Parameters</i>	
θ_{nt}	Voltage phase angle at node n in period t (rad)
g_{it}	Power output of unit i in period t (MW)
r_{it}	Spinning reserve of unit i in period t (MW)
o_{it}	Binary variable $\{0,1\}$, 1 when generation offer of unit i in period t is accepted and 0 otherwise
u_{it}	Commitment variable $\{0,1\}$, 1 when unit i is committed in period t
v_{it}	Startup variable $[0,1]$, 1 when unit i is started up in period t
w_{it}	Shutdown variable $[0,1]$, 1 when unit i is shut down in period t
g_i^{be}	Break-even power output of unit i (MW)
g_i^{min}	Minimum power output of unit i (MW)
g_i^{max}	Maximum power output of unit i (MW)
r_i^{max}	Maximum spinning reserve limit of unit i (MW)
$\Delta\theta^{\text{max}}$	Maximum voltage phase angle difference between adjacent nodes (rad)
RD_i	Maximum ramp-down limit of unit i (MW)
RU_i	Maximum ramp-up limit of unit i (MW)
DT_i	Minimum down time of unit i (hours)
UT_i	Minimum up time of unit i (hours)
E_{it}^{max}	Maximum energy generation offer of unit i in period t (MW)

Symbol	Description (units)
E_{it}^{\min}	Minimum energy generation offer of unit i in period t (MW)
R_{it}^{\max}	Maximum reserve offer of unit i in period t (MW)
R_{it}^{\min}	Minimum reserve offer of unit i in period t (MW)
D_{nt}	Electrical demand at node n in period t (MW)
B_{nm}	Electrical susceptance of transmission line between nodes n and m (S)
FN_{nm}^{\max}	Continuous power rating of transmission line between nodes n and m (MW)
pe_{it}	Energy price in period t at the node where unit i is located (\$/MWh)
pr_{it}	Spinning reserve price in period t at the node where unit i is located (\$/MW-h)
<i>Functions</i>	
$AC_{it}()$	Average cost of generation unit i in period t (\$/MWh)
$SC_{it}()$	Startup cost of generation of generation unit i in period t (\$/h)
$GC_{it}()$	No load and variable production cost of unit i in period t (\$/h)
$RC_{it}()$	Spinning reserve cost of generation unit i in period t (\$/h)

INTRODUCTION

The operation of the power grid is facing multiple challenges, brought about by increasing diversity and variability of generation and demand resources, the emergence of disruptive technologies and the evolution of the grid's regulatory and transactional models. Therefore, new policies and tools are required to successfully answer these challenges [1], [2]. In addition, during the operations phase –unlike the planning and design stages– an electrical power system is constrained to make use of the existing resources that are available at the time. This defining characteristic limits the ability of the system to respond to the dynamic requirements of real-time electricity demand and changing operating conditions. For this reason, appropriate operative decisions are fundamental to meet the objective of providing efficient and reliable power supply and ensure the sustainability of electricity services.

Operating a large interconnected bulk power system¹ comprises a number of different activities, including operational planning, generation scheduling and dispatch, real-time monitoring and control, corrective actions and post-operative analyses. All of them important and susceptible to be affected by new grid requirements. But, arguably, the core operating problem is to schedule generation to supply the expected system demand, which entails defining

¹ The part of the electricity grid composed of the interconnected generation plants, transmission lines and related equipment. Distribution networks connect to the bulk power system.

the commitment (on/off status) of generation units, the dispatch of energy and different generation services, and the allocation of transmission capacity.

In a liberalized and competitive environment, generation scheduling seeks to match electricity supply and demand maximizing economic surplus (a proxy of social benefit), while complying with established security and quality operating standards. In a simpler setting, the objective can be formulated as to meet demand at minimum cost² complying with required service standards. Generation scheduling can be performed days to hours ahead of real-time operation, but most market-based systems have converged to a day-ahead scheduling period with hourly or half-hourly time intervals. This scheduling horizon represents a convenient tradeoff between having sufficient certainty and detail of operating assumptions and the feasibility and timeliness to carry out the required calculations.

This dissertation approaches the problem of generation scheduling in the context of competitive wholesale electricity markets, where different agents rival each other to provide generation services [3], [4]. In this case, the result of the final allocation of generation resources affects not only the service provided to the end consumers, but the distribution of benefits among market participants. Two main issues, relevant for the operation of the future power grid, are addressed. In first place, the uncertainty about the real-time availability of generation units, which makes it necessary to reserve (and pay for) spare generation capacity, in order to ensure a continuous and reliable supply. In this respect, the traditional and current practice of using fixed and deterministic reserve requirements does not ensure deliverability of reserves under network congestion and leads to inefficient market outcomes.

² For instance when there is not demand bidding, when demand is considered price-inelastic for calculation purposes or in the case of regulated and vertically integrated utilities.

In second place, the hierarchical and centralized operating structure prevailing at the present time concentrates decision-making in system and market operators. This type of organization limits the decision autonomy of individual agents, increases the complexity of generation scheduling models and processes, and gives rise to discussions about the fairness of resource allocation and market payments. As power systems grows larger in the number and diversity of participants, these limitations become more significant.

Accordingly, Part I of the dissertation studies the centralized day-ahead scheduling of energy and contingency reserves via stochastic optimization, proposing and illustrating models to efficiently allocate and price energy and locational reserves throughout the power grid. In Part II, a distributed day-ahead generation scheduling model is presented and applied to allocate energy and reserves among competing generators. The distributed scheduling model is based on price forecasting, individual commitment decisions and a straightforward market clearing process.

PART I

STATE-BASED STOCHASTIC CO-OPTIMIZATION OF ENERGY AND LOCATIONAL CONTINGENCY RESERVES

Chapter 1 Problem Statement

The fundamental objective of power systems planning and operation is to provide a reliable and efficient electricity service to customers. In particular, a critical aspect of the bulk power system reliability is the security of real-time operations, which refers to the ability of the system to withstand sudden disturbances. The typical disturbance in the power grid is the unplanned loss of a major system component –called a contingency–, normally a generation unit or transmission line [5].

The analysis of power systems security has two facets. First, the system must be able to settle into a post contingency feasible operating condition. Second, the system must be able to reach that new state. To meet the first requirement, a steady-state analysis verifies that no physical constraints are violated during the post contingency operating condition, whereas the second aspect involves the dynamic analysis of power system stability [6]. Part I is concerned with the static security analysis after the occurrence of a generation contingency.

1.1 Co-Optimization of Energy and Reserves

In general, system security –also called operational reliability– is preserved by examining and mitigating the effect of a set of more likely or “credible” contingencies, usually the loss of single major elements in the system. Accordingly, the standard “*N-1*” reliability criterion requires the bulk power system to stay within its operating limits after the occurrence of a single contingency event [7]. Compliance with the *N-1* reliability criterion without loss of load or curtailing of firm transfers is mandatory in United States (and other regulatory jurisdictions in North America), in accordance with NERC’s reliability standards TPL-001-4 and TOP-004-2 [8], [9]. Moreover, system operators have to restore operations to respect proven reliable system limits within 30 minutes after a contingency has occurred.

To comply with the *N-1* criterion, adequate generation capacity needs to be available throughout the system, in order to prevent loss of load when a single generation unit or transmission line is unexpectedly disconnected from the power grid. In practice, a security-constrained generation dispatch can deal with transmission outages. However, in order to restore the power balance after a generation failure, enough backup capacity has to be kept standing by, as a contingency reserve. The use of contingency reserves to respond to loss of supply disturbances is prescribed by NERC in the reliability standard BAL-002-1 [10]. The disturbance recovery period is 15 minutes maximum and, after being employed, the contingency reserve should be fully restored within 90 minutes by default. The contingency reserves are the main component of the system’s operating reserve³.

³ Primary and secondary frequency reserves, used during normal operation conditions, are another important component of the operating reserve.

The preferred approach to allocate and price contingency reserves in U.S. regional systems and other competitive electricity markets is to do it simultaneously with energy in the day-ahead resource scheduling process⁴, a procedure known as co-optimization of energy and reserves [11], [12]. This is accomplished by using a security-constrained unit commitment (SCUC) market model, which is the core of the scheduling process and seeks to ensure both the efficiency and reliability of operations. Scheduling power system resources is actually a complex task comprising several stages and details [13]. In fact, there are important differences in the way generation scheduling is implemented in each U.S. regional electricity market. But they also share several common aspects that allow a generalization of the process, as described in [14] and outlined next. With some simplifications, a similar procedure is followed by operators of vertically integrated systems.

An offer-based SCUC is computed daily, to clear market transactions and establish the corresponding optimal generation commitment (on/off status) and dispatch (output levels) schedule, including energy and reserves, for each period of the next operation day. The SCUC is a mixed-integer optimization problem, and the co-optimization of energy and reserves takes into account the cost of providing both products, considering the technical constraints resulting from transmission and generation operational limits and from enforcing other system security requirements. Formulations of the traditional deterministic SCUC problem can be found in [15], [16], and a practical implementation is described in [17].

The next-day generation program is subsequently adjusted for reliability through a day-ahead Reliability Unit Commitment (RUC), to ensure that enough physical generation capacity

⁴ The alternative approach of sequential allocation of energy and reserves has been gradually abandoned due to efficiency and arbitrage issues.

will be available to supply demand the next day. The generation program is also adjusted during the operation day to accommodate changes in network conditions. This is accomplished by carrying out rolling Look-Ahead Unit Commitments (LAUC) that recommit fast-start generators as needed. Finally, a security-constrained economic dispatch (SCED) is used to determine the real-time operation of generators, according to the actual load and grid conditions.

1.2 Locational Contingency Reserves

In the SCUC model, the *N-1* security criterion is enforced for single line outages through additional power balance constraints. This ensures, in a preventive manner, that the system will be able to reach a new feasible power flow distribution, without loss of load, after losing a single transmission line. In the case of generation outages, the *N-1* standard is met by imposing a global reserve requirement that needs to be kept during normal operation, so it can be employed after a contingency occurs. The contingency reserve required is generally based on some heuristics such as the largest expected generation outage or a percentage of the expected demand or both [15]. The first and most common criterion seems to relate the reserve with a “credible” worst contingency⁵, whereas the second is not widely used⁶. Thus, the decision about the required amount of system reserves stems more from judgement and accumulated operating experience, rather than from actual reliability calculations.

⁵ NERC standard BAL-002-1 requires enough reserve to cover the most “severe” single contingency

⁶ In the past, the operating reserve was also intended to cover unexpected load changes, for instance due to the connection/disconnection of big users, and hence the relation with a percentage of the demand. In modern power bulk systems, large demand jumps between dispatch periods are rare, smaller than generation outages and/or just taken by the regulation reserve. A few regional systems like WECC still keep reserve requirements based on a percentage of demand, but they admit the lack of technical justification for it, other than operational tradition. See <https://www.wecc.biz/Reliability/BAL-002-WECC-2%20-%20Guidance%20Document.pdf>

This global reserve requirement should be met with spare capacity of fast generation units already online, or “spinning” reserve⁷, but it can also be fulfilled with available capacity of offline but fast-starting units, or “nonspinning” reserve⁸. Upon request, the contingency reserve should be typically delivered in a maximum of 10 to 15 minutes, sustained for 30 to 60 minutes, and reestablished in 60 to 90 minutes. On the other hand, the division between spinning and nonspinning reserve is rather arbitrary. PJM, for instance, requires that 100% of the contingency reserve be synchronized to the grid, and it schedules an additional 50% as nonspinning reserve. Its neighbor NYISO, in contrast, requires that at least 50% of the total reserve should be spinning but the rest can be nonspinning, and a similar rule applies to CAISO [18].

A number of problems have been identified with the use of a fixed reserve requirement in the determination of the day-ahead SCUC. A central and well-known criticism is that this method does not guarantee *N-1* security against generation outages, since transmission congestion may prevent the effective use of reserves when a contingency occurs [19]. The reason is that the feasibility of reserve delivery during the post contingency states is not verified, therefore failing to define appropriate locational reserves throughout the system.

As a consequence, system operators need to run offline contingency analyses, and frequently resort to manually adjust generation dispatch to comply with security criteria using out-of-market corrections, a procedure that is economically inefficient [20]. A common but partial fix is to divide the system into reserve zones, based on known transmission bottlenecks.

⁷ Note that other online reserves, e.g. frequency regulation reserves, are also spinning, which may create confusion given the lack of uniformity on the definitions of generation reserves. Here the term “spinning reserve” is exclusively applied to the contingency reserve that is synchronized to the power grid, which is its more common usage.

⁸ Some demand response resources may also be qualified to provide non-spinning reserve.

Then, reserve requirements are defined for each zone in the SCUC, resulting in the allocation of zonal reserves. The zonal method mitigates the problem of reserve delivery, but it is still based on ad-hoc definitions of zones and their reserve requirements, and it does not guarantee $N-1$ compliance for all generation outages [21].

In addition, this method for scheduling generation reserves is purely deterministic, not taking into account the probability of failure of generation units. Therefore, it treats all outages as having equal risk and impact, increasing system costs [22]. The allocation of contingency reserves based on a global requirement does not provide an operation program to dispatch reserves either. That is, what reserves to use after a generation outage has occurred, which should vary according to the specific contingency realized. Lastly, the separation between spinning and nonspinning reserve lacks technical bases as indicated before.

From an economic perspective, the current pricing approach in competitive markets is to pay reserves a single clearing price, computed as the marginal (purchase) cost or shadow price of the system-wide requirement (or shadow prices of the zonal requirements). This method is not efficient in the sense that it does not remunerate the actual reserves required in the system, in terms of location and quantity. Therefore current reserve prices do not provide adequate economic signals for operation and investment in generation capacity.

Setting a contingency reserve requirement through a reliability proxy, like the loss of the largest unit online, could be suitable for a system without transmission constraints. However, it has serious shortcomings for real networks where transmission congestion is permanent instead of a transitory condition. Zonal reserve requirements mitigate the effects of congestion, but they are still loosely related to the set of credible contingencies that need to be addressed under the $N-1$ criterion. A better approach is to determine a spatial distribution of the reserves that allows the

system to effectively respond to the actual conditions present after a contingency has occurred, or post contingency state. These reserves are necessarily locational, ensuring deliverability of energy under any of the different possible contingencies selected for examination.

1.3 Objective and Organization of Part I

The purpose of this Part I of the dissertation is to formulate a practical and computationally efficient method, consistent with established operational practices in market-based systems, to optimally allocate and price locational contingency reserves under a set of credible single generation outages, enforcing the $N-1$ reliability standard. This method co-optimizes energy and reserves considering the cost of post contingency corrective actions, the effect of transmission congestion on the allocation of reserves, and the stochastic nature of the problem by modeling the probability of failure of generation units and associated post contingency states.

This chapter has characterized the research problem of Part I by providing background information on the scheduling of contingency reserves in power systems, describing the shortcomings of current allocation methods and stating the purpose of this Part. The rest of the Part is organized as follows: Chapter 2 reviews relevant academic literature and discusses research gaps and the contribution of the work; Chapter 3 explains the general approach and proposed methods to allocate locational contingency reserves; Chapter 4 presents numerical results of simulations on the IEEE Reliability Test System 96; and Chapter 5 summarizes findings and discusses policy implications for power system reliability and the operation of reserve markets.

Chapter 2 Literature Review and Discussion

This chapter reviews the academic literature related and relevant to the purpose of Part I, identifies research gaps on this field and explains the main contributions of the work.

2.1 Review of Relevant Related Work

There is a vast literature related to scheduling generation to meet power system security standards. Most practical applications are deterministic, but there is a growing interest in how to model and incorporate uncertainties in the scheduling process. Also a number of researchers have studied and proposed specific methods to efficiently allocate operating reserves. The following section reviews some of the more relevant works in these areas.

2.1.1 Generation Rescheduling and Security Constrained Unit Commitment

The concept of using generation rescheduling as a corrective action to find an optimal security-constrained solution for economic dispatch problems has long been discussed, of which [23] and [24] are illustrative examples. In both cases, an optimal power flow (OPF) scheduling model with pre contingency operating constraints is complemented with post contingency constraints that are met by redispatching generation to ensure system security. The authors propose different methods to solve this security-constrained OPF problem, but do not address reserves cost or allocation. The main barrier to implement the corrective rescheduling approach has been computational complexity, since the inclusion of multiple contingencies increases the size and complicates an already difficult scheduling problem.

Security-constrained unit commitment is a major extension of the conventional unit commitment (UC) problem [25], [26], [27], that includes network and contingency-related security constraints [28], [29], [30]. The size and complexity of UC problems, combined with substantial expected operation cost savings from improved solutions, have attracted continuous interest on developing better algorithms and incorporating new functionalities [31]. Nowadays, the deterministic SCUC model has become a key tool of operational planning and daily system operations [32], and it is the core calculation program supporting the day-ahead operation of modern electricity markets [33], [34].

A comprehensive review of modeling issues and of analytical and computational challenges to solve the SCUC problem is provided in [32], indicating that the integration of contingency analysis into the SCUC is still a work in progress. Due to their high computational requirements, decomposition and iterative techniques are commonly used to solve UC and SCUC problems for large systems [35], [36]. The Lagrangian Relaxation (LR) algorithm was the preferred solution method for years [37], but during the last decade there has been a significant move towards the use of mixed-integer programming (MIP) algorithms, after substantial advances achieved in linear programming solvers [38], [39]. As a consequence, the formulation of MIP-based UC problems keeps evolving through research oriented to attain faster and more efficient solutions [40], [41], [42], [43].

Advances in computational capability and large-scale optimization methods have also attracted renewed interest in mixing or replacing preventive scheduling with corrective actions to provide for contingencies in the deterministic SCUC model, as this may lower overall operation

costs or enhance reliability⁹. Thus, [44] proposes a LR-based method with a mixed preventive/corrective contingency dispatch and [45] provides a MIP-based method to include post contingency rescheduling after generation outages. In [46] transmission switching techniques are implemented using a UC model that is made strictly $N-1$ compliant through post contingency security constraints. And [47] develops a SCUC model with post contingency corrective recourse constraints to enforce soft $N-k$ reliability criteria. These latter models do not address reserve allocation nor pricing. Therefore, they implicitly assume that unused capacity is made available at no cost and ignore potential economic tradeoffs between providing energy and reserves through co-optimization.

2.1.2 Uncertainty Management and Stochastic Unit Commitment

In recent years there has been a renewed and marked interest in stochastic formulations of the unit commitment problem, or SUC, in order to preserve system reliability under uncertainty, as reviewed in [48], [49] and [50]. Most SUC formulations are motivated by the increasing penetration of renewable generation in the power grid as reviewed in [51]. The main sources of uncertainty for centralized generation scheduling stem from demand deviations, actual output of variable generation and equipment outages¹⁰. Demand deviations are produced by load forecast errors and by real-time load fluctuations around the constant (average) power assumed for any dispatch period. Variations on non-dispatchable generation output are due to the intermittent production of some type of technologies, especially renewables like wind and solar PV generation, and associated forecast errors. On the other hand, generation and transmission

⁹ This type of UC formulations is sometimes called Contingency-Constrained Unit Commitment CCUC

¹⁰ Other applications like self-scheduling may consider other sources of uncertainty, for example energy prices volatility or primary fuel cost and availability.

outages are considered purely random events, occurring due to equipment failure, although they are indeed affected by use and maintenance activities.

Demand forecast deviations in a short-term horizon (day-ahead or less) have been traditionally small and managed through load–frequency control resources. On the contrary, variable generation forecast deviations can be significant, in both intra-dispatch periods and from period to period [52]. The additional uncertainty from variable production increases as renewable generation penetration grows and requires the availability and deployment of flexible resources to compensate it [53]. Frequently, expected generation from variable resources is subtracted from the forecasted demand to form the “net load” faced by the fleet of dispatchable generation, which exhibits higher variability than any of its individual components¹¹. Demand and variable generation or net load uncertainty can be characterized by continuous single or joint probability distribution functions. On the contrary, the primary electrical equipment is considered to be in service or not¹², so the aggregate availability of system components is modeled through discrete probability distribution functions [54].

a. Approaches to Stochastic Unit Commitment

Generation scheduling based on probabilistic methods and stochastic optimization is an appealing option to efficiently account for uncertainties and provide flexibility to system operations. Different approaches used in SUC problems vary in the representation of uncertainty and the solution methods. Uncertainty modeling can be classified in scenario representation, uncertainty sets and probabilistic constraints. Problem formulations are based on stochastic

¹¹ See for instance the description of California’s net load curve or “Duck Curve” (CAISO, 2016), at https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

¹² In special cases, equipment derating is also considered as discrete steps of available capacity.

programming (single-stage and two- or multi-stage with recourse) [55], robust optimization [56] and stochastic dynamic programming [57]¹³. Scenarios, meaning a finite number of possible realizations of the uncertain quantities, are used with most stochastic programming (SP) models. Here, probability weights are assigned to each scenario, usually a single path on a scenario tree, and the objective function is an expected value or other probabilistic measure to be optimized¹⁴. The technical constraints are enforced throughout all scenarios.

Probabilistic scenarios can be synthesized from analytical expressions, generated from regression-based forecasting techniques or sampled from stochastic simulations (e.g. Montecarlo). Unless the underlying probability distribution is known, it is discrete and has a tractable range of values, a set of scenarios is always an approximate description of the uncertainty space. Without accounting for model and forecasting errors, the more scenarios used the more accurate is the uncertainty representation. However, increasing the number of scenarios also increases the size of the problem and limits its computational tractability [58].

In SP-based UC problems, and depending on the specific application, single (one source, like wind generation) or composite (several sources, like renewable production plus equipment outages) scenarios are generated. Statistical and heuristic techniques are often applied to select, combine and reduce the number of scenarios [59], in order to achieve a balance between accuracy and tractability. Thus, [60] discretizes the continuous probability distribution function of the net load forecast error from demand and wind power generation, [61] considers several

¹³ Here we only consider mathematical programming techniques. Meta-heuristic optimization methods are useful to rapidly find an approximate solution, but do not offer a guarantee of optimality.

¹⁴ Expected value is a risk-neutral measure; mean-variance and value-at-risk measures can be used to reflect risk-averse decision making.

discrete scenarios combining generation outages and load forecast deviations, and [62] generates time-dependent spatially correlated wind scenarios to use with SP models.

The SUC is a difficult problem and finding a valid solution is an important issue¹⁵. In this respect, some formulations relax one or several problem constraints to ensure computational tractability or to avoid solutions that are too costly. Thus, it is quite common that SUC models allow solutions where the load is not entirely served in some scenarios. The non-served load or Energy not Served (ENS) is penalized in the objective benefit/cost function using the traditional concept of Value of Lost Load (VoLL). The VoLL expresses the customers' maximum willingness to pay for avoiding load curtailment, generally in energy units (\$/MWh). Another approach is to relax security-related constraints via probabilistic or chance-constrained programming, where the solution is permitted to meet selected constraints or a reliability index only up to a certain confidence level. In both cases, system reliability is ensured only in a probabilistic sense.

Robust optimization UC models use a different strategy, focusing on the range of uncertainty instead of the underlying probability distribution. Based on deterministic uncertainty sets, robust UC minimizes the worst-case cost over the possible outcomes of the uncertain parameters. Robust UC formulations avoid the computational burden of including a large number of scenarios, but solutions are generally very conservative. In addition, the identification of the worst case depends on the reliability criterion used. An alternative method is to use interval programming techniques, where the range of uncertainty is represented by upper and lower bounds around a central value, and the objective is to find the best base solution that is

¹⁵ The deterministic UC problem belongs to the NP-hard complexity class and the stochastic formulations are significantly larger than the related deterministic problem.

feasible within that range. Lastly, stochastic dynamic programming (SDP) is apt for sequential decision-making under uncertainty, but its utilization is limited by the inherent “curse of dimensionality” of its recursive algorithm. SDP can be applied to UC models with a few units, and a series of approximate methods have been developed to overcome computational complexities of larger models. Nonetheless the application of SDP algorithms for UC problems is limited.

b. Applications of Stochastic Unit Commitment

Early works on stochastic UC optimization models were limited by computing capabilities [63], [64]. Later implementations of stochastic programming for UC introduced decomposition techniques but did not incorporate the full range of generation operational constraints or any network representation [65], [66], [67], [68]. With increased computational power, more recent works have extended SP models to consider resource constraints, variable generation, network aspects, and different solution algorithms [69], [70], [71], [72]. On a related approach, [73] and [74] use the SP scenario-based framework to find robust SCUC solutions that accommodate the expected variability of wind generation and withstand single generation outages, respectively. Chance constrained SP is used in [75] to supply a stochastic system demand with high probability, in [76] to limit the probability of wind power spillages, and in [77] to meet the stochastic net load with specified probability under an $N-k$ security criterion.

Computational complexity is still a big challenge for SUC, so applications with detailed uncertainty representation in large systems require advanced decomposition techniques and parallelization, or simply are not solvable in a timely manner with current computational capabilities. A comparison of SUC and scenario-based SCUC using high performance computing is provided in [78]. There, the authors note first the difficulty of having a detailed

representation of uncertainty through a tractable number of scenarios, whose selection and weighing is not obvious and have a significant impact on the performance of the adopted model. Second, they found that SUC is better in terms of minimizing expected cost, but SCUC runs faster and obtain a more reliable solution.

As pointed out before, the alternative robust and interval optimization techniques require less detailed information about the distribution of uncertain outcomes and therefore solve faster, but by construction they tend to deliver conservative solutions. Thus, the robust UC model of [79] provides coverage against expected wind power excursions, whereas [80] proposes an adaptive robust UC solution to respond to uncertain nodal power injections. Similarly, [81] presents a robust UC with an uncertain wind distribution and $N-1$ security but without network representation. In both [82] and [83] a robust contingency-constrained UC model is used to enforce generic $N-k$ security criteria; the first one without network representation and the second assuming fixed contingencies all day long.

Interval optimization (IO) is applied in [84] to incorporate variable wind power and in [85] to account for volatile nodal injections. Numerical comparisons between scenario-based, robust and interval optimization solutions to the UC problem under wind uncertainty are provided in [86], [87], indicating that stochastic programming is the most cost-efficient approach, but it requires sensibly more computing time. The robust and interval solutions are more reliable but are sensitive to the uncertainty bounds chosen. A two-stage SDP formulation to UC with wind uncertainty is proposed in [88]. Instead of scenarios wind generation is represented as a Markov stochastic process, but the simplified model used shows the computational limitations of this approach.

Considering the strengths and weaknesses of different stochastic methods, hybrid formulations like [89], [90] have been proposed recently, which seems a promising research area. Interestingly, most SUC models enforce contingency constraints but do not provide an explicit representation of generation reserves, in both quantity and prices, which is needed for compatibility with current market designs. The justification is that adequate reserves are implicitly calculated in the UC stochastic or base case solution, but nothing is said about how or whether the market participants that provide the reserves are remunerated. In general, energy and reserves settlement and pricing with stochastic models is an area where more research is needed.

2.1.3 Operation Reserves Allocation and Pricing

Keeping a generation reserve based on deterministic reliability criteria has been a fundamental element of power systems operational security for many years and, in spite or because of the heuristic procedures commonly used in practice, how to determine adequate operating reserve requirements has been a recurrent topic of research. In general, efforts have been directed to introduce probabilistic reliability criteria, refine deterministic reliability criteria (e.g. zonal reserves), co-optimization of energy and reserves, calculation of locational reserves, and generation scheduling via stochastic optimization.

a. Probabilistic Reserve Criteria and Methods

In a pioneer work [91] used a probabilistic method to find the spinning reserves needed to keep a uniform level of risk, measured by the loss of load probability (LOLP), at each dispatch period of the day and assuming sufficient transmission capacity. The authors did not say what would be an acceptable risk level, but recognized that it should be related to the cost of achieving it and it may vary from period to period. The use of probabilistic reserve calculations combined

with UC methods is first presented in [92] and [93], in order to attain an optimal generation schedule with a pre-determined reliability risk level. Later, [37] defines the “marginal utility” of a unit of reserve as the product of the VoLL and the LOLP, identifying that at the optimum this value must be equal to the shadow price of reserves. In fact, the evolution of a whole field of reliability evaluation techniques, and the application of related probability criteria and system risk indices to power systems planning and operation is reviewed at large in [54], where the authors acknowledge that deterministic techniques were still predominant in utility practices in the 1990s.

In order to find the optimal amount of reserves, [94] uses a UC model to calculate the spinning reserve requirement that meets a pre-specified risk index; the proposed iterative method checks and adjusts any candidate schedule to meet this index. The authors do not recommend any specific risk level and recognize that system risk indexes lack an intuitive quantifiable interpretation. They point out that the optimal reserve should balance, at the margin, the cost of carrying the reserve and the benefit from lower expected energy not supplied (EENS) valued with the system VoLL. An alternative approach is presented in [95], where the incremental value of operating reserves is computed as the associated reduction on expected system outage costs. Outage costs are calculated as the lost consumer surplus from non-supplied energy valued at prevailing energy market prices instead of VoLL. Here, the value of reserves is expressed as an hourly demand curve or benefit function that can be used in competitive markets to efficiently allocate the operating reserve.

A self-contained probabilistic scheduling model is proposed in [96], where a loss-of-load risk index is integrated within the UC optimization. This is accomplished using a system-dependent function that approximates the spinning reserve required to obtain a target LOLP for a

given schedule, which in turn is included as a linear constraint of the UC model. Similarly, a combined probabilistic reliability metric is considered in [97] for a single-period market-clearing model. The hybrid criterion applied is to keep the LOLP and ELNS below a pre-specified level, through linearized constraints that are incorporated in a UC-type calculation. This method is extended in [98] to solve a reliability-constrained UC with interruptible load, and in [99] to solve the SCUC of a multi-area power system.

The cost/benefit approach to determine optimal reserves based on VoLL is applied by [100] to determine a flexible reserve requirement to be used in a market-clearing model, and by [101] to define the input of a conventional UC with spinning reserve constraints. The latter model is extended in [102] to account for added uncertainty of wind generation. In [103] wind power uncertainty is integrated in the calculation of reliability indices, which are used to set operating reserve requirements through a risk level or a cost/value function. Reserve valuation and the construction of demand curves for spinning reserves based on VoLL is further discussed in [104] considering generation dynamics and risk preferences, and in [105] including load and wind power forecast errors.

As described above, the results of a number of probabilistic reserve formulations rely on the estimated cost of the EENS and are very sensitive to the VoLL assumed. However, this measure of the cost of electricity service interruptions differs across customer categories and depends on a series of factors like the time and frequency of interruptions, their duration and size, and consumers' perceptions and expectations, as discussed in [106]. In fact the authors question the validity of this concept as a proxy of reliability worth. In practice different customer's valuations are averaged, aggregated, normalized and weighed to estimate a

representative system VoLL. A comprehensive review of VoLL calculation methodologies and approaches is provided in [107], cautioning against single estimates of this value.

b. Deterministic and Stochastic Methods

The definition of zonal reserve requirements is currently the dominant approach to apply deterministic reliability criteria in the operation of electricity markets [108], including most RTO/ISOs in North America. Accordingly, a line of research has aimed to improve the methods to define and implement zonal reserves addressing the issue of reserve deliverability. Thus, [109] presents a market clearing framework for energy and reserve co-optimization implemented in ISO NE. This model uses a system-wide reserve requirements for the first contingency (*N-1* criterion) and a zonal requirement for a second contingency (*N-1-1* criterion) within predefined areas, checking reserve deliverability for nested reserve zones. Reserves are paid market clearing prices at each zone.

An enhanced zonal reserve procurement approach implemented in MISO is presented in [110]. This method incorporates post contingency transmission constraints for zonal reserve deployment in the SCUC optimization. Besides meeting a system-wide requirement, zonal reserves are determined to cover the largest generation outage within each zone while satisfying a set of selected inter-zone transmission constraints. Selected resources receive zonal marginal prices reflecting congestion effects. On a different perspective, [111] proposes to define reserve zones using network information and statistical methods, and [112] proposes a dynamic reconfiguration of the zones by modeling the uncertainty of operating conditions.

Cost allocation of contingency reserves is discussed in [113], proposing to charge generators in function of historic data on number and size of forced outages, and more recently in [114], proposing to charge customers in function of individual demand curves for reserves.

The issues of reserve pricing and deliverability considering network constraints in electricity markets are brought up by [115], illustrating the calculation of marginal reserve prices under transmission congestion. In the same context [116] presents a joint energy and reserve security-constrained market-clearing model. Instead of using an exogenous input, the model determines the up and downward spinning reserves required to survive a set of credible contingencies. The authors argue that only marginal nodal “security” prices should be defined instead of separate prices for different reserves. Their model is deterministic and only examines short-term generation dispatch without multi-period constraints. This formulation is generalized in [117] to couple energy and a group of primary, secondary and tertiary spinning reserves, using a single-period probabilistic model with load shedding.

A deterministic SCUC-based auction model for energy and ancillary services is proposed in [118] to be used in day-ahead markets. The model determines reserve requirements that meet transmission constraints for a base case and a set of selected contingencies, applying an iterative process with decomposition techniques. In [119] a deterministic single-period AC OPF model is used to co-optimize energy and reserves considering a list of contingencies by using an evolutionary algorithm, but the convergence to a solution is rather slow.

Most stochastic models use scenario-weighted co-optimization of energy and reserves, effectively modeling the uncertainty from generation outages and other factors. A first model of probabilistic locational scheduling and pricing of reserves, integrated with an energy market, was presented in [120] and extended in [121]. This formulation minimizes expected energy and reserve cost over a base case and predefined contingencies, enforcing post contingency network constraints to find the optimal location of “responsive” reserves. The model is applied to a

single-period generation dispatch problem with spinning reserves, and to calculate real-time but not day-ahead prices.

A stochastic multi-period market clearing model for energy and reserves is proposed in [122], [123], based on a SUC with a probabilistic security criterion, including post contingency constraints and the cost of corrective actions. Load shedding is allowed but EENS is penalized in the cost function using the VoLL. Generation reserves –spinning and nonspinning– are calculated as the maximum difference between post and pre contingency dispatch values. The solution is based on two-stage stochastic programming with scenarios and “bundle” non-anticipatory constraints, assuming that once reserves are deployed they are continuously used the rest of the day. The model is computationally costly and it is solved under several simplifying assumptions for tractability. A similar but simpler formulation (without multi-period constraints) is presented in [124], where reserve scheduling is considered part of first-stage decisions.

The work in [125] focuses on pricing schemes for energy and reserves with stochastic programming. The authors use a single-period lineal dispatch model with contingencies to discuss day-ahead and real-time pricing alternatives, aiming to preserve generator revenue sufficiency. A long-term stochastic SCUC model with hybrid probabilistic security criteria is presented in [126], using Monte Carlo simulation to generate composite scenarios. The cost of EENS is included in the objective function and a maximum LOLE is used as a constraint, but reserves are not explicitly calculated.

A combined approach is proposed in [127], specifying a minimum reserve requirement within a two-stage scenario-based SUC formulation. Here composite uncertainty from generation availability and load forecast is modeled without considering network aspects. The authors claim that this combined policy is more robust and improves system expected

performance, given the inherent limitations of scenario representation, but they ignore reserve costs. References [128], [129], formulate two-stage SUC problems to determine reserve requirement on systems with significant wind power but do not model contingencies.

Reference [130] develops an AC OPF-based stochastic framework to co-optimize multiple resource across several scenarios, including energy and up/down spinning reserves. Reserves are determined to cover a set of single contingencies while minimizing ELNS cost. The base model considers coupling constraints among scenarios but not intertemporal constraints. In a related work, [131] presents a stochastic contingency-based OPF model to procure energy and spinning reserves in a day-ahead market with deterministic security. This one-stage model computes distributed reserves to overcome single contingencies and load deviations. Reserves define a redispatch range around a base schedule for generation units, and shadow prices are used to reflect the marginal cost of reserves.

The above stochastic framework is extended in [132] to model a multi-period look-ahead OPF with UC decisions, considering uncertain nodal injections and single contingencies. The model includes energy storage, load-following ramping reserves and contingency-based spinning reserves. The full problem formulation considers an AC network representation, but a DC approximation is suggested for implementation. A reduced set of scenarios and other simplifications are considered for computational tractability.

In a recent work [133] proposes an approximated method to solve a SCUC accounting for contingencies and wind generation uncertainty. First, nodal spinning reserve requirements are computed using a single-period contingency-constrained probabilistic OPF with UC decisions and without considering the cost of corrective actions. Next, these requirements are enforced in

a standard multi-period UC with interval optimization for wind generation. The approximated less than optimal results are justified by the sake of computational tractability.

2.2 Research Gaps and Part I Contributions

The precedent literature review shows advances but also several research gaps in the procedures to schedule contingency reserves for a secure power system operation. This section synthesizes the results of the review and discusses relevant areas where improvement is needed, as well as the contributions of the proposed approach in regard to some of those needs.

2.2.1 Characteristics and Limitations of Alternative Reserve Allocation Methods

The current practice to schedule generation resources in U.S. electricity markets is to co-optimize energy and reserves through a day-ahead SCUC market model, using a simplified linear (DC) network representation. A global contingency reserve or a few zonal reserve requirements are defined to protect system operations against loss of supply from generation failures, in order to comply with the $N-1$ security standard. The reserve requirements are incorporated in the SCUC as part of the set of security constraints. This approach enables a market-based allocation of reserves in a timely manner, but a number of shortcomings are openly recognized, mainly from the definition of the required reserve, the uncertain delivery of reserves and the deterministic modeling. Therefore the efficiency and reliability of the resulting allocation of reserves is questionable.

Modeling generation rescheduling as a corrective balancing action with network representation, in order to determine the reserves actually needed in the system, can improve the sizing and distribution of contingency reserves, especially with regard to their deliverability. This method translates into a set of post contingency security constraints that can be directly

incorporated to the SCUC to find locational reserves, instead of using exogenous requirements. Variants of this concept have been tried before, but its application has been hindered by computational limitations, as the formulation significantly increases the size and complexity of an already difficult UC problem. Based on continuous advances in computing capabilities and algorithms to solve UC problems, feasible formulations have been proposed in the form of a contingency-constrained UC that hopefully should render tractable solutions for practical applications in large-scale systems (e.g. [45], [46]). But these formulations are still deterministic, and tend to ignore the cost of corrective actions and reserves pricing.

On the other hand, the penetration of renewable intermittent generation has produced a surge of interest in stochastic versions of the UC problem. The purpose is to schedule generation that is flexible enough to provide for the uncertainty of variable generation output and failures. Scenario-based stochastic programming is the preferred method, usually in the two-stage with recourse version. The main focus has been predominantly to model variable generation plus load fluctuations, the system “net load”, with generation and transmission outages just being added to complement existing scenarios or to create a few ones. The final result is the calculation of a “super” operating reserve that should provide enough spare capacity and flexibility for the system to handle all sources of uncertainty. Frequently the reserve is implicit in the final schedule, as the models do not explicitly quantify or price reserves.

Stochastic optimization is indeed a powerful mathematical tool, able to improve the efficiency and reliability of generation scheduling under uncertainty. However, the following issues need to be addressed before trusting SUC to schedule generation energy and reserves.

1. A scenario or state-based uncertainty representation is more appropriate to model discrete probability distribution functions, as for generation and transmission outages, than

continuous distribution functions, as in the case of variable renewable generation. In consequence, even not accounting for model risk¹⁶, a considerable number of scenarios or states are needed to have a minimally acceptable representation of a continuously distributed uncertainty, which in turn significantly increases the size and computational complexity of the problem. For large systems, this means that a valid solution would not be attainable in a reasonable period of time for operations planning.

2. Using composite scenarios from different sources of uncertainty in SUC problems is problematic. First, it demands an even greater number of scenarios to describe the uncertainty space, worsening the complexity problem. Second, it mixes up continuous and discrete probability distribution functions, complicating scenario selection and weighing. It also undermines the representation of the discrete probability function, which can be more completely described independently.
3. Different methods may be needed to handle different sources of uncertainty. Thus, robust optimization could be a good choice for problems addressing variable renewable generation or net load, as it does not require scenarios and has a lower computational burden. UC with interval programming may be even a better choice in this case, as it produces less conservative solutions than a RUC. On the contrary, stochastic programming is appropriate when the uncertainty can be represented by a reasonable set of known discrete values as is the case of generation outages. Therefore, a hybrid formulation can be more efficient to tackle multiple uncertainties than using composite scenarios.

¹⁶ That is, knowing the probability distribution function with certainty.

4. Combining different sources of uncertainty also implicitly assumes that the same type of reserves works for each of them. This is not the actual operational practice in power systems, where operating reserves for normal and contingency conditions are separated and have different functions and technical characteristics (activation, response time, etc.). In practice, power systems employ different types of regulation and contingency reserves, and additional reserve products may be needed. Thus, to compensate the variability of renewable intermittent generation the best approach could be to have a combination of additional regulation reserve plus a load-following flexible ramp product –or ramping reserve– as implemented in CAISO and being considered in other markets. Failing to differentiate types of reserves and their adequate use, and replacing them with a single super-sized spinning reserve may undermine system reliability.
5. The operation of the bulk power system is multi-stage by nature. That is, the uncertainties are being cleared at different points of the operation horizon. Thus, for a day-ahead SCUC a new operating decision is made at each dispatch period according to the conditions present in the system. Evidently, one-stage stochastic programming models with no recourse possibility are overly simplified, fixing all operating decisions in advance. But also the widespread two-stage stochastic programs with recourse oversimplify system operations assuming that at some specific period, usually the beginning of the day, all uncertainties are revealed¹⁷. In addition, many formulations fix in the first stage variables that can be modified during the operation day, as is the case of the commitment of fast-start generators. Clearly, a multi-stage stochastic program gives better solutions but it is much harder to

¹⁷ For instance assuming that at that point system operators will know the output of all wind generator for the rest of the day.

model and solve than a single or two-stage program, as the number of scenarios or states grow combinatorially. Therefore there is a difficult but unavoidable trade-off between tractability and usefulness of SP-based models.

6. Many SUC models do not explicitly calculate and price reserves. Their results are expressed as a generation schedule flexible enough to handle expected variations on operating conditions, so the reserve would be embedded in the solution and only energy prices are paid. This is incompatible with the current operation of electricity markets in many aspects. Most importantly, it assumes that up and down flexible capacity would be ready and made freely available to system operators when need it. In a for-profit competitive environment, generators most likely will find this premise unacceptable. Moreover, eliminating the reserves as a tradeable product in electricity markets would require a redefinition of how ancillary services are supplied and/or a market redesign.

A separate and far-reaching question is whether and how to use probabilistic reliability criteria, in terms of suitable risk indexes or by means of benefit/cost analysis, instead of deterministic criteria like the *N-1* standard. This topic has been extensively researched and discussed for decades [91], but to the present probabilistic criteria is only used in planning and not for power system operations. Thus, a LOLE target of 1 event in 10 years is widely applied across North America to set generation planning reserve margins [134]. Some authors have pointed out to this important disconnect between long-term planning and operating reserve market design [135].

Among the explanations for this situation are the difficulty to select appropriate reliability indices and to establish minimum acceptable risk levels for operation, or to evaluate a standardized cost of non-served energy. There is also a risk aversion component, since a

probabilistic reliability measure means that the standard may not be met in certain occasions (many but not all periods). On the contrary, deterministic reliability criteria seeks to ensure a continuously secure operation. In addition, the day to day practice has shown that deterministic reliability criteria can be enforced without excessive cost for the system. For these, and may be other reasons of practical order, it is unlikely that in the foreseeable future the $N-1$ reliability criterion is going to be replaced by a probabilistic standard for system operation. Therefore, a practical solution implementable in current electricity markets should consider the application and full enforcement of the $N-1$ security standard. However, it is likely that probabilistic reliability criteria can be applied in the future to the occurrence of multiple non-simultaneous contingencies.

2.2.2 Contributions of the Proposed Reserve Allocation Method

Clearly, the allocation of locational contingency reserves is preferable to establishing zonal reserve requirements, considering both the reliability and efficiency of power system operation. As reviewed above, a number of stochastic contingency-based UC models have been proposed to co-optimize energy and reserves, but only a reduced set of them consider the explicit allocation of locational contingency reserves. Many of these models use probabilistic reliability criteria, do not consider complete multi-period constraints or the full day-ahead horizon, do not consider the cost of corrective actions, do not assign nonspinning reserves, do not make use of line emergency ratings or ignore other operational characteristics. Also, most are scenario-based models, frequently using a two-stage approach and a reduced set of scenarios or other approximations and simplifications for the sake of computational tractability.

Actually, the main hurdles to overcome for a successful implementation of an efficient and practical method to allocate contingency reserves are not mathematical “constraints”, instead they can be stated as follows:

1. The day-ahead generation scheduling solution, including energy and reserves, should be available in a relative short period of time (a few hours), so the market and technical operations can proceed according to the required daily timeline.

This challenge is plainly expressed by the technical personnel of MISO –one of the largest ISOs in North America– when referring to alternative contingency-constrained approaches to allocate reserves, as follows [110, p. 539]:

The real world problem faced by MISO shows that the work studied in ... is very critical and valuable. While it is possible to mathematically expand the formulations presented in these papers to model the MISO reserve deliverability problem, the real challenge is to make these models solvable within an acceptable time frame. MISO is managing one of the largest electricity markets. The network model includes 42,705 buses with 8,300 defined contingencies and 1,258 generation units in the market. To meet the market solution time requirement of 2~3 hours in day-ahead and every 5 min in real time, it is very challenging to include even the pre-contingency network model in security constrained unit commitment (SCUC) and SCED, let alone post-contingency network representation. In practice, SCUC and SCED incorporate pre- and post-contingency transmission constraints identified through other processes or applications.”

In general, faster computational times for UC problem have been achieved by advances in computational resources (hardware) and algorithms (solvers) [136]. But time reductions can also be accomplished by the use of problem decomposition [34], [55] and improved modeling formulations [43], [137]. This latter work, for instance, specifically investigates alternate modeling approaches in order to reduce the computational cost of SUC applications. Accordingly, stochastic SCUC formulations reducing solution times are valuable by this very reason.

2. The day-ahead generation scheduling solution, including energy and reserves, should be delivered in a way compatible with the market design and serving the purposes of market operations. That is, it should provide the quantity of reserves allocated to each generation unit and produce prices to settle reserve markets. In addition, the solution should be stable and reproducible, so it can be reviewed for market participants and other stakeholders or audited by market monitors, regulators or other competent authorities.

Besides the obvious need to deliver optimized quantities and prices by type of operating reserve, this requirement precludes the use of methods based on random simulations (e.g. Montecarlo) whose results are not reproducible. It also requires that the formulation be consistent with operational standard practices, like the need to restore reserves after a period of deployment.

In this context, Part I of the dissertation proposes a computationally efficient stochastic model to schedule energy and locational contingency reserves in a day-ahead market as described next.

In first place the uncertainty from generation availability is represented by a two-state Markov process of unit failure and repair cycles. This reliability model allows calculating the probability of finding a unit out of service (or not) at some specific time, and the probability of a set of discrete states for the entire power generation fleet of the system. In particular those contingencies corresponding to single generation outages are of interest for the purpose of enforcing the $N-1$ security standard.

Then, on the basis of these contingency states and a linearized network representation, the proposed MIP-based UC model minimizes the expected total generation cost of supplying the load for the 24 hourly periods of the next day, including the cost of the corrective rescheduling

actions necessary to rebalance the system over the set of selected post contingency states, considering transmission effects. The locational reserves are optimization variables internally calculated as the additional generation required to cover all post contingency states. The result of this stochastic contingency-constrained UC model is the optimal allocation of energy and reserves among the generation units of the system. Likewise, efficient marginal energy and reserve prices can be extracted from the optimal generation schedule.

The main contribution of the proposed model is to exploit the characteristics of the scheduling problem and take advantage of power system operational practices to (i) formulate a simplified multi-stage SCUC model of system operation, and (ii) create a stochastic model of contingency states instead of the commonly used contingency scenarios. The resulting compact state-based representation has less integer and continuous variables and fewer constraints than its scenario-based counterpart, which reduces the computational burden and solution times of the core MIP problem. In addition, when the system grows in number of units, the number of variables increase linearly, so the model can be scaled-up and still should be tractable when applied to large systems. It can be considered a stochastic extension of the deterministic contingency constrained UC rather than another version of the scenario-based SUC.

The proposed approach addresses many of the reserve allocation issues described at the beginning of this section and it is consistent with standard operational practices, namely the use of line emergency rating on post contingency conditions, the use and reestablishment of reserves after a deployment period and the use of spinning and nonspinning reserves. The corresponding reserve allocation model is computationally efficient and compatible with current electricity market design. The next chapter explains in detail the general approach and methods proposed in this Part of the dissertation.

Chapter 3 General Approach and Methods

The overall purpose of this Part is to formulate an efficient and practical alternative to determine the contingency reserves necessary to fully comply with mandatory *N-1* operational reliability criteria. The required reserves –in type, location and quantity– are allocated and priced within the framework of the generation scheduling process followed in U.S. competitive electricity markets, in a manner compatible system operation and reserve markets. The general approach and methods applied are described here below.

3.1 Characterization of Contingency Reserves

To identify the contingency reserves required in the bulk power system, it is necessary to differentiate the role that preventive and corrective actions play to guarantee operational security. In the first place, transmission line outages are subject to preventive control, since enforcing the feasibility of the SCUC solution under different line contingencies ensures that the system will remain within its operational limits after the failure of a single transmission line. This is accomplished by redistributing power flows and without any immediate operator intervention. There is no explicit allocation of reserves, but they are implicit in the “security-constrained” dispatch of generation. This preventive control is effective to handle line outages, although it inherently increases operating costs.

On the other hand, contingency reserves are kept as a preventive measure for generation outages, but a corrective control will always be required to restore the power unbalance created by the loss of supply [138]. The corrective control action requires manually ramping up

generators with “reserved” available capacity, in order to meet system demand until a new secure economic dispatch can be found and reserves are reestablished. Although not strictly required, the system may also benefit from ramping down other generation units to reduce overall costs or even for feasibility of the post contingency redispatch. Accordingly, to meet the *N-1* security standard, the contingency reserve needed during normal operation is the additional capacity required for the system to quickly respond to any credible single generation outage and to operate in a post-contingency state without load shedding. The spare capacity needed from a particular generation unit is the difference between its network-constrained post and pre-contingency dispatch levels. As several credible generation contingencies are considered, the actual locational reserve required from a unit is the maximum difference across all those contingencies.

In principle, contingency reserves should be online, as spinning reserve. However, because frequency-responsive reserves start responding immediately to power mismatches, there is some acceptable time within which the reserve should be deployed, usually ten to fifteen minutes¹⁸. This also allows fast-start units to provide contingency reserves, even if they are offline, as nonspinning reserve. Additionally, besides starting up offline units to rebalance the system, at least theoretically there could be an economic benefit from shutting down a unit after a contingency occurs. Hence, locational contingency reserves can be “upward” spinning and non-spinning reserves (r^{sp+} , r^{ns+}), which is consistent with their conventional definition. But it is also possible to define “downward” spinning and non-spinning reserves (r^{sp-} , r^{ns-}), as explained above. The different types of locational reserves are indicated in Figure 1.

¹⁸ Ten minutes is the standard maximum response time for contingency reserves in North America, for this reason they are sometimes called 10-minute reserves, like in NYISO.

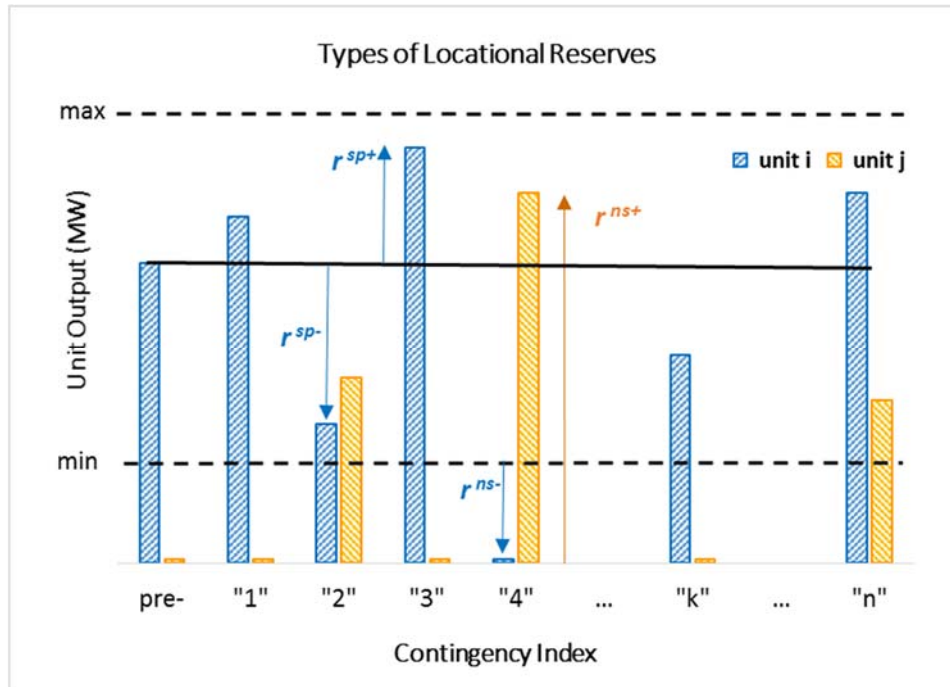


Figure 1 – Four types of locational contingency reserves

3.2 Stochastic and Operations Model for Reserve Allocation

Contingency reserves need to be assigned for every market period during the day-ahead scheduling process, so they are co-optimized with energy and allocated using a unit commitment market model. Reserved capacity is kept available to be used in case a contingency occurs –a single generator outage at a particular time– which is a random event. Therefore, the model needs to incorporate a stochastic representation on the uncertain generation outages with associated probabilities. All things considered, a stochastic security-constrained UC model is required to co-optimize energy and locational reserves. The objective is to minimize the expected total cost to serve demand, across the possible operation states of the system.

Another important factor to consider is that the post contingency state reached after using the contingency reserve is stable but insecure, in the sense that the system would not be able to survive a new contingency. Therefore, this condition is allowed to persist until system operators

can redispatch all available resources again (including slow online and offline units), restore the reserves, and reestablish a secure operation, usually in a period of 30 to 60 minutes [10]. To do this, the usual approach is to provide an additional reserve to be able to restore the contingency reserve in a timely manner. This reserve is called the 30-minute, replacement or supplemental reserve¹⁹ and is not required to be synchronized to the grid.

The immediate practical implication is that, as the contingency reserve is used during a relatively short post contingency period of time, the operators can use the short term emergency ratings of transmission lines during that period [139], [140], which are above the normal continuous rating. The ability of using the emergency rating could make a difference between finding or not a feasible solution to a network-constrained post contingency (re)dispatch. Another consequence is that the system is actually expected to respond to an *N-1-1* contingency event, by restoring the reserve after the first contingency²⁰. The reserve allocation model should incorporate this operational requirements.

3.2.1 The Stochastic UC Model

For the allocation of contingency reserves the uncertain variable of interest is the available capacity in the system. This random variable follows a stochastic process during the day, which for the purposes of the UC model is observed during each dispatch period. A convenient way to represent this process for the scheduling horizon of the UC model is with a multi-stage decision tree as shown in Figure 2 below. The figure shows a decision horizon of 24 hourly dispatch periods for the day-ahead UC. The stages are at the beginning of each dispatch

¹⁹ For instance in PJM, although MISO calls supplemental the 10-minute nonspinning reserve.

²⁰ This extension of the *N-1* standard means that the system should be prepared to cope with a second contingency without loss of load. This could also apply to multiple non-simultaneous contingencies, but the probability of several contingencies during the day is rather low and loss of load would be expected.

period where a dispatch decision is made. Each black circle or node represents a possible state of the system at a period t , with different available capacity, whereas each trajectory from the beginning to the end of the day is a scenario. See Appendix A for a description of the different elements and concepts related to the state-based and scenario-based representation.

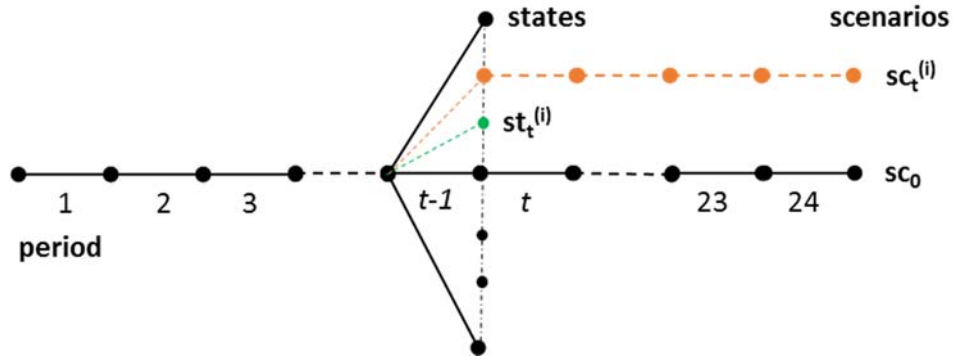


Figure 2 – Decision tree for the SUC model

Under the $N-1$ security standard, the contingencies of interest are single generation outages, that is, the events where only one generation unit is lost. A single generation outage can occur in any period of the day. In consequence, the states in the decision tree of Figure 2 represent different available capacity at the beginning of each period, because no generation unit has failed up to that moment or because of the failure of a single unit i , denoted by $st_t^{(i)}$ ²¹. The representation of Figure 2 is simplified, showing only the possible states of available capacity at period t given that there has not been any contingency before. It also shows two scenarios, the scenario sc_0 on which no contingency occurs during the day, and a generic scenario $sc_t^{(i)}$ where a unit i fails during period t . For convenience and without loss of generality, we will assume that

²¹ Since multiple generation outages are not considered, the sample space of the available capacity variable is not completely counted. Therefore the sum of probabilities of the states or scenarios considered would be different to 1. Calculations can be performed like this, or alternatively assuming that the no-contingency probability is the complement of the probability of having any single contingency.

the contingency occurs right after the beginning of each hourly period, so the system transitions from the pre contingency state to a post-contingency state during the same time period.

A fundamental decision for the stochastic UC model is to define whether the uncertainty on available capacity from single generation outages –and corresponding random variables– is represented by scenarios or states, as discussed in detail in Appendix A. Almost all stochastic SCUC formulations use a scenario-based stochastic programming approach. This is appealing since each scenario is treated as a deterministic SCUC, and the problem is decomposed and solved iteratively until the inter-scenarios non-anticipativity constraints are met up to a tolerance. However the computational cost is very high, because of the multiplication of variables and the many additional constraints of the problem, as explained in Appendix A, especially for a mixed-integer program like the SCUC model.

A major contribution of this Part is to propose a state-based approach to the stochastic SCUC model, aiming to have a more compact representation of the problem and to reduce the computational burden and solution times, a critical aspect for the feasibility and practical applicability of the model. The bases of this approach, which can be better described as a stochastic contingency-constrained UC, are explained in the following section.

3.2.2 The Operational UC Model

The solution of the stochastic UC model also depends on how the power system is expected to operate, or the operational model for the day-ahead UC problem. First of all, since only single contingencies are relevant, the system operates in a normal condition if no contingency occurs. When a generator fails the rest of the units has to be redispatched in order to make up for the lost capacity and to keep supplying the demand, and this is the basis for using corrective rescheduling as a security control. What happens next? To maintain a secure

operation the rest of the day, it is necessary to consider the possibility of a second generation unit failing, add new capacity states to the stochastic model and have the system prepared to respond without loss of load²². This operating mode rapidly populates the decision tree downstream and the problem becomes intractable because of the many possible combinations.

A first alternative is to simply assume away the problem and to focus only in responding to the first contingency, as in the scenario-based approach of [122], [123]. The assumption there is that after a single generation contingency occurs the system is redispatched using the contingency reserve, in order to supply demand at minimum cost and without reserves for the rest of the day. In terms of Figure 2, after the first contingency the system follows the fixed trajectory in orange sc_t . The main problem with this formulation is that results in a non-secure operation (with no reserves) which is not allowed. It also precludes the use of short-term line emergency ratings and unnecessarily constrains the feasible solution set by finding UC solutions for post contingency periods that never will be used.

A different alternative, reflecting current operational practices, is to assume that the system is redispatched and the contingency reserve is used immediately after the first contingency occurs. Then, after a prudent time, the system is dispatched again with security constraints and the contingency reserve is restored by using replacement reserves. Therefore, there is no need to consider the occurrence of successive contingencies, but rather to make sure there is enough offline capacity to replace the contingency reserve. In terms of Figure 2, this is equivalent to truncate the decision tree after one post contingency period, on the green trajectory. Line emergency ratings can be easily included and, from a computational perspective, the main

²² In theory this could apply to several non-simultaneous contingencies, but loss of load would be acceptable in that case.

advantage is that the number of states to be considered is significantly reduced. This is the approach used in Part I for the operational UC model, considering without loss of generality a network-constrained post contingency redispatch lasting for one time period (60 minutes), being this the maximum time before the system can be securely dispatched again and the reserve reestablished.

In summary, the operational model considered for reserves allocation is a type of contingency-constrained unit commitment. Here the system is scheduled to operate normally during the whole day without contingencies, and carry enough locational reserves to be able to survive the loss of a single generation unit, any time during the day, by redispatching generation using the contingency reserve. The system should be able to stay in this stable but not secure post contingency state for a whole period, using the emergency rating of transmission lines if necessary. At the end of this period a new SCUC is expected to be found for the rest of the day, reestablishing the contingency reserve.

Consistently with the operational model, the corresponding stochastic UC model should consider the state probabilities of operating without contingencies and the probabilities of having any single generation outage during the day. The objective of the model is to minimize the expected total operating cost, including energy and reserves, considering system generation costs under the normal conditions (no outages) and the system redispatch costs after a generation outage (post contingencies).

The proposed approach is therefore consistent with standard system operation practices and allows a simpler and compact formulation of the stochastic SCUC, which is fundamental to ensure computational tractability.

3.3 State Probabilities and State Variables

3.3.1 Computing the State Probabilities

The probability of finding the system in a particular post contingency state at period t is equal to the conditional probability of having a single generation outage at period t given that no contingency has occurred before (see Figure 2). Likewise the probability of finding the system in a normal no-contingency state at t is the conditional probability of no having a single generation outage at t given that no contingency has occurred before.

To derive the state probabilities for the stochastic UC model, the uncertainty on generation availability can be represented by a two-state Markov process of unit failure and repair cycles [54]. This well-known generation reliability model allows calculating the probability of finding a generation unit available (up) or not available (down) at some specific time, and in general the probability of a set of discrete available capacity states for the entire generation fleet of the system at some time. Appendix B presents the generation reliability model and how to calculate the up and down probabilities.

Accordingly, assuming that all generation units are available at the beginning of the scheduling horizon and have exponentially distributed times of unit failure and repair (with constant rates), the probability of finding a unit i available or not available at a period t can be calculated with the formulas of Appendix B²³. Likewise, if pu_{it} and pd_{it} are those probabilities, it is possible to find the conditional probabilities of the unit failing or not failing at a period t given that it has not failed before, p_{it} and $\overline{p_{it}}$ respectively, using (1) and (2) below. Finally,

²³ Depending on available data, the long-run failure probability, the unavailability index or the forced outage rate of the unit can also be used.

based on these values and assuming statistical independence of generation failures, it is possible to calculate the probabilities of the capacity states over the scheduling horizon.

$$p_{it} = p d_{it} \left(\prod_{r=1}^{t-1} p u_{ir} \right) \quad (1)$$

$$\overline{p}_{it} = p u_{it} \left(\prod_{r=1}^{t-1} p u_{ir} \right) \quad (2)$$

The probability calculations can be simplified by assuming that repair times are longer than the one-day scheduling horizon, so once a unit fails it will be unavailable for the rest of the day. With this assumption, the conditional probability of a unit i failing at time t and not before is approximately $p_{it} = 1 - \exp(-\lambda_i \cdot t)$. Accordingly, $\overline{p}_{it} = 1 - p_{it}$ is the conditional probability that unit i has not failed at period t or before. From now on we will assume that the conditional probabilities p_{it} and \overline{p}_{it} are known.

Given the single failure probabilities for each unit and time period, and assuming generation units fail independently, we can find the probability $p_t^{(k)}$ of the post contingency state (t, k) where only unit k fails at period t and no unit has failed before, as follows:

$$p_t^{(k)} = \overline{p}_{1t} \cdot \overline{p}_{2t} \cdots p_{kt} \cdots \overline{p}_{Kt} \quad (3)$$

Likewise, the probability $p_t^{(0)}$ of finding the system in a no-contingency state during period t is equal to the probability of no unit failing at period t or before:

$$p_t^{(0)} = \overline{p}_{1t} \cdot \overline{p}_{2t} \cdots \overline{p}_{kt} \cdots \overline{p}_{Kt} \quad (4)$$

The sum of (3) and (4) is different to 1 because there are states with multiple contingencies that are not considered in the model. Therefore, to normalize the calculations it is also possible to define $p_t^{(0)}$ as the probability of the system not having any single contingency

during period t , as shown in (5). For numeric simulations and comparison with deterministic calculations we use this approach.

$$p_t^{(0)} = 1 - \sum_k p_t^{(k)} \quad (5)$$

3.3.2 State Variables and Problem Size

The generalized deterministic UC problem, scheduling a number of generators over a time horizon divided in periods, includes a group of integer variables, a group of continuous variables and a set of problem constraints of different type [25]. Integer variables are defined for each generator i and time period t ; the number of these variables depends on the problem formulation but includes at least one binary variable representing the commitment state of each unit at every period, u_{it} . This variable is 1 when the generator is on (committed) and is 0 when the generator is off (no committed). The continuous variables are associated to generator and transmission network states, for instance the power output (dispatch) for each generator i at period t , g_{it} . Figure 3 shows how periods, variables and state probabilities are related for the SUC problem, where the superscript indicates whether is a no-contingency (0) or post contingency state (k).

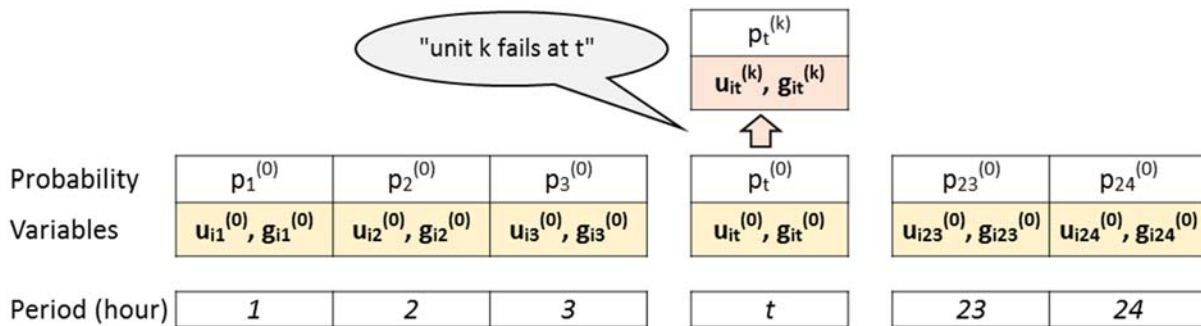


Figure 3 – Stochastic UC variables and state probabilities

The no contingency state variables correspond to the commitment and dispatch of generation units under “normal” dispatch conditions, whereas the post contingency state variables correspond to the commitment and dispatch values found after a corrective redispatch action is carried out without the failed unit. In any case the no contingency solution of the stochastic SCUC is necessarily different to the deterministic SCUC solution, even if a standard fixed reserve is used, since the former is flexible enough to respond to the set of selected contingencies considered.

If K is the number of generation units and T is the number of periods of the scheduling horizon, then there are T no-contingency states and $K \cdot T$ post contingency states. Therefore, defining η_v as the number of different variables, the state-based SUC problem has $(KT + T) \cdot \eta_v$ variables in total, and this applies to both integer and continuous variables. In comparison, the scenario-based SUC problem has $(KT^2 + T) \cdot \eta_v$ variables, so approximately T times more²⁴, including integer variables. More importantly, if we add η_g generators to the problem, the number of variables of the state-based SUC increases by $\eta_g \cdot T$, whereas for the scenario-based SUC the number of variables increases by $\eta_g \cdot T^2$. The difference is therefore a factor of T and the advantage of the state-based approach in terms of scalability is evident.

The deterministic UC also includes a set of numerous constraints whose type and number depends on the problem formulation. There are equality constraints for power balances and inequality constraints for operating limits, constraints with integer or continuous variables exclusively and constraints with both type of variables, intra-period and inter-period constraints. If we denote by η_c the number of basic constraints per period, the state-based SUC adds $K \cdot T \cdot \eta_c$

²⁴ This factor is 24 for the day-ahead UC problem

constraints to the problem whereas the scenario-based SUC adds $K \cdot T^2 \cdot \eta_c$ constraints, again larger by a factor of T . Moreover, the scenario-based approach adds approximately $\frac{1}{2}K \cdot T^2 \cdot \eta_v$ bundle or non-anticipativity constraints.

Then, if more generation units are included in the problem, the increase in the number of basic constraints of the scenario-based SUC is larger than the corresponding increase for the state-based version by a factor of T and by thousands of additional non-anticipativity constraints. One can conclude that scalability of the state-based model is manageable, whereas is a big challenge for the scenario-based approach, considering that large systems can have hundreds to thousands of generating units.

In summary, the more compact formulation of the state-based SUC results in a smaller size problem, in terms of number of variables and constraints, when compared to the equivalent scenario-based SUC problem. The difference is roughly by a factor of T , the number of periods of the scheduling horizon, normally 24 for the day-ahead UC model. As the UC is a MIP problem, the size difference has a big impact on computational burden and solution times. The computational advantage of the state-based approach over the scenario-based modeling increases for larger systems, as the state-based SUC scales up more “slowly”, in number of variables and constraints, than the scenario-based SUC formulation.

Chapter 4 Reserve Allocation Models

Based on the general approach and methods described in the previous chapter, next we formulate two stochastic SCUC models to co-optimize energy and locational contingency reserves as part of the day-ahead scheduling process. In general the models minimize total expected daily operation costs, considering generation startup, dispatch, reserve and redispatch costs across the no contingency and post contingency states. For simplicity a demand benefit function and generation shutdown costs are not explicitly represented, but they can be easily added to the models.

These reserve allocation models are mixed integer programs (MIP), with a compact formulation by using state-based stochastic representation instead of the commonly used scenario-based approach [141]. This avoids the replication of variables and constraints per scenario and the use of non-anticipativity constraints, which is computationally very costly for the unit commitment problem. The SCUC models are contingency constrained including static security constraints, network constraints, generation power limits and ramping limits.

The transmission network is modeled using a dc-power-flow linear approximation for computational tractability. All problem constraints of the SCUC models are linear or linearized, so the characteristics of the cost functions define the type of MINLP or MILP problem. Thus, a quadratic generation cost function determines a quadratic MIP problem, whereas a piecewise linear approximation or a stepwise supply offer function define a linear MIP problem (MILP). For notation see Nomenclature.

4.1 Co-optimization of Energy and Spinning Reserves

The first model co-optimizes energy and spinning reserves, which is consistent with most practical applications. This formulation fixes the commitment decisions of the no contingency states, so only online generation can be redispatched to balance power on a post contingency state. The problem minimizes expected generation cost in order to supply forecast demand meeting the $N-1$ security standard over the 24 hours of the operation day. Offer-based generation costs include startup, dispatch and spinning reserve costs with no contingencies plus post contingency redispatch costs. The objective function to minimize is:

$$\sum_{t \in T} p_t^{(0)} \left\{ \sum_{i \in I^{(0)}} [SC_{it}(v_{it}) + GC_{it}(u_{it}, g_{it}^{(0)}) + RC_{it}(r_{it}^{sp})] \right\} + \sum_{t \in T} \left\{ \sum_{\substack{k \in K \\ k \neq 0}} p_t^{(k)} \left(\sum_{i \in I^{(k)}} GC_{it}(u_{it}, g_{it}^{(k)}) \right) \right\} \quad (6)$$

The decision variables are u_{it} , v_{it} , w_{it} (integer) and $g_{it}^{(k)}$ (continuous); the spinning reserves variables (r^{sp+} , r^{sp-}) are explicitly represented but they are function of other decision variables instead of independent optimization variables. Also notice that there are not integer variables for the post contingency states, which further reduces the number of variables and the computational burden.

4.1.1 Problem Constraints

The different constraints of the co-optimization problem (6) are described below. Some are characteristic of SCUC problems and others are specific to the present formulation.

a. *Nodal power balances*

Equations set (7) are dc power flows for no contingency conditions and single generation outages, whereas (5) are dc power flow equations for single transmission outages, in particular

$B_{nm}^{(l)}$ is 0 when the line nm is out.

$$\sum_{i \in I_n} g_{it}^{(k)} - \sum_{m \in M_n} B_{nm}^{(0)} \cdot (\theta_{nt}^{(k)} - \theta_{mt}^{(k)}) = D_{nt}; \quad \forall n \in N, k \in K, t \in T \quad (7)$$

$$\sum_{i \in I_n} g_{it}^{(0)} - \sum_{m \in M_n} B_{nm}^{(l)} \cdot (\theta_{nt}^{(l)} - \theta_{mt}^{(l)}) = D_{nt}; \quad \forall n \in N, l \in L, t \in T \quad (8)$$

b. *Static security limits*

Equations (9) set limit the maximum voltage angle difference between connected nodes, whereas (10) set maximum power flow limits on transmission lines for no contingency and post contingency conditions. Notice that transmission line emergency power ratings are used in (11) and (12) for post contingency states.

$$-\Delta\theta^{\max} \leq (\theta_{nt}^{(k)} - \theta_{mt}^{(k)}) \leq +\Delta\theta^{\max}; \quad \forall n \in N, m \in M_n, k \in K, t \in T \quad (9)$$

$$-FN_{nm}^{\max} \leq B_{nm}^{(0)} \cdot (\theta_{nt}^{(0)} - \theta_{mt}^{(0)}) \leq +FN_{nm}^{\max}; \quad \forall n \in N, m \in M_n, t \in T \quad (10)$$

$$-FE_{nm}^{\max} \leq B_{nm}^{(0)} \cdot (\theta_{nt}^{(k)} - \theta_{mt}^{(k)}) \leq +FE_{nm}^{\max}; \\ k \neq 0, \forall n \in N, m \in M_n, k \in K, t \in T \quad (11)$$

$$-FE_{nm}^{\max} \leq B_{nm}^{(l)} \cdot (\theta_{nt}^{(l)} - \theta_{mt}^{(l)}) \leq +FE_{nm}^{\max}; \\ l \neq 0, \forall n \in N, m \in M_n, l \in L, t \in T \quad (12)$$

c. *Generation operating limits*

Equations (13)–(16) set generation power and ramp limits for no contingency conditions. Notice that the power limits (13)–(14) consider energy and reserves.

$$g_{it}^{(0)} - r_{it}^{sp-} \geq g_i^{\min} \cdot u_{it}; \quad \forall i \in I^{(0)}, t \in T \quad (13)$$

$$g_{it}^{(0)} + r_{it}^{sp+} \leq g_i^{\max} \cdot u_{it}; \quad \forall i \in I^{(0)}, t \in T \quad (14)$$

$$g_{i,t}^{(0)} - g_{i,t-1}^{(0)} \leq RU_i \cdot u_{i,t-1} + SU_i \cdot (1 - u_{i,t-1}); \quad \forall i \in I^{(0)}, t \in T \quad (15)$$

$$g_{i,t-1}^{(0)} - g_{i,t}^{(0)} \leq RD_i \cdot u_{it} + SD_i \cdot (1 - u_{it}); \quad \forall i \in I^{(0)}, t \in T \quad (16)$$

Equations (17)–(20) set generation power and ramp limits for post contingency states.

Equation (17) removes the failed generation unit and (18) fixes the dispatch of all units that do not qualify to provide reserves. Equation (19) set redispatch limits for units able to provide reserves, and (20) enforces the 10-minute ramp constraint for these units.

$$g_{\kappa t}^{(k)} = 0 \quad ; \quad \kappa: \text{unit out in state } k, k \neq 0, \forall k \in K, t \in T \quad (17)$$

$$g_{it}^{(k)} = g_{it}^{(0)}; \quad i \neq \kappa, i \neq j, \forall i \in I^{(k)}, j \in J^{(k)}, t \in T \quad (18)$$

$$g_j^{\min} \cdot u_{jt} \leq g_{jt}^{(k)} \leq g_j^{\max} \cdot u_{jt}; \quad k \neq 0, \forall j \in J^{(k)}, k \in K, t \in T \quad (19)$$

$$RD^{10}_j \leq g_{jt}^{(k)} - g_{jt}^{(0)} \leq +RU^{10}_j; \quad k \neq 0, \forall j \in J^{(k)}, k \in K, t \in T \quad (20)$$

Equation (21) ensures that the system has sufficient replacement reserve to restore the contingency reserve and respond to a second contingency, enforcing an $N-1-1$ security criterion.

Notice that the replacement reserve is not required to be online and is not ramp-constrained.

$$\sum_{i \in I^{(k)}} (g_i^{\max} - g_{it}^{(k)}) \geq u_{it} \cdot g_i^{\max}; \quad k \neq 0, \forall i \in I^{(k)}, k \in K, t \in T \quad (21)$$

d. Generation startup and shutdown constraints

Equations (22)–(23) define the unit startup and shutdown sequence, and (24)–(25) enforce minimum unit up and down time restrictions for no outage conditions.

$$v_{it} - w_{it} = u_{i,t} - u_{i,t-1}; \forall i \in I^{(0)}, t \in T \quad (22)$$

$$v_{it} + w_{it} \leq 1; \forall i \in I^{(0)}, t \in T \quad (23)$$

$$v_{it} \leq u_{i,t+q}; \quad q = 1, \dots, \min[(UT_i - 1), T - t], \forall i \in I^{(0)}, t \in T \quad (24)$$

$$w_{it} \leq 1 - u_{i,t+q}; \quad q = 1, \dots, \min[(DT_i - 1), T - t], \forall i \in I^{(0)}, t \in T \quad (25)$$

4.1.2 Spinning Reserves Allocation and Pricing

a. Spinning locational reserves

The locational spinning reserves required from each generation unit are calculated using equations (26)–(28) below. Notice that both upward and downward spinning reserves are allocated (see Figure 1).

$$r_{it}^{sp+} = \max_k \left[\left(g_{it}^{(k)} - g_{it}^{(0)} \right), 0 \right]; \forall i \in I^{(0)}, t \in T \quad (26)$$

$$r_{it}^{sp-} = \max_k \left[\left(g_{it}^{(0)} - g_{it}^{(k)} \right), 0 \right]; \forall i \in I^{(0)}, t \in T \quad (27)$$

$$r_{it}^{sp} = r_{it}^{sp+} + r_{it}^{sp-} \leq R_{it}^{sp-max}; \forall i \in I^{(0)}, t \in T \quad (28)$$

The total spinning reserve provided by a unit is the sum of allocated upward and downward reserve. In consequence, a generation unit i providing spinning reserve at period t has to be available to be dispatched at that period within the range $[g_{it}^{(0)} - r_{it}^{sp-}, g_{it}^{(0)} + r_{it}^{sp+}]$.

The right hand term in (28), R_{it}^{sp-max} , is a physical limit or the maximum amount of spinning reserves that a generator is willing to provide. Total system reserves are the sum of the reserves assigned to each unit.

b. Spinning reserve pricing

As discussed in Chapter 1, current reserve pricing methods do not provide adequate economic signals for generation operation and investment, and as is the case for energy, locational marginal prices for reserves should provide those signals. However calculating reserve LMPs is not a simple extension of energy LMPs. Reference [13] establishes the following objectives for an efficient reserve pricing method: differentiate energy and reserve prices, use locational reserves to find nodal prices and apply marginal cost principles.

There is no evident way to establish a nodal price for locational reserves, or to have independent shadow prices for energy and reserves, and some works have looked into these aspects [116], [121]. However, most efforts have been oriented to reserve allocation overlooking reserve pricing, and more research is still required. This work does not attempt to provide a comprehensive method to locational reserve pricing, but a practical approach to calculate marginal nodal prices for reserves, according to the pricing objectives described above.

First, it is assumed that any actual energy opportunity cost arising from providing spinning reserves is recovered as a separate make-whole payment. Therefore, spinning reserve offers should only reflect the cost of making the capacity available to the system and, from the point of view of generators, there is no difference between providing upward or downward spinning reserve. Accordingly, in (6) both types of spinning reserves have the same cost, that is, no separate offers are required for up and down reserves.

The pricing of locational spinning reserves is then based on the marginal cost of allocated reserves: the marginal reserve cost on each node sets the nodal contingency reserve price. Therefore, defining ρ_{nt}^{SP} as the locational price of spinning reserves at node n in period t , reserve prices are calculated as follows:

$$\rho_{nt}^{sp} = \max_i [RC_{it}(r_{it}^{sp})]; \{i \in I_n : r_{it}^{sp} > 0\}, \forall n \in N, t \in T \quad (29)$$

4.2 Co-optimization of Spinning and Nonspinning Reserves

The use of nonspinning reserves to meet the contingency reserve requirements is a standard practice of power system operations in North America. This practice recognizes that there is no need for fast start generation to be permanently online to provide reserves, as this would increase generation costs. However, as discussed in Chapter 1, the division between spinning and nonspinning reserve lacks technical basis. One of the contribution of this work is to provide an efficient method to allocate both spinning and nonspinning reserves.

To include nonspinning reserves in the scheduling problem, it is necessary to allow capable generation units to start and ramp up to provide energy to rebalance the system after a contingency occurs, as upward nonspinning reserve. Generation units can also be allowed to shut down if this lowers redispatch costs, and we say that they provide downward nonspinning reserve (see Figure 1). To co-optimize nonspinning reserves it is necessary to consider the cost of procuring and starting up the nonspinning reserve in the objective function²⁵. Consequently, the function to minimize is:

$$\begin{aligned} & \sum_{t \in T} p_t^{(0)} \left\{ \sum_{i \in I^{(0)}} [SC_{it}(v_{it}^{(0)}) + GC_{it}(u_{it}^{(0)}, g_{it}^{(0)}) + RC_{it}^{sp}(r_{it}^{sp+}, r_{it}^{sp-}) \right. \\ & \quad \left. + RC_{it}^{ns}(r_{it}^{ns+}, r_{it}^{ns-})] \right\} + \\ & \sum_{t \in T} \left\{ \sum_{\substack{k \in K \\ k \neq 0}} p_t^{(k)} \left(\sum_{i \in I^{(k)}} [SC_{it}(v_{it}^{(k)}) + GC_{it}(u_{it}^{(k)}, g_{it}^{(k)})] \right) \right\} \end{aligned} \quad (30)$$

²⁵ Shut-down costs are not explicitly represented as in the previous model.

The decision variables are $u_{it}^{(k)}$, $v_{it}^{(k)}$, $w_{it}^{(k)}$ (integer) and $g_{it}^{(k)}$ (continuous); the spinning and nonspinning reserve variables (r^{sp+} , r^{sp-} , r^{ns+} , r^{ns-}) are explicitly represented but they are function of other variables. Notice in (30) that there are integer variables for all post contingency states, which complicates the problem.

We assume that units providing upward nonspinning reserves will not fail to start, so we can use the same state probabilities that we used in the previous case, where only spinning reserves were considered²⁶. In general, assigning upward nonspinning reserves should reduce expected reserve costs even incurring on additional but low probability startup costs.

4.2.1 Problem Constraints

The nodal power balance and static security constraints are identical to the previous problem. Below we list the generation-related constraints that are different or specific to the co-optimization of energy, spinning and nonspinning reserves.

a. Generation operating limits

Equation (31) replaces (19) to set generation power limits for post contingency states, considering the commitment status of the unit.

$$g_j^{\min} \cdot u_{jt}^{(k)} \leq g_{jt}^{(k)} \leq g_j^{\max} \cdot u_{jt}^{(k)} ; k \neq 0, \forall j \in J^{(k)}, k \in K, t \in T \quad (31)$$

b. Generation startup and shutdown constraints

Equations (32) turns off the failed unit and (33) fixes the commitment status of all units that do not qualify to provide reserves.

$$u_{\kappa t}^{(k)} = 0 ; \kappa: \text{unit out in } k, k \neq 0, \forall k \in K, t \in T \quad (32)$$

²⁶ In fact failure to start a reserve could be considered a second contingency.

$$u_{it}^{(k)} = u_{it}^{(0)}; i \neq \kappa, i \neq j, \forall i \in I^{(k)}, j \in J^{(k)}, t \in T \quad (33)$$

Equations (34)–(35) define the unit startup and shutdown sequence for post contingency states, and (36)–(37) set minimum unit up and down time restrictions considering transitions to those states.

$$v_{it}^{(k)} - w_{it}^{(k)} = u_{it}^{(k)} - u_{it}^{(0)}; k \neq 0, \forall i \in I^{(k)}, k \in K, t \in T \quad (34)$$

$$v_{it}^{(k)} + w_{it}^{(k)} \leq 1; k \neq 0, \forall i \in I^{(k)}, k \in K, t \in T \quad (35)$$

$$v_{it} \leq u_{i,t+q}^{(k)}; q = 1, \dots, \min[(UT_i - 1), T - t], k \neq 0, \\ \forall i \in I^{(k)}, k \in K, t \in T \quad (36)$$

$$w_{it} \leq 1 - u_{i,t+q}^{(k)}; q = 1, \dots, \min[(DT_i - 1), T - t], k \neq 0, \\ \forall i \in I^{(k)}, k \in K, t \in T \quad (37)$$

4.2.2 Spinning Reserves Allocation and Pricing

The locational spinning reserves required from each generating unit are calculated using equations (38)–(40) below.

$$r_{it}^{sp+} = \max_k [(g_{it}^{(k)} - g_{it}^{(0)}) \cdot u_{it}^{(0)} \cdot u_{it}^{(k)}, 0]; \forall i \in I^{(0)}, t \in T \quad (38)$$

$$r_{it}^{sp-} = \max_k [(g_{it}^{(0)} - g_{it}^{(k)}) \cdot u_{it}^{(0)} \cdot u_{it}^{(k)}, 0]; \forall i \in I^{(0)}, t \in T \quad (39)$$

$$r_{it}^{sp} = r_{it}^{sp+} + r_{it}^{sp-} \leq R_{it}^{sp-max}; \forall i \in I^{(0)}, t \in T \quad (40)$$

As before, the spinning reserve provided by a unit is the sum of the assigned upward and downward reserve, and total spinning reserve is subject to a physical or offer limit R_{it}^{sp-max} in (40). The spinning reserves allocated to the unit define the range upwards and downwards within which it can be dispatched.

The locational nonspinning reserves required from each generating unit are calculated using equations (41)–(43) below.

$$r_{it}^{ns+} = \max_k [(g_{it}^{(k)}) \cdot (1 - u_{it}^{(0)}) \cdot u_{it}^{(k)}, 0]; \forall i \in I^{(0)}, t \in T \quad (41)$$

$$r_{it}^{ns-} = \max_k [(g_i^{\min}) \cdot u_{it}^{(0)} \cdot (1 - u_{it}^{(k)}), 0]; \forall i \in I^{(0)}, t \in T \quad (42)$$

$$r_{it}^{ns+} \leq R_i^{ns_max}; \forall i \in I^{(0)}, t \in T \quad (43)$$

The conventional upward nonspinning reserve is also subject to a physical or offer limit $R_i^{ns_max}$ in (43), whereas the downward nonspinning reserve can only be 0 or the minimum generation limit of the unit (see Figure 1). A generation unit offline and providing upward nonspinning reserves at period t should be ready to start up within 10 minutes in case of a contingency at t . Likewise, a unit online and providing downward nonspinning reserves at period t should be ready to shut down within 10 minutes at t .

Notice that the reserve equations (38), (39), (41) and (42) are non linear, but they can be linearized to solve the problem as a MILP. For instance, (38) and (41) can be replaced by (44) and (45) below.

$$r_{it}^{sp+} \geq (g_{it}^{(k)} - g_{it}^{(0)}) - g_i^{\max} \cdot (2 - u_{it}^{(k)} - u_{it}^{(0)}); \forall i \in I^{(0)}, t \in T \quad (44)$$

$$r_{it}^{ns+} \geq g_{it}^{(k)} - g_i^{\max} \cdot u_{it}^{(0)}; \forall i \in I^{(0)}, t \in T \quad (45)$$

With regard to reserve pricing, it is assumed that any start-up or shut-down cost actually incurred by using nonspinning reserves is remunerated as a separate make-whole payment. Therefore nonspinning reserve offers only reflect the availability of the unit and consequently (30) assumes that both types of nonspinning reserves have the same cost, that is, no separate offers are required for up and down reserves.

The pricing of the locational nonspinning reserves is also based on the marginal cost of the reserves assigned in each node. Then, besides the spinning reserve prices ρ_{nt}^{sp} established in (29), we define nodal nonspinning reserve prices ρ_{nt}^{ns} as follows:

$$\rho_{nt}^{ns} = \max_i [RC_{it}^{ns}(r_{it}^{ns+}, r_{it}^{ns-})]; \{i \in In : r_{it}^{ns+} + r_{it}^{ns-} > 0\}, \forall n \in N, t \in T \quad (46)$$

Finally, the stochastic SCUC models presented in this section can be adapted to co-optimize energy and any specific types of reserves, for instance only upward spinning reserve or only upward spinning and nonspinning reserves.

Chapter 5 Numerical Simulations

In order to test the validity of the proposed methods and evaluate their computational tractability, we carried out numerical simulations to co-optimize energy and locational contingency reserves over a 24-hour horizon period, using the IEEE one-area Reliability Test System 96 [142]. Three different cases were simulated, Case 1 compares the proposed allocation with a conventional method, Case 2 investigates the value of assigning downward spinning reserves and Case 3 co-optimizes spinning and nonspinning reserve.

5.1 Test System Characteristics and Data

The one-area RTS96 system has 24 buses, 32 generation units and 38 transmission lines, with two voltage levels of 230 and 138 kV. The topology of the system is shown in Figure 4. The RTS96 has a total installed capacity of 3,405 MW and the annual peak load is 2,850 MW. Bus data, branch data and system load profile are provided in [142, Table 1, Table 12 and Tables 2–5]. For the simulations, we chose the hourly load profile corresponding to the day of higher consumption in the year (2nd day of calendar week 51 for a winter peaking system). Generator data, including size, type, fuel, forced outage rate, heat rate, startup heat, cycling and ramping data are provided in [142, Table 6 and Tables 8–10]. On the original data we corrected a jump in the load profile at hour 01 and added the initial conditions of generation units.

The RTS96 lacks generation flexibility, since besides some nuclear and hydro units, it is mostly composed of conventional steam plants burning coal or fuel oil. In order to add fast-response and peaking capacity, necessary to deploy spinning and non-spinning reserves, we

replaced the original 3x100 MW steam units at node 7 with a group of gas turbines of the same size. On the other hand, the RTS96 system has ample transmission capacity. A preliminary examination of power flows indicated that even at maximum peak load there was not a single congested transmission line. As our goal was to evaluate the allocation of reserves under transmission congestion, we reduced the continuous and long-term emergency ratings of the transmission line between nodes 16 and 17 to 250/300MW respectively.

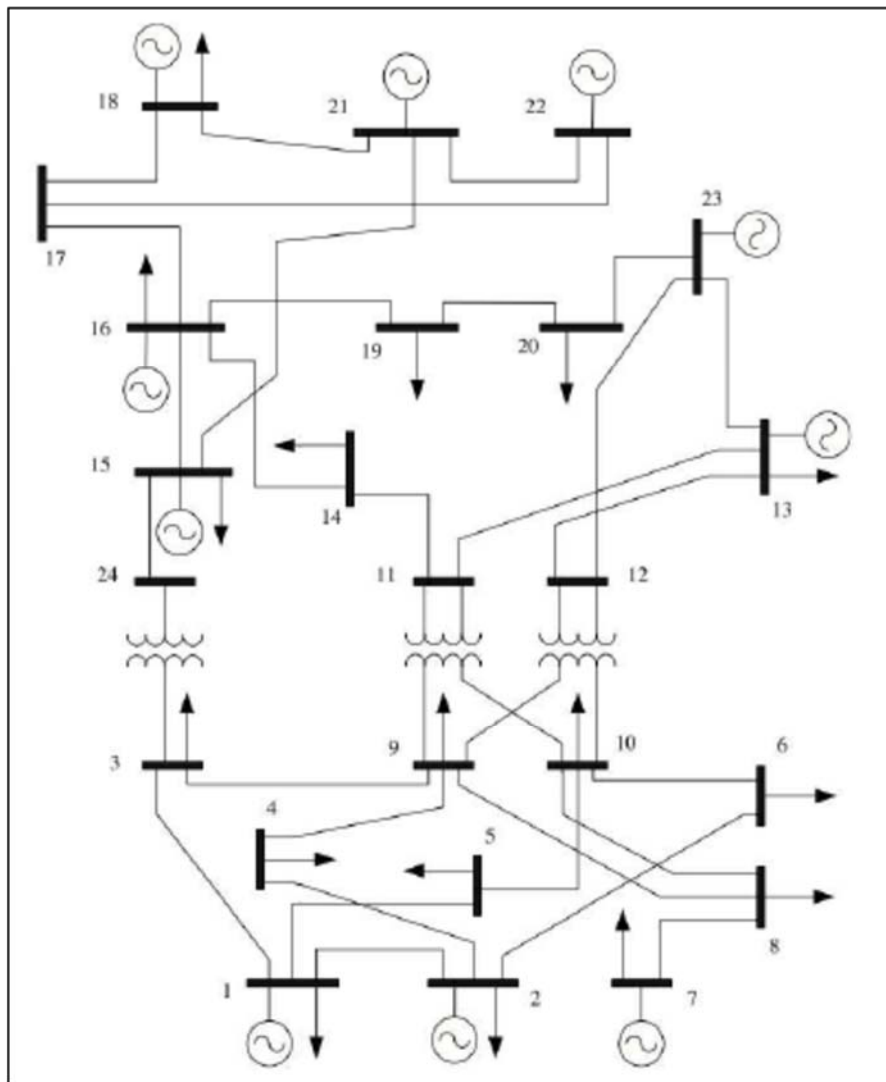


Figure 4 – IEEE one-area Reliability Test System 96

The RTS96 data provide the incremental heat rate of thermal units at four output levels. The lower level was considered as the minimum power output of each unit and the rated capacity as its maximum power output. The ramp rate (MW/min) of each unit was used to compute 60-minute inter-period and 10-minute contingency ramp up and ramp down limits. The physical limits of each unit were used to compute its maximum reserve limits. The incremental heat rate data was combined with average fuel costs for year 2015 [143], to build a piecewise linear generation cost function GC for each generator. Likewise, the fuel cost data was used to calculate the startup cost SC of the units, assuming hot starting. Finally, spinning and nonspinning reserve costs, RC^{sp} and RC^{ns} , were assumed to be equivalent to 20% and 10% of the highest marginal energy costs of each unit, respectively. Under these cost assumptions, the stochastic SCUC models used in the simulations were all mixed-integer linear problems.

Table 1. Test System Generation Units Data

No. x Size (MW)	Type	Fuel	Total MW
2 x 400	Nuclear	Nuclear	800
1 x 350	Steam	Coal	350
3 x 197	Steam	Fuel Oil #6	591
4 x 155	Steam	Coal	465
3 x 100	Gas Turbine	Fuel Oil #2	300
4 x 76	Steam	Coal	304
6 x 50	Hydro	---	300
4 x 20	Combustion Turbine	Fuel Oil #2	80
5 x 12	Steam	Fuel Oil #6	60

Fuel cost (\$/MMBTU): Fuel oil #2 \$13.90, Fuel oil #6 \$10.20, Coal \$2.20, Uranium \$0.80.

Generation units number, size, type and fuel cost are shown in Table 1 above. In principle, the contingency scenarios to be considered correspond to the outage of any single unit

of the system at any of the 24 hourly periods of the UC horizon. For the purpose of the simulations and without loss of completeness, the contingency scenarios selected were those corresponding to distinct outages. That is, those of units different in size or units located in different nodes of the system. Thus, 14 generation outages and 336 contingency scenarios were simulated. Actually, a more reduced set of credible contingencies could have been selected by disregarding outages of smaller units that are dominated by outages of bigger units. In effect, the simulation results confirmed that only outages above 100 MW were relevant.

5.2 Reserve Allocation Simulation Cases

With the data described in the previous section, we simulated the day-ahead co-optimization of energy and locational contingency reserves for the IEEE RT96 test system, using the stochastic SCUC models formulated in Chapter 4. To focus on the effect of generation outages on contingency reserves, the security constraints (8) and (12) related to transmission outages were not enforced, and neither the replacement reserve requirement of (21).

The objective of the simulations were to (i) compare the results of allocating contingency reserves using a conventional method vs the proposed locational method; (ii) evaluate the effect of including “downward” reserves in addition to the traditional “upward” reserves, and (iii) to investigate the feasibility and impact of co-optimizing spinning and nonspinning reserves.

The MILP optimization models were coded using OPL language (ILOG) and solved with CPLEX v12.6.1 [144], with pre-specified solution gap of 0.1%, using a laptop computer with 2.10 GHz CPU and 4GB of RAM. The programming codes can be found in Appendix C. The results of the simulations are described next.

5.2.1 Case 1 – Global Reserves vs Locational Reserves

In Case 1 we wanted to compare the results of co-optimizing energy and contingency reserves using a conventional method vis-à-vis the proposed locational method. To do this we first simulated the results of a deterministic SCUC with a spinning reserve requirement. The initial option was to apply a traditional fixed requirement based on the heuristic of a reserve equal to the capacity of “largest unit online”. An exogenous spinning reserve requirement SR_t is then imposed as an additional constraint of the optimization problem. For the RTS96 system the required hourly reserve would be equal to 400 MW (see Table 1).

This ad-hoc assignment can lead to overscheduling (reliable but uneconomic) or underscheduling (not secure but less costly) reserves. In fact, it is better to define a reserve requirement equal to the maximum generation online but not necessarily the largest unit. This reserve requirement constraint is enforced in (40). We called this requirement as a global reserve and this approach the global reserve method. In this case the total reserve is not an exogenous value but another decision variable of the optimization problem.

$$\sum_i r_{it}^{sp} \geq g_{it} + r_{it}; \forall i \in I, t \in T \quad (47)$$

We used the global and locational reserve methods to allocate upward spinning reserves in the test system²⁷; the main characteristics of both problems are compared in Table 2 and the total reserve assigned each hour is shown in Table 3. The stochastic model is a much bigger problem in terms of variables and constraints, but notice that it has the same number of integer variables as the deterministic problem, which favors tractability.

²⁷ The conventional methods based on a fixed or global reserve requirement only optimize spinning reserves.

Table 2. Case 1 – Problem Size and Solution Time

Parameter	Global Reserves	Locational Reserves
No. of variables	6,001	34,753
Binary	2,304	2,304
Other	3,697	32,449
No. of constraints	11,917	87,037
No. of nonzero elements	29,221	212,893
Solution time (s)	22.8	360.7

Table 3. Case 1 – Total Hourly Contingency Reserves

H	Load (MW)	Global (MW)	Locat. (MW)	H	Load (MW)	Global (MW)	Locat. (MW)
01	1795.5	400.0	370.0	13	2707.5	400.0	400.0
02	1795.5	400.0	370.0	14	2707.5	400.0	400.0
03	1710.0	400.0	352.8	15	2650.5	400.0	400.0
04	1681.5	400.0	355.6	16	2679.0	400.0	400.0
05	1681.5	400.0	355.6	17	2821.5	400.0	400.0
06	1710.0	400.0	352.8	18	2850.0	400.0	400.0
07	2109.0	400.0	400.0	19	2850.0	400.0	400.0
08	2451.0	400.0	400.0	20	2736.0	400.0	400.0
09	2707.5	400.0	400.0	21	2593.5	400.0	400.0
10	2736.0	400.0	400.0	22	2365.5	400.0	400.0
11	2736.0	400.0	400.0	23	2080.5	400.0	400.0
12	2707.5	400.0	400.0	24	1909.5	400.0	400.0

The global method solved in seconds and the locational method in a few minutes²⁸. Also notice that the locational method was able to adjust the required reserves according to the demand of off-peak hours. Figure 5 and Figure 6 compare the spatial distribution of reserves and

²⁸ The specific characteristics of this problem, with many identical units, affects the solution time, because the branch-and-bound algorithm used by the MILP solver has to sort and explore a number of different combinations that produce the same result. Some preprocessing in terms of adding small cost differentials between identical units should result in a faster solution convergence.

prices at a specific time period (hour 22). The global method allocates more reserves in fewer nodes, compared to the locational method, and there is a single global price vs varying locational prices per node.

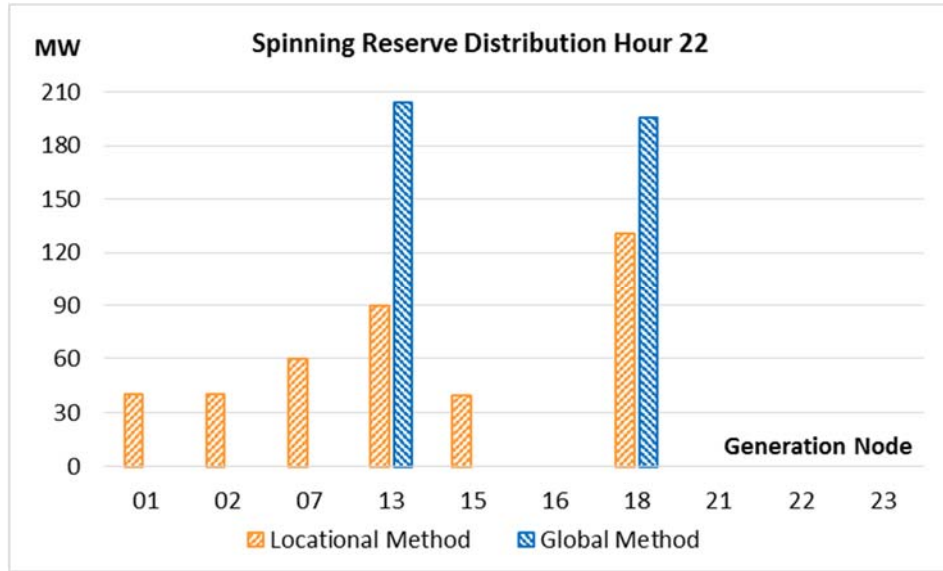


Figure 5 – Spatial distribution of spinning reserves, hour 22

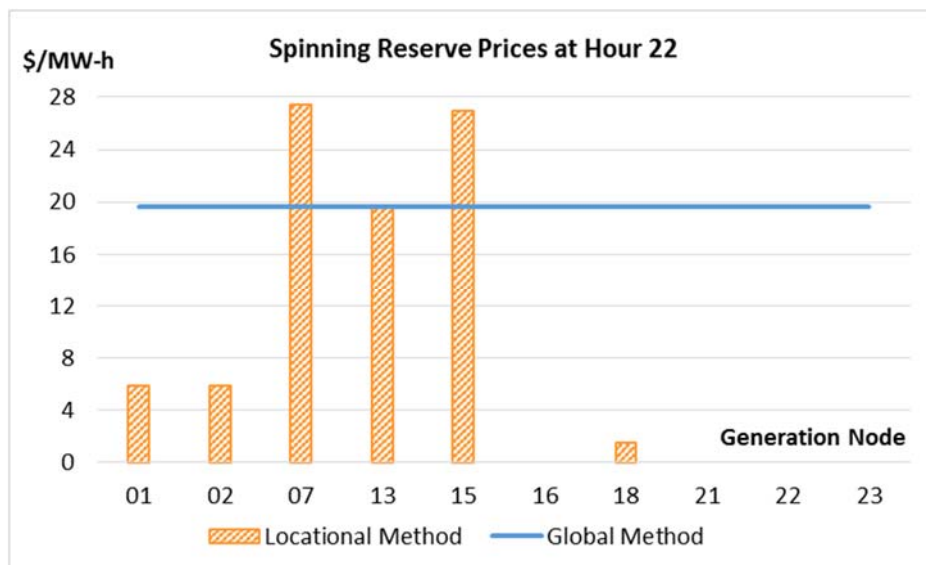


Figure 6 – Spatial distribution of reserve prices, hour 22

Figure 7 shows the total amount of spinning reserves allocated to generators at node 15 over the day, with a marked difference between the results of both methods.

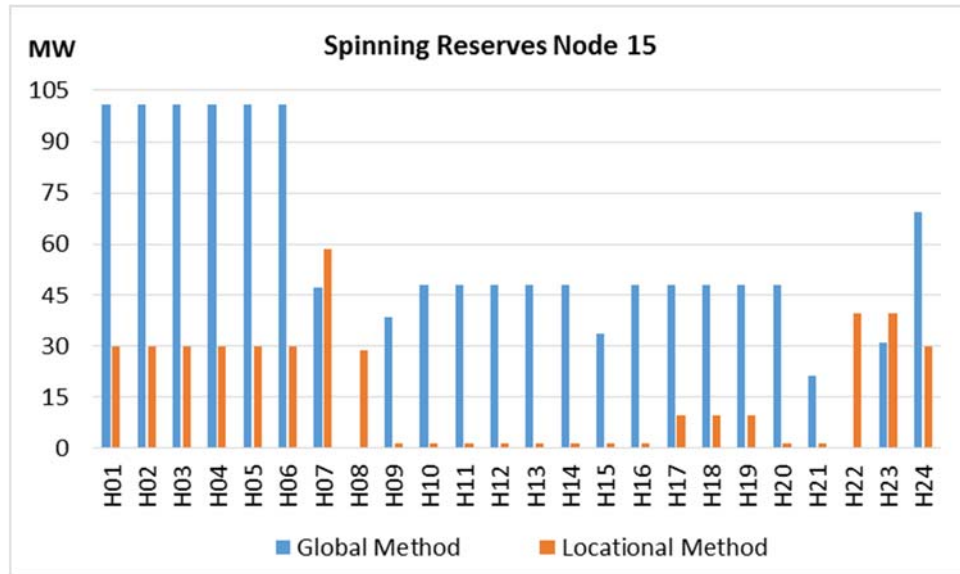


Figure 7 – Hourly allocation of spinning reserves at generation node 15

To compare generation costs with each method, total cost is divided into dispatch cost (no contingencies), startup cost, reserve cost and redispatch cost (post contingency). Dispatch and startup cost are the “energy” costs, and reserves plus redispatch are “security” costs. The costs of both methods are not directly comparable, because the global reserve method is deterministic, whereas the locational method is stochastic. To make a fair comparison the expected generation cost by using the global method was estimated as follows: first, redispatch costs were calculated for all selected contingencies, using a VoLL of \$5,000/MWh to value any energy not served; then the state probabilities of the stochastic locational method were applied to the deterministic solution costs to find the expected value.

Table 4 compares the costs of both methods. In general, total generation costs are dominated by dispatch costs (approximately 90%) followed by reserve costs (around 7%). Startup and redispatch costs are around the same order of magnitude. Energy related costs are also bigger than security costs, the latter accounting for around 8% to 9% of total cost. Generation costs (energy and security) of the global method are lower, as expected, because it is

a less constrained problem, although redispatch costs are higher because of ENS in some contingencies. In summary, the global method schedule resulted in a more economic but unreliable operation, whereas the locational method was able to find a 24-hour *N-1* secure dispatch at a reasonable additional cost of around 4%.

Table 4. Case 1 – Cost Comparison

Cost (\$)	Global Method	Locational Method
Dispatch	1,156,667	1,197,631
Startup	20,959	23,523
<i>Energy</i>	<i>1,177,626</i>	<i>1,221,155</i>
Reserve	87,050	102,499
Redispatch	22,269	13,230
<i>Security</i>	<i>109,319</i>	<i>115,728</i>
Total	1,286,944	1,336,883

5.2.2 Case 2 – The Value of Downward Spinning Reserve

A generation outage creates a capacity deficit in the system that must be covered by ramping up standby reserves. That is the reason why, conventionally, all contingency reserves are “upwards”²⁹ (contrary to regulation reserves that act up and down). However, the definition of locational reserves allows assigning contingency reserves “downwards”, by reducing generation or shutting down units (see Figure 1), if that lowers total operation costs. In Case 2 we wanted to evaluate the convenience of allocating downward reserves in addition to upward reserves, using the test system. First, to probe the concept, we simulated the addition of downward spinning reserves at no cost. As a result, effectively the locational method assigned hourly downward spinning reserves in the range of 90 MW to 130 MW to obtain a lower cost

²⁹ Contrary to regulation reserves that normally act in both up and down directions.

solution. However, it took much more computational effort (solution time was 1 hour, that is 10 times higher), and the reduction in cost was only 0.03% in total, which is lower than our solution tolerance. The reduction was essentially due to lower redispatch costs (-2.3%).

Now, when we included the cost of the downward spinning reserves in the simulation, the result was that no downward reserves were allocated, since the additional reserve cost is not compensated by the reduction in redispatch costs. In consequence, we found no value in defining and adding a downward spinning reserve product to the tested system. Even if some cost reductions were achievable, they should be marginal anyway, given the lower weight of redispatch costs on the total, and it probably would not justify the increase in computational complexity.

Given this result, we are even more skeptical about the value of adding downward nonspinning reserves. Especially because shutting down a unit as a response to a generation contingency has implications beyond the redispatch period considered in our model (for instance if the unit cannot be restarted shortly), that we cannot capture in the simulations. Intuitively, shutting down units in a post contingency state seems a risky operational practice.

5.2.3 Case 3 – Co-Optimization of Spinning and Nonspinning Reserves

Having nonspinning reserves as part of the contingency reserve is a common practice in power system operations. The concept is that fast-starting units can also respond in a post contingency condition without sacrificing reliability. Starting up a unit has a cost and there is certain risk that a nonspinning reserve could fail to start when required, which would be a sort of *N-2* event. But the benefit is that, since generation outages are infrequent, keeping reserves offline is less expensive, lowering dispatch and reserve costs.

This trade-off is reflected in heuristic operational rules to allocate a nonspinning reserve, normally as a percentage of the spinning reserve, without further technical basis to decide what part of the contingency reserve should be offline. In Case 3, we aimed at testing the validity of the locational method to co-optimize spinning and nonspinning reserves and wanted to investigate the efficiency of the result. Therefore, we simulated the co-optimization of energy, spinning and nonspinning reserves in the test system using the locational method and compared results with Case 1, where only energy and spinning reserves were co-optimized. Consistently with the analysis of Case 2, we only considered upward reserves –spinning and nonspinning- for this purpose.

The main characteristics of both problems are compared in Table 5. As expected, including nonspinning reserves increased problem size, especially in terms of the number of integer variables, since it considers starting up units in every contingency scenario. The solution time almost doubled when compared with Case 1, but it was still within an acceptable range (10 minutes). Table 6 shows the total amount of spinning and nonspinning reserves assigned each hour. The locational method assigned an appreciable amount of nonspinning reserves during the intermediate and peak load periods and none for valley periods, where reserve requirements are lower and there is more head room in dispatched units.

Also notice that the optimal amount of nonspinning reserves as percentage of total contingency reserves varies hour by hour, from 0% at minimum load up to above 70% at peak load. Comparing with Case 1 (Table 3), the total amount of hourly contingency reserves in both cases is very similar, with small differences due to the minimum power limits of the units. But in Case 3 the reserve is optimally divided into spinning and nonspinning parts. In both cases solutions are fully *N-1* compliant.

Table 5. Case 3 – Problem Size and Solution Time

Parameter	Only Spinning Reserves	Spinning & Nonspinning Reserves
No. of variables	34,753	56,873
Binary	2,304	23,656
Other	32,449	33,217
No. of constraints	87,037	153,661
No. of nonzero elements	212,893	406,645
Solution time (s)	360.7	615.1

Table 6. Case 3 – Spinning and Nonspinning Hourly Contingency Reserves

H	Load (MW)	Spin. (MW)	Nonsp. (MW)	H	Load (MW)	Spin. (MW)	Nonsp. (MW)
01	1795.5	370.0	0.0	13	2707.5	155.0	252.8
02	1795.5	370.0	0.0	14	2707.5	126.2	273.8
03	1710.0	352.8	0.0	15	2650.5	126.2	273.8
04	1681.5	355.6	0.0	16	2679.0	126.2	273.8
05	1681.5	355.6	0.0	17	2821.5	121.4	278.6
06	1710.0	352.8	0.0	18	2850.0	117.5	283.5
07	2109.0	155.0	245.8	19	2850.0	117.5	282.5
08	2451.0	126.2	273.8	20	2736.0	155.0	252.8
09	2707.5	126.2	273.8	21	2593.5	126.2	273.8
10	2736.0	126.2	273.8	22	2365.5	130.4	269.6
11	2736.0	126.2	273.8	23	2080.5	178.7	221.3
12	2707.5	155.0	252.8	24	1909.5	326.0	74.0

Figure 8 shows the hourly generation schedule for the test system, including energy, spinning reserves and nonspinning reserves. Table 7 compares the solutions in terms of costs. As expected, there are appreciable cost savings in reserve and startup costs, but even more in dispatch costs because the model is able to find a less constrained dispatch solution. The effect on redispatch costs is negligible. Overall, security but especially energy costs are reduced by including nonspinning reserves, and total savings in operation costs is 8.4%.

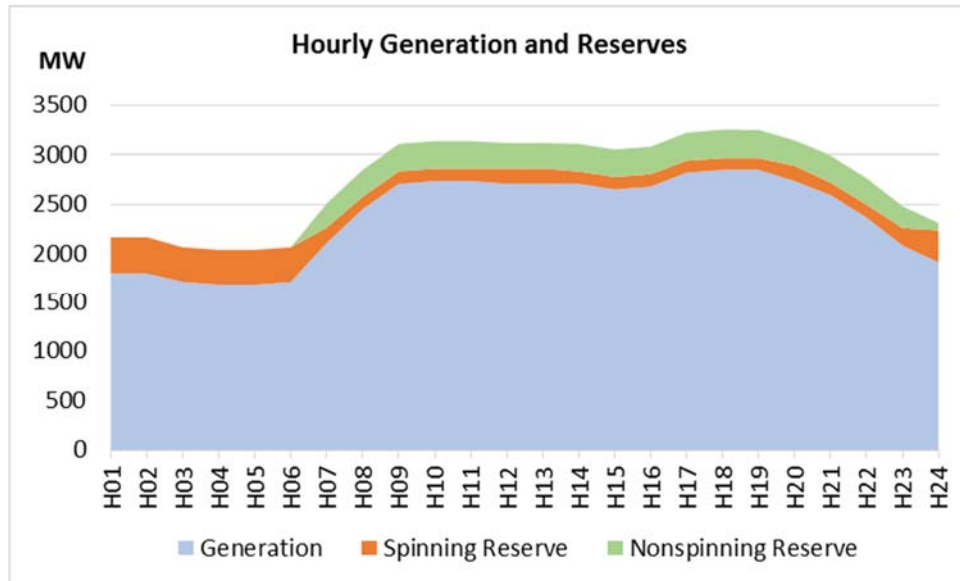


Figure 8 – Case 3 Hourly Energy and Reserves Schedule

Table 7. Case 3 – Cost Comparison

Cost (\$)	Only Spinning Reserves	Spinning & Nonspinning Reserves
Dispatch	1,197,631	1,131,690
Startup	23,523	12,683
<i>Energy</i>	<i>1,221,155</i>	<i>1,144,373</i>
Reserve	102,499	66,516
Redispatch	13,230	13,623
<i>Security</i>	<i>115,728</i>	<i>80,139</i>
Total	1,336,883	1,224,512

Summarizing, the application of the locational method resulted in an efficient allocation of spinning and nonspinning reserves in the test system, and their co-optimization created sizable operating cost savings for the system.

5.3 State-Based Approach Computational Efficiency

To estimate the efficiency of the proposed stochastic state-based approach for day-ahead generation scheduling, we compared the results obtained in the numerical simulations presented in this Chapter and in [145] with the results of a similar simulation carried out in [123] (Bouffard et al., 2005). This latter work used a scenario-based stochastic scheduling model and the same test system. The main characteristics and assumptions of both cases are summarized next.

Table 8. Simulations Comparison – Characteristics

	Prada and Ilić, 2016 [145]	Bouffard et al., 2005 [123]
Test System	One-area IEEE RTS 96	One-area IEEE RTS 96
Hourly Demand	2 nd day of week 51 (winter peak)	2 nd day of week 45 (winter peak)
Security criteria	Deterministic N-1	Probabilistic N-1
Contingencies	Generation outages	Generation outages
Type of Reserves	Locational	Locational
Stochastic model	State based	Scenario based
Optimization Model	MILP	MILP
ENS allowed	No	Yes
VOLL (\$/MWh)	\$5,000 (only for verification)	\$3,000 (peak), \$2000 (off-peak)
Must-run units	No	2x400 MW (nuclear) 6x50 MW (hydro)
Demand offers	No	Spinning reserve ($\leq 2\%$)
Fuel costs (\$/MBTU)	\$2.2 coal, \$10.2 fuel oil 6, \$13.9 fuel oil 2, \$0.8 uranium	\$1.2 coal, \$2.3 fuel oil 6, \$3.0 fuel oil 2, \$0.6 uranium
Nonspinning reserves	Yes	No, pre and post contingency commitment variables set equal
Binary variables	Commitment, Startup, Shutdown	Only Commitment (plus additional constraints)
Credible contingencies	All non-identical units: 14 units, all sizes	6 Units ≥ 197 MW: 2x400 MW, 1x 350 MW, 3x197 MW

According to the above Table, the characteristics of both simulations are comparable, but in many aspects [123] is a simpler problem (ENS allowed, demand participation, must-run units,

fewer outages, fewer integer variables) seeking to ensure computational tractability. Below we compare the results of both simulations, considering only spinning reserve allocation.

Table 9. Simulations Comparison – Results

	Prada and Ilić, 2016 [145]	Bouffard et al., 2005 [123]
Solver	CPLEX 12.6.1 / ILOG	CPLEX 9.0.2 / GAMS
Duality Gap	0.1%	1%
Number of variables	34,753	1,018,033
Binary variables	2,304	576
Number of constraints	87,037	1,754,981
Loss of Load	No	Yes, 161 MW
Costs	n.a.	n.a.
Solution time (minutes)	6.0	40.7

The proposed state-based model has 30 times fewer variables, 20 times fewer constraints and solved almost 7 times faster. Generation costs are not comparable because different fuel costs assumptions.

The difference in size is based on the stochastic model as explained in Chapter 3 and Appendix A. Besides the problem size, gains on performance of the solver may explain part of the speed difference, but just partially. But, on the other side, our model is solved to a ten times smaller tolerance, which makes a big difference in how soon an acceptable solution can be obtained.

One can conclude that, based on this comparison, the proposed state-based approach is computationally more efficient than the scenario-based models. In addition, as discussed in section 3.3.2, a state-based model can be scaled up with smaller dimensionality problems than the scenario-based problems. This aspect is critical for practical implementation on large systems.

Finally, it is important to point out that the comparison model could not implement a solution with nonspinning reserves, for a relatively small test system like the IEEE RTS 96, a characteristic shared by most of reserve optimization models found in the literature. In contrast, an optimal allocation of spinning and nonspinning reserves in a reasonable time was achieved in the model of Case 3.

Chapter 6 Conclusions of Part I

The optimal calculation and distribution of contingency reserves in power systems have long been discussed, both from the point of view of operational reliability (security) and of economic efficiency. Nevertheless, current practices to allocate spinning and nonspinning reserves produce workable solutions but still have serious shortcomings as discussed in the introduction of this Part. In general there is a consensus on the main problems –deliverability, uncertainty modeling, etc.– and therefore the requirements of a good solution, but up to now the computational complexity of the proposed methods has been a limitation to its development and application.

Recently, advances in computational power and algorithms to solve large optimization problems have brought new opportunities to improve the methods to determine optimal contingency reserves for secure real-time operations. This work contributes to this field by developing new state-based formulations for the day-ahead stochastic co-optimization of energy and locational contingency reserves. These formulations model the uncertainty of generation outages and enforce full compliance of the widely used (and frequently mandatory) $N-1$ reliability standard under transmission congestion. The proposed methods exploit the structure and characteristics of the problem, according to actual power system operational practices, to improve the computational tractability of the problem. The proposed stochastic contingency-constrained UC models were used to simulate different cases of contingency reserve allocation in the IEEE one-area RTS96 system.

The simulations confirmed that conventional methods cannot account for congestion on post contingency states, so it does not guarantee the security of operations or require cumbersome and costly offline and out-of-market corrections. On the contrary, the proposed locational method is able to find an $N-1$ secure dispatch at a reasonable extra cost. Optimal locational reserves, both spinning and nonspinning, vary according to the demand and conditions of the system, indicating that the use of fixed reserve requirements for both types of reserve is inefficient. Additionally, the simulations indicated little value of assigning “downward” contingency reserves, but they confirmed sizable cost savings from the co-optimization of spinning and nonspinning reserves. Overall, considering problem size, solution time and comparisons with scenario-based models, the simulations showed the computational efficiency of the proposed formulations for the tested system.

Moreover, based on our analysis, it is expected that the compact state-based stochastic SCUC models presented in this Part can be scaled up to be used in larger systems and still be tractable, but further simulations are needed to confirm it. In any case, some problem simplifications, several decomposition methods, improved SCUC models and algorithm parallelization can also be applied to solve problems of larger size, for implementation in real-world systems. Additional research in this direction is required.

Finally, one limitation of the proposed methods is that they rely on a linear approximation of the network model, which introduces simplifications that may result on suboptimal solutions or require additional corrections. The integration of full AC network models with UC formulations is an area where future research is greatly required.

PART II

DISTRIBUTED DAY-AHEAD SCHEDULING OF ENERGY AND CONTINGENCY RESERVES

Chapter 7 Problem Formulation and Methods

7.1 Introduction

The expected growth of distributed energy resources and the deployment of smart grid technologies make us envision future electric energy systems that will be very different to the existing power grid, with market participants playing a more active role than in the present. In particular, producers, consumers and different resource aggregators, enabled by new technologies, will demand more autonomy in their operating decisions, seeking to maximize their own benefits and manage their own risks. This instead of delegating and relying on the decisions of an “omniscient” central operator acting on their behalf.

This evolution will challenge the existing hierarchical and command-and-control structures in place today to operate power systems, based on a centralized decision-making concentrated in system and market operators. These entities are well-meaning, but they lack first-hand information and rely themselves on approximated models. Still, their decisions have a big impact on market agents’ operations and financial performance. Consequently, future electric systems should migrate to multi-layered open access decision models, with decentralized

but coordinated decision-making through appropriate feedback signals [146]. In this direction, a Dynamic Monitoring and Decision Systems (DyMonDS) framework has been proposed to support future sustainable energy services [1], [147]. The DyMonDS approach implements non-hierarchical and distributed alternative models for the operation of the electrical grid.

7.1.1 Related Work

With regard to non-centralized generation scheduling via unit commitment, most previous work has looked into the problem of self-dispatch of generators. In this framework, generation companies conduct a UC to find the profit-maximizing use of their units. Thus [148] addresses the optimal response of a thermal unit selling both energy and spinning reserve into a spot market as a price-taker, using MILP. This approach is extended to also minimize the risk from uncertain prices in [149], [150]. As prices are the main inputs for these type of problems, they are also called Price-Based Unit Commitment (PBUC).

In limited situations a generator connected to a power grid actually know prices in advance or is allowed to self-dispatch, being normally part of a centralized UC. Also, with electricity deregulation and the introduction of competition, generators participate in centralized scheduling and market mechanisms through generation offers. Therefore, there has been interest in applying the PBUC, based on estimated prices, to build generation offer curves and to establish optimal market offer strategies for a unit or a portfolio of generation resources.

A particular application of PBUC is in markets where only simple offers of quantity and price are accepted³⁰, therefore requiring to internalize start-up cost and other operating constraints. Thus [151] investigates methods to include start-up and shut-down constraints in

³⁰ Instead of complex offers including detailed cost information and technical characteristics of units.

strategic offers to competitive markets, and it argues that in effect commitment decisions are decentralized and incorporated in the generators offer strategies. Also [152] presents methods to select and optimize offer strategies based on self-scheduling requirements.

The work in [153] develops a MIP-based PBUC model to optimally schedule energy and reserves in a pool-based electricity market, in [154] a self-scheduling and energy offer model with unit constraints is formulated using Lagrangean Relaxation, and [155] compares LR- and MIP-based formulations of the PBUC. In general MIP has more modeling capabilities and obtain best solutions than LR, but computational burden increases rapidly for larger problems. An optimal bidding strategy for a generator participating in energy and reserve markets, using a stochastic PBUC with uncertain market prices, is presented in [156].

One problem about using PBUC-based offers in electricity markets is that final market prices can be different to generators estimates or projections, and there is no chance to readjust the offers, so the final result may be suboptimal for generators and the system. Another approach to decentralize scheduling decisions is to let the system operator post hourly energy prices, let generators prepare offers with those prices, clear the market, recalculate and post new prices, and iterate until an equilibrium is reached. The optimality of this price discovery process is justified based on its equivalence to the duality techniques like LR applied to solve the centralized UC problem. An interesting debate has ensued about the pros and cons of centralized vs. decentralized UC.

Centralized scheduling with perfect information should in theory determine the most efficient unit commitment. But its practical implementation in a market with multiple participants raises issues of efficiency and equity. First, as the system operator has imperfect information provided by self-interested agents, there is no guarantee that the result is a global

optimum. Secondly, the solution algorithms used in practice produce near optimal solutions that are unstable and volatile. In fact many similar solutions (having similar cost) can be found with significant differences in the remuneration of individual agents [157].

The arguments against a decentralized self-committed market are that it cannot properly coordinate the dispatch decisions of multiple competing participant, and not fully integrate transmission effects and security constraints, resulting in productive efficiency losses [158]. Moreover, it is argued that advances in computation capability and optimization algorithms like MIP produce better and more stable solutions, with smaller optimality gaps than former LR algorithms. In addition, although equity issues are reduced but not eliminated, the use of “make-whole” payments in electricity markets to recover unpaid costs can help to reduce generators revenue volatility [159].

The main issue at stake seems to be a balance between operations efficiency and decision autonomy sought by participants. A comparison between centralized and decentralized UC in [160] concludes that, on certain circumstances, the decentralized UC leads to lower social welfare than centralized UC. The reason is that the optimal solution may require some generators to incur losses, a result that cannot be enforced in self-committed schemes. It also shows that prices should rise above marginal cost on a decentralized UC.

A scheme for self-scheduling of independent market participants in a power pool is proposed in [161], based on an iterative price auction emulating the dual LR solution of a centralized UC. Given a set of nodal prices, generators choose production to maximize profits and inform quantities to a central entity. This entity verifies power balance and dispatch feasibility and update prices otherwise, until convergence to a solution. Reaching an equilibrium depends on several notions of profit optimality and coherence of generators response. The

conditions to achieve an efficient equilibrium in decentralized unit commitment –based on price iterations– are articulated in [162], relying on augmented prices to induce generators efficient commitment without incurring losses and therefore maximizing profits. The main claim of the authors is the existence of equilibrium prices for a decentralized UC.

With respect to security requirements, [163] shows the use of price incentives to maintain system security in a decentralized operating environment, where many participants maximize their benefits. It also points out the demanding communication, computing and control capabilities required to forecast, calculate and transmit information to the participants in such an environment. On the other hand [164] defines a price-based decision-making process for generators to participate in a reserve market for power system reliability, also considering the option of selling energy in the spot market. In other recent works, [165] have proposed a decentralized day-ahead UC framework of two levels, with regional coordinators replacing a centralized entity in order to reach a price consensus; [166] and [167] describe methods to solve a large-scale distributed UC using alternative decomposition techniques.

Beyond theoretical efficiency, convergence and equilibrium issues, the main obstacle for the implementation of decentralized UC schemes based on iterative processes is practicality. In effect, it takes too many iterations to reach a solution within an acceptable tolerance band. This would imply a continuous exchange of information between a system operator or coordinator and multiple independent agents. Actually, unless the process is fully automated, it is unfeasible to complete more than a few iterations during the day-ahead timeline.

7.1.2 General Approach and Contributions

In the line of work of DyMonDs, in this Part II we formulate a distributed model to optimally schedule energy and spinning reserves in a day-ahead market. The proposed method is

based on the coordination between a set of individual generators and a market and reliability responsible entity or market coordinator “MC”. For the purposes of the model, the load is assumed passive in the day-ahead stage, and the objective is to determine an optimal commitment and dispatch of generation units for the next day, seeking to minimize the cost of energy and reserves required to supply forecast load and meet security standards. However, a price-responsive load could be easily added by introducing demand bids and maximizing a social benefit objective function.

Generators are considered independent profit-maximizing agents. Based on expected price information, generators should decide whether to commit or not their units and provide simple energy and reserve hourly offers for the market coordinator to clear the market. These offers should internalize generators’ technical constraints (power and ramp limits, minimum on/off times). The Market Coordinator is responsible to clear energy and reserve markets day ahead, in order to supply forecast demand at minimum cost, based on generators offers. As reliability responsible, the MC should verify that system-wide (network) operating limits are met.

The main contribution of Part II is to develop and illustrate the implementation of a practical distributed SCUC model for the day-ahead scheduling of energy and reserves. The proposed method is price-based but does not rely on multiple iterations between generators and a market coordinator. The method uses forecasting, augmented pricing and locational signals to induce efficient commitment of generators based on firm prices. In addition, rules of rational behavior are provided to create simplified generators offers, consisting only in a quantity range. These simple offers significantly simplify the market-clearing process and facilitates enforcing network and security operational constraints.

7.2 Model Description

The components and the information exchange flow of the distributed market-based model for generation scheduling are illustrated in Figure 9. As indicated, generators and the Market Coordinator are supported by calculation platforms to make pricing and production decisions. Generators use a price-based unit commitment model to maximize profit in response to a posted 24-hour schedule of energy and reserve prices, meeting their technical restrictions. For its part, the MC uses load and price forecast models (or services) and a power system simulator to minimize energy and reserve purchase costs without violation of power flows and other system operating limits.

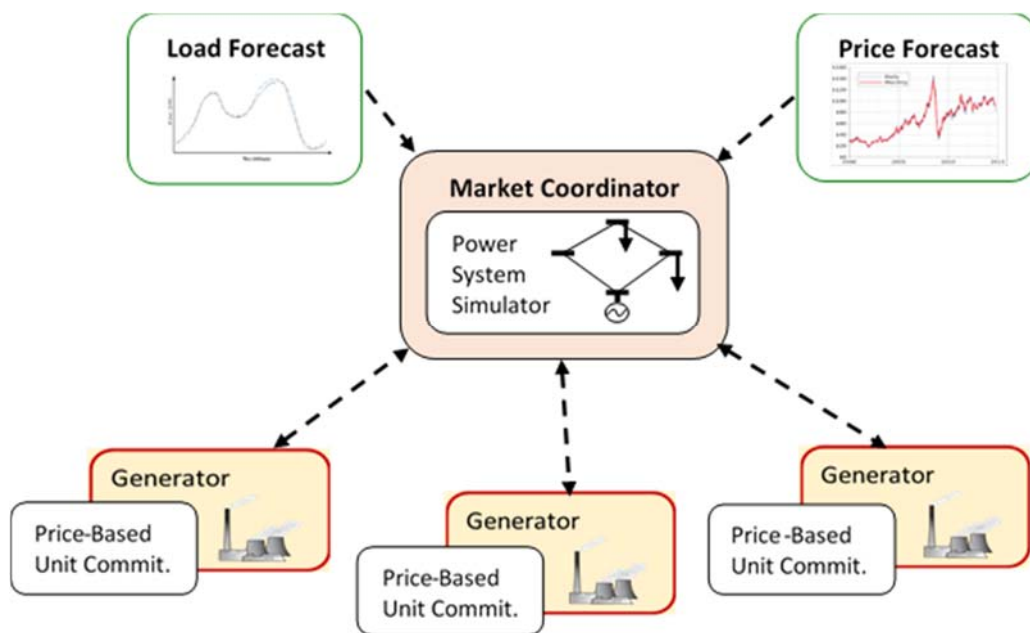


Figure 9 – Organization and information exchange for the distributed scheduling model

With reference to Figure 9, a generation schedule is obtained through a distributed process of calculations and exchange of information between independent generators and a market coordinator. The sequence of events required to schedule energy and spinning reserves is described below:

- 1) Initially, the MC obtain forecast information of expected load on each bus of the network and expected energy and reserve prices at the nodes where generators are located. The load and price forecast modules should be based on econometric, statistical, production or other type of models. For the purposes of the proposed scheduling model the forecasts are assumed to be known.
- 2) The MC informs to generators the schedule of energy and reserve prices for the next day³¹. These prices are to be understood as the minimum prices to be paid in the day-ahead market for scheduled energy and reserves.
- 3) The generators use a price-based unit commitment model to maximize profit from selling energy and reserves in the day-ahead market at the offered prices, meeting their technical restrictions. The result is a decision of when to commit their units over the scheduling horizon, as well as the optimal use of generation –energy and reserves– when committed.
- 4) Based on the profit-maximizing commitment, the generators prepare single supply offers of energy and reserves for each time period. The offers specify the minimum and maximum amount of each product that each generator is willing to provide at the offered prices, or zero when they do not want to run at those prices.
- 5) The MC receives the supply offers and check that there is enough supply to meet the expected demand on each time period. Otherwise she reviews prices upwards at the nodes where there is a shortage and ask involved generators to review their offers.

³¹ The information could be publicly posted or informed to each generator individually. The latter alternative should be preferable to mitigate market power.

- 6) The MC clears the market at each time period, finding optimal power flows that minimizes energy and reserve procurement costs, meeting demand and reserve requirements and without violation of the system operating limits. At each period the MC solve an independent OPF problem with network and security constraints, using a DC or AC network model³².
- 7) The MC sends the final day-ahead schedule and prices to each generator to check feasibility. If a generator cannot follow the assigned dispatch schedule, he/she can update his offer or report a limitation. Then, the MC can review and adjust the schedule accordingly.

7.3 Mathematical Formulation

Next we formulate the optimization problems used by the MC and generators to find in distributed way the next-day generation schedule. For the notation see Nomenclature.

7.3.1 Centralized Solution Benchmark

In order to compare the results of the distributed scheduling model, a benchmark centralized solution is computed first. The centralized model solved is the following unit commitment problem, minimizing the startup, energy and spinning reserve cost over the scheduling period:

$$\min_{g_{it}, r_{it}} \sum_t \sum_i [SC_{it}(v_{it}) + GC_{it}(u_{it}, g_{it}) + RC_{it}(r_{it})] ; \forall i, \forall t \quad (48)$$

Subject to:

$$\sum_{i \in I_n} g_{it} - \sum_{m \in M_n} B_{nm} \cdot (\theta_{nt} - \theta_{mt}) = D_{nt} ; \quad \forall n, \forall t \quad (49)$$

³² An OPF can be used since there are not intertemporal constraints. Also, as the generation offers are linear the AC OPF problem is tractable.

$$-FN_{nm}^{max} \leq B_{nm} \cdot (\theta_{nt} - \theta_{mt}) \leq FN_{nm}^{max}; \forall n, \forall m \in M_n, \forall t \quad (50)$$

$$g_i^{min} u_{it} \leq g_{it}; \quad \forall i, \forall t \quad (51)$$

$$g_{it} + r_{it} \leq g_i^{max} u_{it}; \quad \forall i, \forall t \quad (52)$$

$$-RD_i \leq g_{i,t} + r_{it} - g_{i,t-1} \leq RU_i; \quad \forall i, \forall t \quad (53)$$

$$\sum_i r_{it} \geq g_{it} + r_{it}; \quad \forall i, \forall t \quad (54)$$

$$r_{it} \leq r_i^{max} u_{it}; \quad \forall i, \forall t \quad (55)$$

$$v_{it} - w_{it} = u_{i,t} - u_{i,t-1}; \quad \forall i, \forall t \quad (56)$$

$$\sum_{\tau=t-(UT_i-1)}^t v_{i\tau} \leq u_{i,t}; \quad \forall i, \forall t \in [UT_i, T] \quad (57)$$

$$\sum_{\tau=t-(DT_i-1)}^t w_{i\tau} \leq 1 - u_{i,t}; \quad \forall i, \forall t \in [DT_i, T] \quad (58)$$

The problem (48)–(58) is a compact and efficient version of a SCUC, where (49)–(50) represent the network constrained power flows, (51)–(53) enforce generation operating limits, (54)–(55) define a global spinning reserve requirement, and (56)–(58) model the startup and shutdown constraints.

7.3.2 Distributed Scheduling Model

Two models are required for the proposed distributed scheduling model, a price-based unit commitment for the generators and an OPF-based market clearing model for the MC. Additionally, generators are expected to follow a rational procedure to prepare and submit offers to the MC.

a. *Generator Price-Based Unit Commitment (PBUC)*

Each available generator i will maximize their individual market profit as follows:

$$\max_{g_{it}, r_{it}} \sum_t [p e_{it} \cdot g_{it} + p r_{it} \cdot r_{it} - SC_{it}(v_{it}) - GC_{it}(g_{it}, u_{it}) - RC(r_{it})] ; \forall t \quad (59)$$

Subject to:

$$g_i^{min} u_{it} \leq g_{it} ; \quad \forall i, \forall t \quad (60)$$

$$g_{it} + r_{it} \leq g_i^{max} u_{it} ; \quad \forall i, \forall t \quad (61)$$

$$-RD_i \leq g_{i,t} + r_{it} - g_{i,t-1} \leq RU_i ; \forall i, \forall t \quad (62)$$

$$r_{it} \leq r_i^{max} u_{it} ; \quad \forall i, \forall t \quad (63)$$

$$v_{it} - w_{it} = u_{i,t} - u_{i,t-1} ; \quad \forall i, \forall t \quad (64)$$

$$\sum_{\tau=t-(UT_i-1)}^t v_{i\tau} \leq u_{i,t} ; \quad \forall i, \forall t \in [UT_i, T] \quad (65)$$

$$\sum_{\tau=t-(DT_i-1)}^t w_{i\tau} \leq 1 - u_{i,t} ; \quad \forall i, \forall t \in [DT_i, T] \quad (66)$$

Equations (60)-(66) are equivalent to equations (51)-(58) except for the reserve requirement. The solution of the PBUC defines the preferred commitment and dispatch schedule of each generator for the next day. The resulting profit-maximizing dispatch of each unit i is denoted by g_{it}^* and r_{it}^* .

b. *Formation of Generators Supply Offers*

The PBUC run by each generator defines for each time period whether its unit should be committed at the offered prices and the corresponding profit maximizing energy and reserves

dispatch. To prepare the offers to submit to the day-ahead market, generators are expected to follow these rational rules:

- 1) If the unit is offline in the PBUC at a particular time period, the generator should not submit an offer for that period. The reason is that at the offered prices the unit would not recover variable and no load costs of being online.
- 2) For the periods where the unit is online in the PBUC, the generator should offer the profit-maximizing quantity (g_{it}^*) as the maximum amount he is willing to provide to the market at the offered price. In fact, he can still make a profit selling less energy at the same price, although not the maximum one.
- 3) On the other hand, the minimum quantity that can be sold to the market –at the offered price– is the maximum between the minimum technical output of the unit (g_i^{\min}) and the generation break-even point (g_i^{be}). That is, the minimum output where marginal cost is still greater or equal to average cost. If this quantity is greater than the maximum output of the unit, it means that the unit should not be committed.
- 4) Consequently, the generation offer of the generator is simply 0 or the quantity range within which he is willing to produce energy, at the offered energy price, for each time period of the day.
- 5) For reserves, the profit-maximizing quantity (r_{it}^*) represents the minimum amount the generator should be willing to provide at the offered price. Selling less reserves and more energy is not profit maximizing.

- 6) The maximum amount of reserves to be offered is the difference between the maximum capacity and the minimum output offered, or a lower value that the generator chooses as maximum reserve (r^{\max}).

The rules to prepare energy (E) and reserve (R) generation offers are presented in (67)–(68) below and illustrated in Figure 10, where g_i^{\min} and g_i^{be} are the minimum and break-even power output of unit i (MW), and pe_{it} and pr_{it} are the offered energy (\$/MWh) and reserve (\$/MW-h) prices at unit i node and period t .

$$E_{it}^{\min} = \max\{g_i^{\min}, g_i^{\text{be}}\} \text{ and } E_{it}^{\max} = g_i^* ; \quad \forall i, \forall t \quad (67)$$

$$R_{it}^{\min} = r_{it}^* \text{ and } R_{it}^{\max} = \min\{r_i^{\max}, g_i^{\max} - E_{it}^{\min}\} ; \quad \forall i, \forall t \quad (68)$$

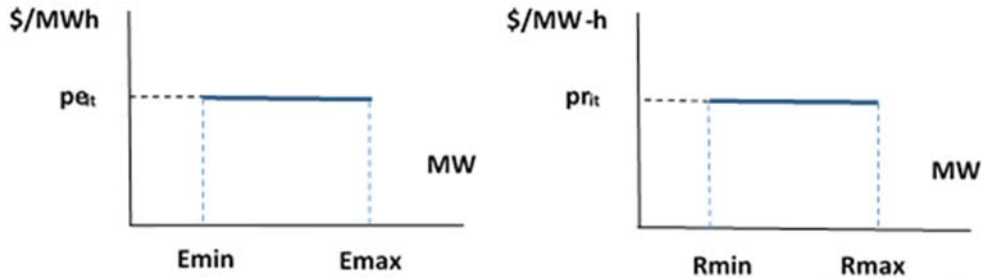


Figure 10 – Energy and reserve generation supply offers

c. Market Clearing Model

The market coordinator clears a joined energy and reserve market for each hour, finding quantities of energy and reserves to procure in order to minimize the cost of supplying demand while meeting network and security constraints. The market-clearing problem to be solved is the following:

$$\min_{g_{it}, r_{it}} \sum_i [p e_{it} \cdot g_{it} + p r_{it} \cdot r_{it}] ; \quad \forall t \quad (69)$$

Subject to:

$$\sum_{i \in I_n} g_{it} - \sum_{m \in M_n} B_{nm} \cdot (\theta_{nt} - \theta_{mt}) = D_{nt} ; \quad \forall n, \forall t \quad (70)$$

$$-FN_{nm}^{max} \leq B_{nm} \cdot (\theta_{nt} - \theta_{mt}) \leq FN_{nm}^{max} ; \quad \forall n, \forall m \in M_n, \forall t \quad (71)$$

$$\sum_i r_{it} \geq g_{it} + r_{it} ; \quad \forall i, \forall t \quad (72)$$

$$E_{it}^{min} \cdot o_{it} \leq g_{it} \leq E_{it}^{max} \cdot o_{it} ; \quad \forall i, \forall t \quad (73)$$

$$R_{it}^{min} \cdot o_{it} \leq r_{it} \leq R_{it}^{max} \cdot o_{it} ; \quad \forall i, \forall t \quad (74)$$

$$g_{it} + r_{it} \leq E_{it}^{max} + R_{it}^{min} ; \quad \forall i, \forall t \quad (75)$$

Constraints (70), (71) and (72) are equivalent to (49), (50) and (54). Equations (73)-(75) ensure that the offer limits are met. Notice that o_{it} is an integer variable so this market-clearing model is a MILP problem.

Chapter 8 Distributed Scheduling Simulations

This chapter presents the results of the numerical simulations carried out to implement and illustrate the proposed distributed day-ahead scheduling model.

8.1 Test System Description

The test system is a six-bus three-generator system adapted from [15]. The topology is shown below and the bus, branch and generation technical data is included in Appendix D. The system has three generation buses, three load buses, and eleven transmission lines. Total installed capacity is 530 MW and maximum demand is 330 MW. Generator capacities are 200 MW at bus 1 (G1), 150 MW at bus 2 (G2) and 180 MW at bus 3 (G3).

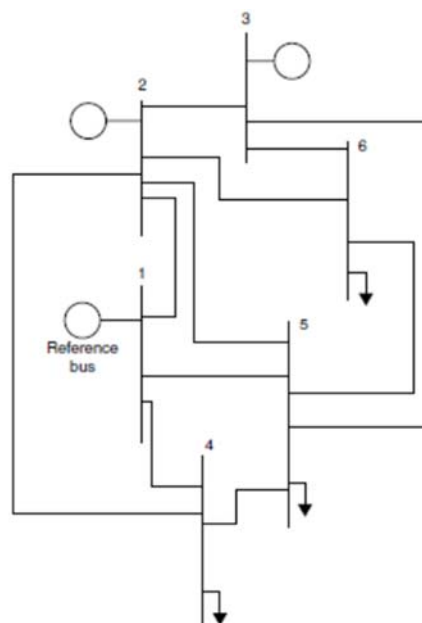


Figure 11 – Six-bus test system (source: Wood et al., 2014)

The system load profile is defined over a horizon of 12 time periods, as shown in Figure 12. Total load varies between 180 MW and 330 MW, and demand at each of the three load buses 4, 5 and 6 varies between 60 and 110 MW respectively. The power factor of the three loads L4, L5 and L6 is 0.98.

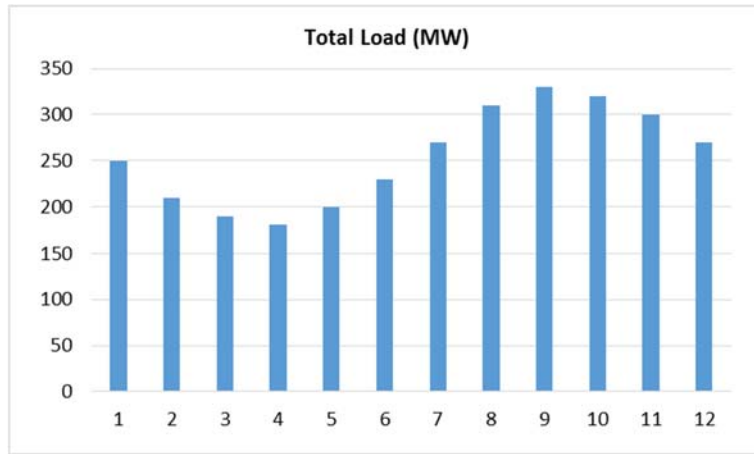


Figure 12 – Test system load profile

Generation cost (\$/h) is given as a quadratic function of generated power (MW), such that $C(P) = a.g^2 + b.g + c$. Generation cost coefficients a (\$/MW²), b (\$/MW) and c (\$), other cost data and initial conditions can be found in Appendix D. Any two generators can carry all the load of the system and generators G1 and G3 can supply alone the minimum load. Therefore, energy and reserves should be allocated with economic criteria. The following table presents the main cost assumptions, where MgC is marginal cost.

Table 10. Generation Cost Assumptions

ID	P max (MW)	P min (MW)	MgC max (\$/MWh)	MgC min (\$/MWh)	No Load Cost (\$/h)	Startup (\$)	Reserve (\$/MW-h)
G1	200	50.0	13.80	12.20	213.1	300.0	4.00
G2	150	37.5	13.00	11.00	200.0	150.0	3.00
G3	180	45.0	13.50	11.50	240.0	100.0	3.00

The objective of the simulations was to schedule generation energy and reserves for the test system over the 12-period operation horizon. Notice that the objective functions (48) and (59) are quadratic functions so mixed-integer quadratic programming (MIQP) is required for the centralized and PBCU models, whereas the market clearing model is a MILP problem.

The models and simulations were implemented using CPLEX v12.6.1. The programming codes in OPL (ILOG) can be found in Appendix E. Also MATPOWER 5.0 [168] (on MATLAB R2016a) was used for OPF runs. The processing equipment was the same used in Part I.

8.2 Simulation No.1 – Energy Only

The first simulation only considers generation energy scheduling, without reserves. All the models described in the precedent chapter were simplified accordingly. The results of the centralized solution are shown below, indicating the power output in MW of each generation unit for all the time periods of the scheduling horizon. As seen in the table, units G1 and G2 are committed all the time, while the more expensive unit G3 is only committed during the peak load period H08-H10. The total operating cost is \$41,942, of which \$41,842 is the cost of energy and there is a \$100 cost corresponding to the startup of unit G3. From period H08 to H11 there is congestion in the network with a few lines reaching the operation limit.

Table 11. Energy Only Centralized Generation Schedule (MW)

Gen.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G1	109.32	84.31	71.81	65.56	78.06	96.81	121.82	114.93	136.90	125.96	168.72	121.82
G2	140.68	125.69	118.19	114.44	121.94	133.19	148.18	122.28	126.48	123.86	131.28	148.18
G3								72.79	66.62	70.18		
Total	250.0	210.0	190.0	180.0	200.0	230.0	270.0	310.0	330.0	320.0	300.0	270.0

8.2.1 Marginal-Cost vs Average-Cost-Based Prices

In a market setting, generators are paid a price for the energy provided, and the associated revenue should recover production costs. Economics dictates that marginal cost pricing is the efficient pricing methodology, and its application to an electrical network produces Locational Marginal Prices (LMPs). However, the UC problem solved in the centralized solution is a mixed-integer mathematical program, and therefore there is not Lagrangean multipliers that can be used as prices. The way to extract LMPs is to fix the optimal commitment and solve the problem again as a convex optimization program and find the corresponding LMPs for each time period. The resulting prices for the energy only simulation, at the nodes where generators are located, are shown below. It can be seen that from H08 to H11 there are spatially differentiated energy prices because of network congestion.

Table 12. Marginal-Cost-Based Prices (\$/MWh) for Energy Only Centralized Solution

Pe	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	12.834	12.568	12.435	12.368	12.501	12.701	12.968	12.894	13.128	13.012	13.468	12.968
G02	12.834	12.568	12.435	12.368	12.501	12.701	12.968	12.507	12.582	12.535	12.667	12.968
G03	12.834	12.568	12.435	12.368	12.501	12.701	12.968	11.912	11.820	11.873	16.487	12.968

If generators are paid LMPs they will recover variables costs but it does not guarantee that they get enough profit to recover no load costs (parameter c in the generation cost data) and startup costs. Hence, make-whole payments may be needed, as it is the standard practice in current LMP-based-markets. This is especially true in the test system, since no load costs are high. In fact, a direct calculation shows that LMPs (Table 12) payments of the optimal generation schedule (Table 11) would produce a loss for each committed generator in every time period, and a total make-whole payment of \$3,067 would be required.

The important consequence is that a distributed market that would offer these LMPs to generators would not induce an optimal commitment and dispatch of generation. In fact, no generator would be willing to run and take a loss, unless an extra payment would be provided. From the mathematical point of view it means that, even if there is no duality gap or if it is small, a distributed method that “solves” the dual optimization problem cannot be used in practice unless make-whole payments are also provided. The reason is that generators cannot be forced to operate at a loss. This was easily verified running the Price-Base Unit Commitment of generators using LMPs, which resulted in that only G3 was willing to run for a few hours, to take advantage of the price peak at H11.

Based on the premise that a distributed market should only remunerate generators via prices, without make-whole payments, the interesting question is if there exists a set of prices that can induce the same optimal generation schedule of the centralized solution. A direct answer is not easy to find³³, but using heuristics one can investigate prices that induce a generation commitment close to the centralized solution. One of such potential set of prices is formed by the prices that exactly allow to recover production costs. Mathematically, they are the prices that are equal to the average cost of production, including prorated startup costs. Those prices are shown below for the test system.

Table 13. Average-Cost-Based Prices for Energy Only Centralized Solution (\$/MWh)

Pe	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	14.21	14.65	15.02	15.27	14.82	14.39	14.07	14.14	13.96	14.04	13.84	14.07
G02	13.01	13.05	13.08	13.10	13.06	13.02	13.01	13.06	13.04	13.05	13.03	13.01
G03	12.84	12.57	12.44	12.37	12.51	12.71	12.97	15.13	15.43	15.25	16.49	12.97

³³ One can formulate a UC problem with the additional constraint that generators will not lose money. This would be a non-linear non-convex problem whose solution is a challenge by itself.

8.2.2 Distributed Scheduling

After running the generator PBUC using average-cost-based prices, the optimal commitment and dispatch of generators (g^*) is shown in Table 14. In most periods the optimal production is equal to the maximum capacity of the units. This was expected, since the optimization try to dispatch the units where their marginal cost is equal to the offered prices of Table 13, which are higher than LMPs. As a result, at these prices the market will have ample supply for each time period. The reason is that generators will be willing to provide up to its optimal self-dispatch if they are to be paid the offered prices.

Table 14. Generators Profit-Maximizing Commitment and Dispatch (MW)

Gen.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	180.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0
G02	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0
G03	0.0	0.0	0.0	0.0	0.0	0.0	120.0	180.0	180.0	180.0	180.0	144.2
Total	330.0	350.0	350.0	350.0	350.0	350.0	470.0	530.0	530.0	530.0	530.0	494.2

Note that apparently is profitable to commit unit G03 during periods H07 and H12, but this is conditional to running at maximum capacity at periods H08 to H10, which we already know from Table 11 that is not optimal. In effect, after preparing generator supply offers according to the established rules, it is found that it is not profitable for G03 to commit the units at those periods. The reason is that the average cost is \$13.5 at maximum output, which is greater than the offered price of \$12.97.

Tables 15 show the generation energy supply offers submitted by all generators to the market clearing process, for each period of the scheduling horizon, in response to the average-cost-based prices offered by the Market Coordinator.

Table 15. Generation Energy Supply Offers

Period	GenID	Pe (\$/MWh)	Emin (MW)	Emax (MW)
H01	G01	14.21	108.60	180.00
H01	G02	13.01	137.45	150.00
H01	G03	12.84	0.00	0.00
H02	G01	14.65	84.14	200.00
H02	G02	13.05	123.58	150.00
H02	G03	12.57	0.00	0.00
H03	G01	15.02	71.79	200.00
H03	G02	13.08	117.44	150.00
H03	G03	12.44	0.00	0.00
H04	G01	15.27	65.53	200.00
H04	G02	13.10	114.13	150.00
H04	G03	12.37	0.00	0.00
H05	G01	14.82	77.89	200.00
H05	G02	13.06	121.33	150.00
H05	G03	12.51	0.00	0.00
H06	G01	14.39	96.59	200.00
H06	G02	13.02	132.64	150.00
H06	G03	12.71	0.00	0.00
H07	G01	14.07	121.55	200.00
H07	G02	13.01	137.45	150.00
H07	G03	12.97	0.00	0.00
H08	G01	14.14	114.53	200.00
H08	G02	13.06	121.33	150.00
H08	G03	15.13	70.15	180.00
H09	G01	13.96	136.12	200.00
H09	G02	13.04	126.11	150.00
H09	G03	15.43	64.31	180.00
H10	G01	14.04	125.00	200.00
H10	G02	13.05	123.58	150.00
H10	G03	15.25	67.67	180.00
H11	G01	13.84	164.98	200.00
H11	G02	13.03	129.06	150.00

Period	GenID	Pe (\$/MWh)	Emin (MW)	Emax (MW)
H11	G03	16.49	50.13	180.00
H12	G01	14.07	121.55	200.00
H12	G02	13.01	137.45	150.00
H12	G03	12.97	0.00	0.00

For the market-clearing stage, a standard OPF solver was used (Matpower 5.0). The market-clearing problem is an OPF problem, except for the integer variable that defines whether a generation offer is accepted or not. However, Matpower 5.0 includes a single-period “unit de-commitment” algorithm, based on a combinatorial heuristic, which can run with the standard DC OPF, and can be used to simulate the binary decision. Since there are not inter-temporal constraints, it is possible to clear each market period individually, greatly simplifying the problem. The resulting final dispatch of generation units for each market period is shown in the following table.

Table 16. Energy Only Distributed Generation Schedule (MW)

Gen.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	108.60	84.14	71.79	65.53	77.89	96.59	121.55	115.75	137.61	126.74	164.98	121.55
G02	141.40	125.86	118.21	114.47	122.11	133.41	148.45	124.10	128.08	125.59	135.02	148.45
G03								70.15	64.31	67.67		

Note that the market-clearing process did not take the offer of generator G03 at period H11, and the commitment of units of the distributed solution is equal to the centralized solution of Table 11. The total operating cost is essentially the same, \$41,946 of the distributed UC vs \$41,942 of the centralized solution. In terms of individual dispatch, the differences are small, as indicated below, in the order of 3.5% for G03.

Table 17. Centralized vs Distributed Energy Generation Dispatch Difference (%)

Gen.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	-0.66%	-0.20%	-0.03%	-0.05%	-0.22%	-0.23%	-0.22%	0.71%	0.52%	0.62%	-2.22%	-0.22%
G02	0.51%	0.14%	0.02%	0.03%	0.14%	0.17%	0.18%	1.49%	1.27%	1.40%	2.85%	0.18%
G03									-3.63%	-3.47%	-3.58%	

8.2.3 Discussion

We also used a standard AC OPF solver to do the market clearing process, which is beneficial to ensure the feasibility of the final solution and minimize security corrections. We found differences between the AC and DC solutions, mainly due to the increase of generation to provide for energy losses and the varying voltage profile to allow AC reactive power flows. On the other hand the DC OPF solver exhibited numerical and convergence problems at some periods, for instance during peak demand conditions when the transmission network is congested³⁴. In general the AC OPF solver had less convergence problems and provided more stable solutions.

From the market clearing solution is possible to find LMPs for each time period, but it is clear that using them to pay for dispatched energy would not provide enough revenue to pay all generators their offer costs³⁵. On the other hand, a pay-as-bid pricing methodology –paying generator the offered nodal prices– can ensure recovery of energy costs, but may provide little profits to make the market sustainable. Table 18 shows the profit/loss for generation units under such a pay-as-bid policy.

³⁴ In some cases it was necessary to relax transmission limits to find a solution.

³⁵ Mainly because of generation units constrained to operate at minimum output.

Table 18. Generators Profit/Loss with Pay-as-Bid Pricing (+/- \$)

P/L (\$)	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12	StUp	Total
G01	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.5	1.2	1.8	0.0	0.0	0.0	4.5
G02	0.8	1.1	0.5	0.2	0.4	0.2	1.5	1.5	0.9	1.0	2.1	1.5	0.0	11.8
G03								25.0	25.0	25.0			-100.0	-25.1

On the other hand a single-marginal-price policy, paying a uniform price equal to the most expensive offer accepted at each time period, would provide more robust profits as indicated below.

Table 19. Generators Profit/Loss with Single Marginal Price Policy (+/- \$)

P/L (\$)	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12	StUp	Total
G01	0.0	0.0	0.0	0.0	0.0	0.0	0.0	116.1	203.5	155.1	0.0	0.0	0.0	474.7
G02	170.5	202.5	229.8	248.6	215.4	183.0	158.8	258.4	307.0	277.3	469.2	158.8	0.0	2879.4
G03								25.0	25.0	25.0			-100.0	-25.1

Note that G03 is a pure peaking unit and does not have profits (so it would need to rely on a capacity market as in current RTOs). Also neither pricing policy ensures full recovery of start-up costs. The reason is that generator G03 was expecting to be online during four time periods (submitted offers for periods H08 to H11) and prorated the startup cost accordingly. However it was committed for three time periods and hence the deficit. A potential solution is to implement offer blocks, specifying consecutive periods of time where an offer is valid. But this would reintroduce inter-temporal constraints and complicate the market clearing process.

In any case, the preliminary dispatch should be informed to generators so they can confirm that it is acceptable, and otherwise report it to the MC for adjustments. On the other hand, the proposed distributed scheduling methodology does not ensure that the solution is

always feasible or profitable. The following table discusses possible situations that can occur during the market-clearing process and how the Market Coordinator should deal with them.

Table 20. Distributed Scheduling Adjustment Actions

Situation	Adjustment Action
1) Not enough capacity is offered to clear the market	MC increases offered prices during the time periods and locations where there is an energy deficit
2) Some generation operating limit (e.g. ramp up limit) is not met in the preliminary scheduling.	The generator can review and update her supply offer (quantities) to meet technical limits, or report a specific constraint so the MC can take into account when clearing the market
3) The preliminary scheduling does not result in full recovery of offered energy at the remuneration prices	The generator can review and update her supply offer to cover the deficit or suggest a price increase that ensure full cost recovery.

8.3 Simulation No.2 – Energy and Reserves

The second simulation considers the distributed scheduling of generation energy and spinning reserves. For the purposes of comparison, the results of the centralized solution are shown in Table 21, indicating the power output and reserved capacity in MW of each generation unit for all the time periods of the scheduling horizon. Given the requirement of having sufficient spinning reserve in the system (54) all the generating units need to be committed, and the main decision is the allocation of energy and reserves among units.

Table 21. Energy and Reserves Centralized Scheduling (MW)

Gen	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	104.43	87.18	78.56	72.58	82.87	95.81	113.06	136.60	152.69	144.35	128.82	113.06
G02	81.52	71.17	66.00	62.42	68.59	76.34	86.68	101.05	111.01	105.85	96.25	86.68
G03	64.05	51.65	45.44	45.00	48.54	57.85	70.26	72.35	66.30	69.80	74.93	70.26
Total	250.0	210.0	190.0	180.0	200.0	230.0	270.0	310.0	330.0	320.0	300.0	270.0

Res	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	20.57	17.82	16.44	17.42	17.13	19.19	21.94	23.40	27.31	25.65	21.18	21.94
G02	43.48	33.83	29.00	27.58	31.41	38.66	48.32	48.95	38.99	44.15	53.75	48.32
G03	60.95	53.35	49.56	45.00	51.46	57.15	64.74	87.65	113.70	100.20	75.07	64.74
Total	125.0	105.0	95.0	90.0	100.0	115.0	135.0	160.0	180.0	170.0	150.0	135.0

Energy cost is \$43,511, reserve cost is \$4,930 and there is no startup costs so the total operating cost is \$48,441. There is network congestion during time periods H08 to H11, with exactly one line reaching its operating limit. Notice that there is no fixed reserve requirement, the optimization process defines how much reserve is needed at each time period. The sum of the generation and reserve of each unit is the committed capacity, and every period the total reserve is equal to the maximum committed capacity. Interestingly, the committed capacity is equal for all generating units unless a unit has reached its maximum capacity, as shown below³⁶.

Table 22. Committed Capacity of Centralized Scheduling (MW)

Cap.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	125.0	105.0	95.0	90.0	100.0	115.0	135.0	160.0	180.0	170.0	150.0	135.0
G02	125.0	105.0	95.0	90.0	100.0	115.0	135.0	150.0	150.0	150.0	150.0	135.0
G03	125.0	105.0	95.0	90.0	100.0	115.0	135.0	160.0	180.0	170.0	150.0	135.0
Total	375.0	315.0	285.0	270.0	300.0	345.0	405.0	470.0	510.0	490.0	450.0	405.0

8.3.1 Marginal-Cost vs Average-Cost-Based Prices

In order to extract price information from the centralized solution it is necessary to fix the commitment of units, solve the corresponding continuous optimization problem and obtain the Lagrangean multipliers of the power balance and reserve constraints. The latter cannot be

³⁶ The reason is that the total reserve is minimized by equalizing the committed capacity among units.

directly interpreted as shadow prices, but after adequate calculations it is possible to find the following marginal prices.

Table 23. Marginal-Cost-Based Prices for Energy and Reserves of Centralized Solution (\$/MWh)

Pe	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	12.782	12.598	12.506	12.443	12.552	12.690	12.874	13.125	13.300	13.208	13.039	12.874
G02	11.782	11.598	11.506	11.443	11.552	11.690	11.874	16.130	22.050	16.215	14.301	11.874
G03	11.782	11.598	11.506	11.443	11.552	11.690	11.874	11.905	17.559	11.868	11.940	11.874

Pr	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000
G02	3.000	3.000	3.000	3.000	3.000	3.000	3.000	7.000	12.740	7.000	5.260	3.000
G03	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	8.740	3.000	3.000	3.000

Paying these energy prices to generators would not recover generation costs and would result in losses for most time periods, actually only G02 would make some profits at the peak load periods. Required make-whole payment would amount to \$3,254. On the other hand, there are not fixed reserve costs, so paying the above prices for reserves would result in no loss and occasional profits at a few peak-load periods.

In any case, a distributed market offering the prices of Table 23, without additional payments, would fail to induce an optimal generation dispatch and would result in undersupply and generation shortages. There may be different sets of prices that could induce an optimal dispatch without extra-payments. One of those sets is formed by prices equal to the average cost of production, allowing full cost recovery. These prices are shown below.

Table 24. Average-Cost-Based Prices for Energy and Reserves of Centralized Solution (\$/MWh)

Pe	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	14.27	14.58	14.81	15.00	14.69	14.41	14.16	13.96	13.88	13.92	14.01	14.16
G02	13.52	13.78	13.96	14.10	13.86	13.64	13.42	16.13	22.05	16.22	14.31	13.42
G03	15.06	15.87	16.46	16.50	16.14	15.42	14.77	14.69	17.56	14.79	14.60	14.77

Pr	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
G02	3.00	3.00	3.00	3.00	3.00	3.00	3.00	7.00	12.74	7.00	5.26	3.00
G03	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	8.74	3.00	3.00	3.00

8.3.2 Distributed Scheduling

When generators are offered the average-cost-based prices as minimum payment for energy and reserves, the profit-maximizing generation values of Table 25 are found using a PBUC. As observed, there is sufficient supply to clear energy and reserve markets. Note that for time periods where reserve prices are above cost, generators do prefer to keep aside some capacity for the reserve market and reduce energy generation.

Table 25. Profit-Maximizing Energy and Reserves Generation (MW)

Gen	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	180.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0	200.0
G02	150.0	150.0	150.0	150.0	150.0	150.0	150.0	101.07	111.19	106.13	96.57	150.0
G03	180.0	180.0	180.0	180.0	180.0	180.0	180.0	180.0	66.6	180.0	180.0	180.0
Total	510.0	530.0	530.0	530.0	530.00	530.0	530.0	481.07	377.79	486.13	476.57	530.0

Res	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
G02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	48.93	38.81	43.87	53.43	0.00
G03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	113.40	0.00	0.00	0.00

Based on the PBCU profit-maximizing quantities and the rules to prepare supply offers, the following are generators energy and reserve offers:

Table 26. Generation Energy and Reserve Offers

Period	GenID	Pe (\$/MWh)	Emin (MW)	Emax (MW)	Pr \$/(MW-h)	Rmin (MW)	Rmax (MW)
H01	G01	14.27	104.16	180.00	4.00	0.00	95.84
H01	G02	13.52	81.10	150.00	3.00	0.00	68.90
H01	G03	15.06	63.94	180.00	3.00	0.00	116.06
H02	G01	14.58	87.09	200.00	4.00	0.00	112.91
H02	G02	13.78	71.03	150.00	3.00	0.00	78.97
H02	G03	15.87	51.55	180.00	3.00	0.00	128.45
H03	G01	14.81	78.22	200.00	4.00	0.00	121.78
H03	G02	13.96	65.73	150.00	3.00	0.00	84.27
H03	G03	16.46	45.36	180.00	3.00	0.00	134.64
H04	G01	15.00	72.35	200.00	4.00	0.00	127.65
H04	G02	14.10	62.23	150.00	3.00	0.00	87.77
H04	G03	16.50	45.00	180.00	3.00	0.00	135.00
H05	G01	14.69	82.56	200.00	4.00	0.00	117.44
H05	G02	13.86	68.54	150.00	3.00	0.00	81.46
H05	G03	16.14	48.50	180.00	3.00	0.00	131.50
H06	G01	14.41	95.46	200.00	4.00	0.00	104.54
H06	G02	13.64	76.00	150.00	3.00	0.00	74.00
H06	G03	15.42	57.70	180.00	3.00	0.00	122.30
H07	G01	14.16	112.74	200.00	4.00	0.00	87.26
H07	G02	13.42	86.17	150.00	3.00	0.00	63.83
H07	G03	14.77	70.24	180.00	3.00	0.00	109.76
H08	G01	13.96	136.12	200.00	4.00	0.00	63.88
H08	G02	16.13	37.50	101.07	7.00	48.93	112.50
H08	G03	14.69	81.45	180.00	3.00	0.00	98.55
H09	G01	13.88	152.29	200.00	4.00	0.00	47.71
H09	G02	22.05	37.50	111.19	12.74	38.81	112.50
H09	G03	17.56	45.00	66.60	8.74	113.40	135.00
H10	G01	13.92	143.27	200.00	4.00	0.00	56.73
H10	G02	16.22	37.50	106.13	7.00	43.87	112.50
H10	G03	14.79	78.51	180.00	3.00	0.00	101.49
H11	G01	14.01	128.80	200.00	4.00	0.00	71.20
H11	G02	14.31	57.74	96.57	5.26	53.43	92.26

Period	GenID	Pe (\$/MWh)	Emin (MW)	Emax (MW)	Pr \$/(MW-h)	Rmin (MW)	Rmax (MW)
H11	G03	14.60	84.34	180.00	3.00	0.00	95.66
H12	G01	14.16	112.74	200.00	4.00	0.00	87.26
H12	G02	13.42	86.17	150.00	3.00	0.00	63.83
H12	G03	14.77	70.24	180.00	3.00	0.00	109.76

The market-clearing process is a mixed-integer problem and was implemented with a DC optimal power flow using CPLEX. To improve solution convergence, a transmission limit was slightly increased. The results of the distributed scheduling of energy and reserves are shown in Table 27³⁷.

Table 27. Energy and Reserves Distributed Generation Schedule (MW)

Gen.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	104.96	87.42	78.91	72.77	82.96	96.30	113.59	136.12	152.29	143.27	128.80	113.59
G02	81.10	71.03	65.73	62.23	68.54	76.00	86.17	92.43	111.11	98.22	86.86	86.17
G03	63.94	51.55	45.36	45.00	48.50	57.70	70.24	81.45	66.60	78.51	84.34	70.24

Res.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	20.04	17.58	16.09	17.23	17.04	18.70	21.41	23.88	27.71	26.73	21.20	21.41
G02	43.90	33.97	29.27	27.77	31.46	39.00	48.83	57.57	38.89	51.78	63.14	48.83
G03	61.06	53.45	49.64	45.00	51.50	57.30	64.76	78.55	113.40	91.49	65.66	64.76

The total operating cost of the centralized and distributed generation schedules are essentially the same, but there are some small differences on the dispatch of the individual generation units between both solutions. Table 28 shows the percentage difference on dispatched energy.

³⁷ The off-the-shelf OPF solver used in the first simulation has limitations to manage integer variables and non-fixed reserve constraints, so it was not used for the second simulation.

The differences are explained mainly by numerical approximations, due the relaxation of the distributed market-clearing problem during peak load periods³⁸.

Table 28. Centralized vs Distributed Generation Dispatch Difference (%)

Gener.	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12
G01	-0.51%	-0.28%	-0.45%	-0.26%	-0.11%	-0.51%	-0.47%	0.35%	0.26%	0.75%	0.02%	-0.47%
G02	0.52%	0.20%	0.41%	0.30%	0.07%	0.45%	0.59%	8.53%	-0.09%	7.21%	9.76%	0.59%
G03	0.17%	0.19%	0.18%	0.00%	0.08%	0.26%	0.03%	12.58%	-0.45%	-2.48%	-2.56%	0.03%

As discussed in the first simulation, a pay-as-bid pricing policy should be used to allow full recovery of generation costs without extra payments. The table below shows generators profit/loss results with such policy. Profits are concentrated during peak-load time periods for some generators, but not all. A single marginal price policy would provide more stable and robust profits.

Table 29. Generators Profit/Loss with Pay-As-Bid Pricing Policy (+/- \$)

P/L (\$)	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	H11	H12	Total
G01	1.2	0.6	1.6	1.1	0.8	1.4	1.1	0.0	0.0	0.0	0.0	1.1	8.9
G02	0.0	0.0	0.0	0.0	0.0	0.0	0.0	490.1	1370.9	499.6	221.1	0.0	2581.6
G03	0.0	0.0	0.0	0.0	0.0	0.0	0.0	25.0	826.1	25.0	25.0	0.0	900.9

³⁸ An AC OPF based market clearing solution should offer better convergence, but it is a non-linear mixed integer problem that even for a single period is hard to solve.

Chapter 9 Conclusions of Part II

The simulation of the proposed distributed method for scheduling generation in an energy-only market shows that, using an appropriate set of prices, it is possible to closely emulate the results of a conventional centralized solution, without need of providing make-whole payments to generators. The method assumes rational profit-maximizing behavior of generators to prepare adequate energy supply offers incorporating technical constraints, minimizes information exchange of individual generators with a market coordination entity and simplifies the market clearing process.

There are different alternatives about how to discover an adequate set of prices. The obvious one is through an iterative process, emulating a distributed Lagrangian Relaxation solution of the centralized UC problem, but ensuring that generators recover their costs. However, the implementation of such a procedure can be slow and cumbersome. This approach can be improved or replaced by a good initial estimate based on price forecasting techniques. The estimates can be refined with a few iteration steps as required.

Actually, price forecasting is a research field in itself [169], and currently there is plenty of methods and techniques aimed to produce good electricity price forecasts, depending on the specific applications. These methods range from classic regression/statistical analysis to modern AI/heuristic methods, including production models, oligopolistic competition, game theory, agent-based simulation, optimization, etc. The combination of these advanced forecasting

techniques with improved system modeling should deliver good price forecasts to implement and gradually improve the results of distributed and decentralized scheduling models.

Likewise, the simulation of the distributed day-ahead scheduling of energy and reserves shows that the proposed method can accommodate transactions in an electricity market with different products and complex security constraints, and still be able to produce results similar to an elaborated centralized solution. The benefits and advantages of distributed decentralized operational procedures for the future electricity grid are multiple. First, stemming from the simplification and transparency of market operations, second from increasing the autonomy and flexibility of operating decisions of the different market agents, and third from reallocating generation risks from consumers to producers. These benefits should outweigh any potential efficiency loss from the implementation of distributed solutions, compared to a theoretical global optimum generation schedule attained via centralized decision-making.

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Appendix A State-Based vs Scenario-Based Stochastic Process Representation

A stochastic process can be described by the different states on which the uncertain variables(s) can be found, or by scenarios that are specific realizations of the process. To illustrate the difference between both representations, we use the example of a stochastic process with three stages as shown in the following scenario-tree diagram.

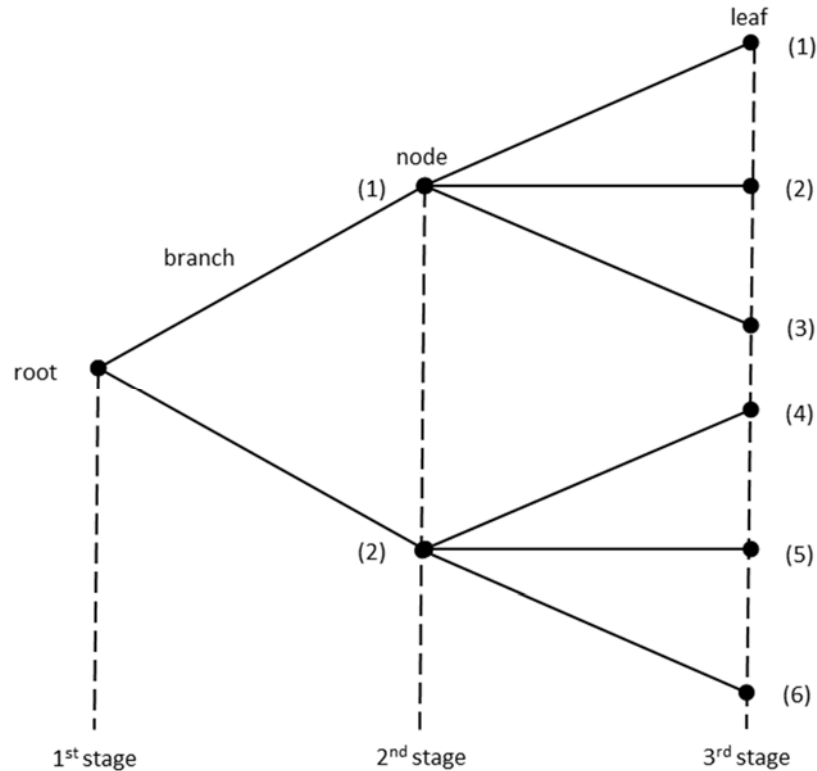


Figure 13 – Representation of a stochastic process by a scenario tree

For convenience, the stochastic process is divided in discrete stages, which are the points in time where a decision is made, based on the value of the random variable(s). A scenario tree is composed of nodes and branches, where the nodes represent the states of the variable(s) or problem at a particular stage, and the branches the transition from one state to another. Each

node has a predecessor and several successors. The first node, at the beginning of the decision horizon is called the root, where the first-stage decisions are made. Nodes connected to the root belong to the second stage, where second-stage decisions are made and so on³⁹. The nodes of the final stage are called the leaves of the tree. A particular trajectory from the root to a leaf is a scenario, so the number of scenarios is equal to the number of leaves.

In the example of Figure 13 there is a single state in stage 1, two states in stage 2 and 6 states in stage 3, for a total of 9 states. In addition there are 6 leaves and therefore 6 scenarios. There are always less scenarios than nodes or states. However a state-based representation of the stochastic process, based on the variables associated to the states, is always more compact than the scenario-based representation, based on the variables associated to the scenarios. The reason is that scenario-based representation replicates the state variables located on shared trajectories. Using the same example with a single random variable \tilde{X} , we need 9 state variables x_{ij} to describe the whole process, where i is the stage and j the state. On the other hand, we need 18 scenario variables x_i^s for the process, where i is the stage and s the scenario.

Moreover, we need to add a number of constraints to the problem, to specify that replicated variables belonging to different scenarios represent the same state, for instance in our example $x_2^1 = x_2^2 = x_2^3$. These are called the *non-anticipativity constraints* indicating that future states cannot be anticipated, so decisions are made with the information available at the moment. At least 4 non-anticipativity constraints are required in this example. The advantage of the scenario representation is that the resulting structure is suitable for applying decomposition

³⁹ The first-stage decisions are also known as here-and-now decision, since they are made before the realization of the stochastic process. Second- and further stage decisions are also called recourse or wait-and-see decisions, because they are made after the uncertainty is cleared partially or totally, so they depend on the specific realization of the stochastic process up to that point.

techniques, especially when there are inter-stage constraints. Thus, each scenario is solved independently, and the algorithm is iterated until all the non-anticipativity constraints are met. The downside is the appreciable increase in computational burden.

A complete enumeration and comparison of the number of states and scenarios depends on the number of random variables, stages and states. For a stochastic process with $I+T$ stages (I root + T decision periods), and assuming there are n_v random binary variables (2 states), we find the following:

$$\text{Number of states} = \text{Number of state-variables} = n_v \cdot 2^{(1+T)} = n_v \cdot 2 \cdot 2^T$$

$$\text{Number of scenarios} = n_v \cdot 2^T$$

$$\text{Number of scenario-variables} = n_v \cdot (1 + T) \cdot 2^T$$

$$\text{Ratio between No. of scenarios and No. of states} = 1/2$$

$$\text{Ratio between No. of scenario-variables and No. of state-variables} = (1 + T)/2$$

$$\text{Number of non-anticipativity constraints} = n_v \cdot [2^{(1+T)} - (1 + T)]$$

For the day-ahead unit commitment problem $T = 24$ (assuming hourly dispatch periods), so the scenario-based representation has nearly 12.5 times more variables of the state-based representation, and around 2^{25} additional constraints. These simple calculations also show that a full multi-stage stochastic optimization problem gets very combinatorial and computationally intractable rapidly. In order to formulate feasible models, the following simplifications are usually made base on the characteristics of the specific problem:

- Use a simplified multi-stage version, omitting some stages, scenarios or states.
- Use a two-stage model, assuming all uncertainty is cleared at some moment
- Only model and optimize over a few representative scenarios

Appendix B Generation Reliability Model

The generation reliability model presented in this Appendix is based on [54] and follows the analysis developed in [170].

B.1 Exponential Distribution of Generation Unit Failures

The availability of a generation unit can be represented by a random variable with an exponential distribution. Thus, if \tilde{T} measures the time the unit is in service before a failure and λ is a positive constant, the probability density function of its up time is given by:

$$f(t) = \lambda \cdot e^{-\lambda t} \quad (\text{B.1})$$

The corresponding cumulative probability function and mean value of \tilde{T} are:

$$P[\tilde{T} \leq t] = F(t) = \int_0^t \lambda e^{-\lambda t} dt = 1 - e^{-\lambda t} \quad (\text{B.2})$$

$$E[\tilde{T}] = \int_0^{\infty} t \cdot \lambda e^{-\lambda t} dt = 1/\lambda = m \quad (\text{B.3})$$

$F(t)$ is the failure distribution of the generation unit, and the inverse of the mean up time m (mean time to failure, MTTF) is the unit failure rate λ , which is assumed constant. The probability of unit failure at a short-time interval Δt is equal to $\lambda \cdot \Delta t$. The down or repair time of the unit is also assumed to be exponentially distributed with a constant repair rate μ , the inverse of the mean down or repair time r (mean time to repair, MTTR). The mean time between failures (MTBF) is $m + r$.

B.2 State Space Representation

The operation of a generation unit can be represented by a simple two-state model in a “service and repair” process as shown in Figure 14, where λ and μ are the unit failure and repair rate respectively. Therefore, the operating lifetime of the unit can be described as

cycles of service (unit up) and repair (unit down) periods, as indicated in Figure 15, whose respective durations T_U and T_D are random variables with exponential probability distributions $f_U(t)$ and $f_D(t)$.

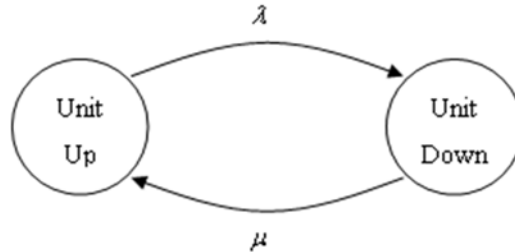


Figure 14 – Two-state model of a generation unit operation

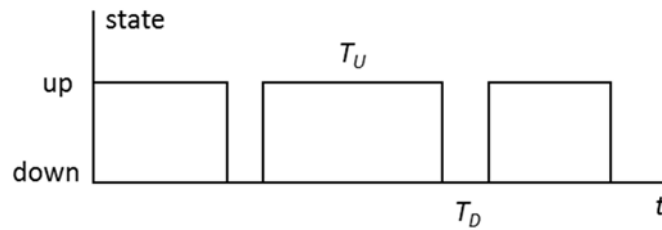


Figure 15 – Generation unit operation cycle

The transition between the up (U) and down (D) states of the generation unit can be characterized as a stochastic two-state Markov process. Thus, the transition probability from U to D is $\lambda \cdot \Delta t$ and from D to U is $\mu \cdot \Delta t$. Solving the two-state Markov process (the details have been omitted), the following expressions for the state probabilities are obtained assuming the unit is put in service at $t = 0$:

$$P_U(t) = \frac{\mu}{\lambda + \mu} + \frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} \quad (\text{B.4})$$

$$P_D(t) = \frac{\lambda}{\lambda + \mu} - \frac{\lambda}{\lambda + \mu} e^{-(\lambda + \mu)t} \quad (\text{B.5})$$

Equation (B.4) gives the probability of the unit to be available and (B.5) the probability of the unit to have failed, both as a function of time. For a period of time large enough, the long-run probabilities converge to the following values:

$$P_U = \frac{\mu}{\lambda + \mu} \quad (\text{B.6})$$

$$P_D = \frac{\lambda}{\lambda + \mu} \quad (\text{B.7})$$

B.3 Unit Unavailability

The conventional definitions of generation unit availability (A) and unavailability (U) are:

$$A = \frac{MTTF}{MTBF} = \frac{m}{m + r} \quad (\text{B.8})$$

$$U = \frac{MTTR}{MTBF} = \frac{r}{m + r} \quad (\text{B.9})$$

Using the reciprocals of m and r , it is easy to show that (B.6) and (B.7) are identical to (B.8) and (B.9). The unavailability index U is a good approximation of the long-run unit failure probability, even when preventive maintenance is considered provided that maintenance is scheduled during low demand periods. The unavailability is then an adequate estimator of the probability of finding a unit out of service at some point in the future

Other parameter commonly used to measure generation units reliability is the Forced Outage Rate (FOR), defined below. If computed over a long period of time, the FOR is equivalent to unit unavailability.

$$FOR = \frac{\sum \text{forced outage hours}}{\sum \text{in service hours} + \sum \text{forced outage hours}} \quad (\text{B.10})$$

Appendix C Part I Programming Codes

The following is the OPL programming code used to implement the simulations of Chapter 5 with CPLEX. All input and output data was stored and handled in MS Access relational databases.

C.1 Case 1 – Global Reserve vs Locational Reserves

```
// DETERMINISTIC UNIT COMMITMENT WITH HEURISTIC GLOBAL SPINNING RESERVES

// Data & Parameters

{string} periods=...;           // number of (hourly) periods
{string} avunits=...;          // available generating units
{string} spunits=...;          // spinning reserve units
{string} nodes=...;            // electrical nodes (buses)
{string} lines=...;            // transmission lines

float base=...;                 // base power (MVA)

tuple unitData {
    string bus; float Pmax; float Pmin;
    float RU; float RD; float RR;
    float UT; float DT;
    float UTo; float DTo; float Uo; float Go;
    float BP1; float BP2; float BP3; float BP4;
    float EC1; float EC2; float EC3; float EC4;
    float SUC; float REC;
}

tuple busData {
    string Type;
    string kV;
}

tuple branchData {
    string fromN;
    string toN;
    float Xpu;
    float FNmax;
}

tuple busTime {
    string bus;
    string time;
}
```

```

tuple genTime {
    string gen;
    string time;
}

unitData unit[avunits]=...;
busData node[nodes]=...;
branchData line[lines]=...;
{busTime} busTimes=...;
{genTime} genTimes=...;
float Dem[busTimes]=...;
float Rmax[genTimes]=...;
float pi= 3.141592654;

// Decision variables

dvar float+ g[avunits][periods];           // generation variable
dvar float+ r[avunits][periods];           // reserve variable
dvar boolean u[avunits][periods];          // commitment variable
dvar boolean x[avunits][periods];          // start up variable
dvar boolean y[avunits][periods];          // shut down variable
dvar float theta[nodes][periods] in -pi..pi; // node voltage angles

// Expressions

dexpr float StartUpCost= sum(t in periods, i in avunits) unit[i].SUC * x[i][t];
dexpr float EnergyCost = sum(t in periods, i in avunits) piecewise {unit[i].EC1->unit[i].BP1;
unit[i].EC2->unit[i].BP2; unit[i].EC3->unit[i].BP3; unit[i].EC4->unit[i].BP4;
unit[i].EC4} g[i][t];
dexpr float ReserveCost= sum(t in periods, i in avunits) unit[i].REC * r[i][t];
dexpr float TotalCost= StartUpCost + EnergyCost + ReserveCost;

// Model

minimize TotalCost;

subject to {

    forall(t in periods)
        swingbusAngle:
            theta["113"][t] == 0 ;

    forall(t in periods, l in lines)
        anglelimits:
            -pi/2 <= theta[line[l].fromN][t]- theta[line[l].toN][t] <= pi/2;

    forall(t in periods, n in nodes)
        DCnodalBalances:
            sum(i in avunits: unit[i].bus == n) ( g[i][t] / base ) -
            sum(l in lines: line[l].fromN == n) ( ( theta[n][t] -
theta[line[l].toN][t] ) / line[l].Xpu ) -
            sum(l in lines: line[l].toN == n) ( ( theta[n][t] -
theta[line[l].fromN][t] ) / line[l].Xpu ) == Dem[<n,t>];

```

```

forall(t in periods, l in lines)
    DCmaxFlows:
        ( -line[l].FNmax / base ) <= ( theta[line[l].fromN][t] - theta
[line[l].toN][t] ) / line[l].Xpu <= ( line[l].FNmax / base ) ;

forall(t in periods, i in avunits)
    minGeneration:
        g[i][t] >= unit[i].Pmin * u[i][t];

forall(t in periods, i in avunits)
    maxGeneration:
        g[i][t] + r[i][t] <= unit[i].Pmax * u[i][t];

forall(i in avunits)
    initialRamp:
        -unit[i].RD <= g[i]["H01"] - unit[i].Go <= unit[i].RU;

forall(t in periods, i in avunits : t!="H01")
    rampLimits:
        -unit[i].RD <= g[i][t] - g[i][prev(periods,t)] <= unit[i].RU;

forall(i in avunits)
    initialStartup:
        x[i]["H01"] - y[i]["H01"] == u[i]["H01"] - unit[i].Uo;

forall(t in periods, i in avunits : t != "H01")
    startupSequence:
        x[i][t] - y[i][t] == u[i][t] - u[i][prev(periods,t)];

forall(t in periods, i in avunits)
        x[i][t] + y[i][t] <= 1;

forall(i in avunits, T in 1..24 : unit[i].Uo == 1 && T <= (unit[i].UT-
unit[i].UTo) )
        u[i][item(periods,T-1)] == 1;

forall(t in periods, i in avunits, T in 1..23-ord(periods,t) : T <=
(unit[i].UT-1) )
        x[i][t] <= u[i][next(periods,t,T)];

forall(i in avunits, T in 1..24 : unit[i].Uo == 0 && T <= (unit[i].DT-
unit[i].DTo) )
        u[i][item(periods,T-1)] == 0;

forall(t in periods, i in avunits, T in 1..23-ord(periods,t) : T <=
(unit[i].DT-1) )
        y[i][t] <= 1 - u[i][next(periods,t,T)];

forall(t in periods)
    spinningReserve:
        sum (i in spunits) r[i][t] >= max (i in avunits) ( g[i][t] + r[i][t] );

forall(t in periods, i in spunits)
    reserveLimits:
        r[i][t] <= Rmax[<i,t>] * u[i][t];

```

```

}

// post-processing results

tuple result {
    string periods;
    string avunits;
    float status;
    float dispatch;
    float reserve;
    float capacity;
}

{result} GlobReserve = { <t,i,u[i][t],g[i][t],r[i][t],g[i][t]+r[i][t]> | t in
periods, i in avunits };

```

```
// STOCHASTIC UNIT COMMITMENT WITH LOCATIONAL SPINNING RESERVES
```

```
// Data & Parameters
```

```

{string} periods=...;           // number of (hourly) periods
{string} avunits=...;          // available generating units
{string} spunits=...;         // spinning reserve units
{string} nodes=...;           // electrical nodes (buses)
{string} lines=...;           // transmission lines
{string} states=...;          // list of generation contingency states

```

```

float base=...;                // base power (MVA)
string gOut[states]=...;      // unit out in contingency state
float weight[states]=...;     // probability of contingency state

```

```

tuple unitData {
    string bus;
    float Pmax; float Pmin;
    float RU; float RD; float RR;
    float UT; float DT;
    float UTo; float DT0; float Uo; float Go;
    float BP1; float BP2; float BP3; float BP4;
    float EC1; float EC2; float EC3; float EC4;
    float SUC; float REC;
}

```

```

tuple busData {
    string Type;
    string kV;
}

```

```
tuple branchData {
```

```

        string fromN;
        string toN;
        float Xpu;
        float FNmax;
        float FEmax;
    }

    tuple busTime {
        string bus;
        string time;
    }

tuple genTime {
    string gen;
    string time;
}

unitData unit[avunits]=...;
busData node[nodes]=...;
branchData line[lines]=...;
{busTime} busTimes=...;
{genTime} genTimes=...;
float Dem[busTimes]=...;
float Rmax[genTimes]=...;
{string} nospunits= avunits diff spunits;
float pi= 3.141592654;

// Decision variables

dvar float+ g[avunits][states][periods]; // generation variable
dvar float+ r[avunits][periods]; // reserve variable
dvar boolean u[avunits][periods]; // commitment variable
dvar boolean x[avunits][periods]; // start up variable
dvar boolean y[avunits][periods]; // shut down variable
dvar float theta[nodes][states][periods] in -pi..pi; // node voltage angles

// Expressions
dexpr float StartUpCost= sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * unit[i].SUC * x[i][t];
dexpr float EnergyCost = sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * piecewise {unit[i].EC1->unit[i].BP1;
unit[i].EC2->unit[i].BP2; unit[i].EC3->unit[i].BP3; unit[i].EC4->unit[i].BP4;
unit[i].EC4} g[i]["0"][t];
dexpr float ReserveCost= sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * unit[i].REC * r[i][t];
dexpr float RedispatchCost= sum(t in periods, s in states, i in avunits : s != "0")
(weight[s]/24) * piecewise {unit[i].EC1->unit[i].BP1;
unit[i].EC2->unit[i].BP2; unit[i].EC3->unit[i].BP3; unit[i].EC4->unit[i].BP4;
unit[i].EC4} g[i][s][t];
dexpr float TotalCost= StartUpCost + EnergyCost + ReserveCost + RedispatchCost;

// Model

minimize TotalCost;

```

```

subject to {

    forall(t in periods, s in states)
        swingbusAngle:
            theta["113"][s][t] == 0;

    forall(t in periods, s in states, l in lines)
        anglelimits:
            -pi/2 <= theta[line[l].fromN][s][t]- theta[line[l].toN][s][t] <= pi/2;

    forall(t in periods, s in states, n in nodes)
        DCnodalBalances:
            sum(i in avunits: i != gOut[s] && unit[i].bus == n) ( g[i][s][t] /
base ) -
            sum(l in lines: line[l].fromN == n) ( ( theta[n][s][t] -
theta[line[l].toN][s][t] ) / line[l].Xpu ) -
            sum(l in lines: line[l].toN == n) ( ( theta[n][s][t] -
theta[line[l].fromN][s][t] ) / line[l].Xpu ) == Dem[<n,t>];

    forall(t in periods, l in lines)
        DCmaxFlows0:
            ( -line[l].FNmax / base ) <= ( theta[line[l].fromN]["0"][t] - theta
[line[l].toN]["0"][t] ) / line[l].Xpu <= ( line[l].FNmax / base ) ;

    forall(t in periods, s in states, l in lines: s != "0")
        DCmaxFlowsk:
            ( -line[l].FEmax / base ) <= ( theta[line[l].fromN][s][t] - theta
[line[l].toN][s][t] ) / line[l].Xpu <= ( line[l].FEmax / base ) ;

    forall(t in periods, i in avunits)
        minGeneration0:
            g[i]["0"][t] >= unit[i].Pmin * u[i][t];

    forall(t in periods, i in avunits)
        maxGeneration0:
            g[i]["0"][t] + r[i][t] <= unit[i].Pmax * u[i][t];

    forall(i in avunits)
        initialRamp0:
            -unit[i].RD <= g[i]["0"]["H01"] - unit[i].Go <= unit[i].RU;

    forall(t in periods, i in avunits : t!="H01")
        rampLimits0:
            -unit[i].RD <= g[i]["0"][t] - g[i]["0"][prev( periods,t)] <= unit[i].RU;

    forall(i in avunits)
        initialStartup:
            x[i]["H01"] - y[i]["H01"] == u[i]["H01"] - unit[i].Uo;

    forall(t in periods, i in avunits : t != "H01")
        startupSequence:
            x[i][t] - y[i][t] == u[i][t] - u[i][prev( periods,t)];

    forall(t in periods, i in avunits)

```

```

    x[i][t] + y[i][t] <= 1;

    forall(i in avunits, T in 1..24 : unit[i].Uo == 1 && T <= (unit[i].UT-
unit[i].UTo) )
        u[i][item(periods,T-1)] == 1;

    forall(t in periods, i in avunits, T in 1..23-ord(periods,t) : T <=
(unit[i].UT-1) )
        x[i][t] <= u[i][next(periods,t,T)];

    forall(i in avunits, T in 1..24 : unit[i].Uo == 0 && T <= (unit[i].DT-
unit[i].DTo) )
        u[i][item(periods,T-1)] == 0;

    forall(t in periods, i in avunits, T in 1..23-ord(periods,t) : T <=
(unit[i].DT-1) )
        y[i][t] <= 1 - u[i][next(periods,t,T)];

    forall(t in periods, s in states, i in avunits: s != "0" && i == gOut[s] )
        g[i][s][t] == 0;

    forall(t in periods, s in states, i in nospunits: s != "0" && i != gOut[s] )
        g[i][s][t] == g[i]["0"][t];

    forall(t in periods, s in states, i in spunits: s != "0" && i != gOut[s] )
        minGenerationk:
            g[i][s][t] >= g[i]["0"][t];

    forall(t in periods, s in states, i in spunits: s != "0" && i != gOut[s] )
        maxGenerationk:
            g[i][s][t] <= unit[i].Pmax * u[i][t];

    forall(t in periods, s in states, i in spunits : s!="0" && i != gOut[s] )
        ramplimitsk:
            g[i][s][t] - g[i]["0"][t] <= unit[i].RR * 10;

    forall(t in periods, s in states, i in spunits: s!= "0" && i != gOut[s] )
        reserve:
            r[i][t] >= g[i][s][t] - g[i]["0"][t];

    forall(t in periods, i in spunits)
        reserveLimits:
            r[i][t] <= Rmax[<i,t>] * u[i][t];
}

// post-processing results

tuple result {
    string periods;
    string avunits;
    float status;
    float dispatch;
    float reserve;
    float capacity;

```



```

}

{result} LocReserve = { <t,i,u[i][t],g[i]["0"][t],r[i][t],g[i]["0"][t]+r[i][t]> | t
in periods, i in avunits };

```

C.2 Case 2 – Upward and Downward Spinning Reserves

```

// STOCHASTIC UNIT COMMITMENT WITH LOCATIONAL UP AND DOWN SPINNING RESERVES

// Data & Parameters

{string} periods=...;           // number of (hourly) periods
{string} avunits=...;          // available generating units
{string} spunits=...;          // spinning reserve units
{string} nodes=...;            // electrical nodes (buses)
{string} lines=...;            // transmission lines
{string} states=...;           // list of generation contingency states

float base=...;                // base power (MVA)
string gOut[states]=...;       // unit out in contingency state
float weight[states]=...;      // probability of contingency state

tuple unitData {
    string bus;
    float Pmax; float Pmin;
    float RU; float RD; float RR;
    float UT; float DT;
    float UTo; float DTo; float Uo; float Go;
    float BP1; float BP2; float BP3; float BP4;
    float EC1; float EC2; float EC3; float EC4;
    float SUC; float REC;
}

tuple busData {
    string Type;
    string kV;
}

tuple branchData {
    string fromN;
    string toN;
    float Xpu;
    float FNmax;
    float FEmax;
}

tuple busTime {
    string bus;
    string time;
}

```

```

}

tuple genTime {
    string gen;
    string time;
}

unitData unit[avunits]=...;
busData node[nodes]=...;
branchData line[lines]=...;
{busTime} busTimes=...;
{genTime} genTimes=...;
float Dem[busTimes]=...;
float Rmax[genTimes]=...;
{string} nospunits= avunits diff spunits;
float pi= 3.141592654;

// Decision variables

dvar float+ g[avunits][states][periods]; // generation variable
dvar float+ ru[avunits][periods]; // reserve up variable
dvar float+ rd[avunits][periods]; // reserve dn variable
dvar boolean u[avunits][periods]; // commitment variable
dvar boolean x[avunits][periods]; // start up variable
dvar boolean y[avunits][periods]; // shut down variable
dvar float theta[nodes][states][periods] in -pi..pi; // node voltage angles

// Expressions
dexpr float StartUpCost= sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * unit[i].SUC * x[i][t];
dexpr float EnergyCost = sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * piecewise {unit[i].EC1->unit[i].BP1;
unit[i].EC2->unit[i].BP2; unit[i].EC3->unit[i].BP3; unit[i].EC4->unit[i].BP4;
unit[i].EC4} g[i]["0"][t];
dexpr float ReserveCost= sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * unit[i].REC * ( ru[i][t] + rd[i][t] );
dexpr float RedispatchCost= sum(t in periods, s in states, i in avunits : s != "0")
(weight[s]/24) * piecewise {unit[i].EC1->unit[i].BP1;
unit[i].EC2->unit[i].BP2; unit[i].EC3->unit[i].BP3; unit[i].EC4->unit[i].BP4;
unit[i].EC4} g[i][s][t];
dexpr float TotalCost= StartUpCost + EnergyCost + ReserveCost + RedispatchCost;

// Model

minimize TotalCost;

subject to {

    forall(t in periods, s in states)
        swingbusAngle:
            theta["113"][s][t] == 0;

    forall(t in periods, s in states, l in lines)
        anglelimits:

```

```

    -pi/2 <= theta[line[l].fromN][s][t]- theta[line[l].toN][s][t] <= pi/2;

    forall(t in periods, s in states, n in nodes)
        DCnodalBalances:
            sum(i in avunits: i != gOut[s] && unit[i].bus == n) ( g[i][s][t] /
base ) -
            sum(l in lines: line[l].fromN == n) ( ( theta[n][s][t] -
theta[line[l].toN][s][t] ) / line[l].Xpu ) -
            sum(l in lines: line[l].toN == n) ( ( theta[n][s][t] -
theta[line[l].fromN][s][t] ) / line[l].Xpu ) == Dem[<n,t>];

    forall(t in periods, l in lines)
        DCmaxFlows0:
            ( -line[l].FNmax / base ) <= ( theta[line[l].fromN]["0"][t] - theta
[line[l].toN]["0"][t] ) / line[l].Xpu <= ( line[l].FNmax / base ) ;

    forall(t in periods, s in states, l in lines: s != "0")
        DCmaxFlowsk:
            ( -line[l].FEmax / base ) <= ( theta[line[l].fromN][s][t] - theta
[line[l].toN][s][t] ) / line[l].Xpu <= ( line[l].FEmax / base ) ;

    forall(t in periods, i in avunits)
        minGeneration0:
            g[i]["0"][t] - rd[i][t] >= unit[i].Pmin * u[i][t];

    forall(t in periods, i in avunits)
        maxGeneration0:
            g[i]["0"][t] + ru[i][t] <= unit[i].Pmax * u[i][t];

    forall(i in avunits)
        initialRamp0:
            -unit[i].RD <= g[i]["0"]["H01"] - unit[i].Go <= unit[i].RU;

    forall(t in periods, i in avunits : t!="H01")
        ramplimits0:
            -unit[i].RD <= g[i]["0"][t] - g[i]["0"][prev( periods,t)] <= unit[i].RU;

    forall(i in avunits)
        initialStartup:
            x[i]["H01"] - y[i]["H01"] == u[i]["H01"] - unit[i].Uo;

    forall(t in periods, i in avunits : t != "H01")
        startupSequence:
            x[i][t] - y[i][t] == u[i][t] - u[i][prev( periods,t)];

    forall(t in periods, i in avunits)
        x[i][t] + y[i][t] <= 1;

    forall(i in avunits, T in 1..24 : unit[i].Uo == 1 && T <= (unit[i].UT-
unit[i].UTo) )
        u[i][item( periods,T-1)] == 1;

    forall(t in periods, i in avunits, T in 1..23-ord( periods,t) : T <=
(unit[i].UT-1) )

```

```

    x[i][t] <= u[i][next(periods,t,T)];

    forall(i in avunits, T in 1..24 : unit[i].Uo == 0 && T <= (unit[i].DT-
unit[i].DTo) )
        u[i][item(periods,T-1)] == 0;

    forall(t in periods, i in avunits, T in 1..23-ord(periods,t) : T <=
(unit[i].DT-1) )
        y[i][t] <= 1 - u[i][next(periods,t,T)];

    forall(t in periods, s in states, i in avunits: s != "0" && i == gOut[s] )
        g[i][s][t] == 0;

    forall(t in periods, s in states, i in nospunits: s != "0" && i != gOut[s] )
        g[i][s][t] == g[i]["0"][t];

    forall(t in periods, s in states, i in spunits: s != "0" && i != gOut[s] )
        minGenerationk:
            g[i][s][t] >= unit[i].Pmin * u[i][t];

    forall(t in periods, s in states, i in spunits: s != "0" && i != gOut[s] )
        maxGenerationk:
            g[i][s][t] <= unit[i].Pmax * u[i][t];

    forall(t in periods, s in states, i in spunits : s!="0" && i != gOut[s] )
        ramplimitsk:
            -unit[i].RR * 10 <= g[i][s][t] - g[i]["0"][t] <= unit[i].RR * 10;

    forall(t in periods, i in spunits)
        reserveUp:
            ru[i][t] == max(s in states: s!="0" && i != gOut[s]) ( g[i][s][t] -
g[i]["0"][t] );

    forall(t in periods, i in spunits)
        reserveDn:
            rd[i][t] == max(s in states: s!="0" && i != gOut[s]) ( g[i]["0"][t] -
g[i][s][t] );

    forall(t in periods, i in spunits)
        reserveLimits:
            ru[i][t] + rd[i][t] <= Rmax[<i,t>] * u[i][t];
}

// post-processing results

tuple result {
    string periods;
    string avunits;
    float status;
    float dispatch;
    float reserveUp;
    float reserveDn;
}

```

```
{result} LocReserve = { <t,i,u[i][t],g[i]["0"][t],ru[i][t],rd[i][t]> | t in periods,
i in avunits };
```

Case 3 – Upward and Downward Spinning Reserves

```
// STOCHASTIC UNIT COMMITMENT WITH LOCATIONAL SPINNING AND NONSPINNING RESERVES

// Data & Parameters

{string} periods=...;           // number of (hourly) periods
{string} avunits=...;          // available generating units
{string} resunits=...;         // reserve units
{string} nodes=...;           // electrical nodes (buses)
{string} lines=...;           // transmission lines
{string} states=...;          // list of generation contingency states

float base=...;                // base power (MVA)
string gOut[states]=...;       // unit out in contingency state
float weight[states]=...;      // probability of contingency state

tuple unitData {
    string bus;
    float Pmax; float Pmin;
    float RU; float RD; float RR;
    float UT; float DT;
    float UTo; float DTo; float Uo; float Go;
    float BP1; float BP2; float BP3; float BP4;
    float EC1; float EC2; float EC3; float EC4;
    float SUC; float SRC; float NRC;
}

tuple busData {
    string Type;
    string kV;
}

tuple branchData {
    string fromN;
    string toN;
    float Xpu;
    float FNmax;
    float FEmax;
}

tuple busTime {
    string bus;
    string time;
}
```

```

tuple genTime {
    string gen;
    string time;
}

unitData unit[avunits]=...;
busData node[nodes]=...;
branchData line[lines]=...;
{busTime} busTimes=...;
{genTime} genTimes=...;
float Dem[busTimes]=...;
float Rmax[genTimes]=...;
{string} noresunits= avunits diff resunits;
float pi= 3.141592654;

// Decision variables

dvar float+ g[avunits][states][periods]; // generation variable
dvar float+ sr[avunits][periods]; // spinning reserve variable
dvar float+ nr[avunits][periods]; // nonspinning reserve variable
dvar boolean u[avunits][states][periods]; // commitment variable
dvar boolean x[avunits][states][periods]; // start up variable
dvar boolean y[avunits][periods]; // shut down variable
dvar float theta[nodes][states][periods] in -pi..pi; // node voltage angles

// Expressions
dexpr float StartUpCost= sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * unit[i].SUC * x[i]["0"][t];
dexpr float EnergyCost = sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * piecewise {unit[i].EC1->unit[i].BP1;
unit[i].EC2->unit[i].BP2; unit[i].EC3->unit[i].BP3; unit[i].EC4->unit[i].BP4;
unit[i].EC4} g[i]["0"][t];
dexpr float ReserveCost= sum(t in periods, i in avunits) (1-(ord(periods,t)+1)*(1-
weight["0"])/24) * ( unit[i].SRC * sr[i][t] + unit[i].NRC * nr[i][t] );
dexpr float RedispatchCost= sum(t in periods, s in states, i in avunits : s != "0")
(weight[s]/24 * piecewise {unit[i].EC1->unit[i].BP1;
unit[i].EC2->unit[i].BP2; unit[i].EC3->unit[i].BP3; unit[i].EC4->unit[i].BP4;
unit[i].EC4} g[i][s][t] + weight[s]/24 * unit[i].SUC * x[i][s][t] );
dexpr float TotalCost= StartUpCost + EnergyCost + ReserveCost + RedispatchCost;

// Model

minimize TotalCost;

subject to {

    forall(t in periods, s in states)
        swingbusAngle:
            theta["113"][s][t] == 0;

    forall(t in periods, s in states, l in lines)
        anglelimits:
            -pi/2 <= theta[line[l].fromN][s][t]- theta[line[l].toN][s][t] <= pi/2;

```

```

forall(t in periods, s in states, n in nodes)
  DCnodalBalances:
    sum(i in avunits: i != gOut[s] && unit[i].bus == n) ( g[i][s][t] /
base ) -
    sum(l in lines: line[l].fromN == n) ( ( theta[n][s][t] -
theta[line[l].toN][s][t] ) / line[l].Xpu ) -
    sum(l in lines: line[l].toN == n) ( ( theta[n][s][t] -
theta[line[l].fromN][s][t] ) / line[l].Xpu ) == Dem[<n,t>];

forall(t in periods, l in lines)
  DCmaxFlows0:
    ( -line[l].FNmax / base ) <= ( theta[line[l].fromN]["0"][t] - theta
[line[l].toN]["0"][t] ) / line[l].Xpu <= ( line[l].FNmax / base ) ;

forall(t in periods, s in states, l in lines: s != "0")
  DCmaxFlowsk:
    ( -line[l].FEmax / base ) <= ( theta[line[l].fromN][s][t] - theta
[line[l].toN][s][t] ) / line[l].Xpu <= ( line[l].FEmax / base ) ;

forall(t in periods, i in avunits)
  minGeneration0:
    g[i]["0"][t] >= unit[i].Pmin * u[i]["0"][t];

forall(t in periods, i in avunits)
  maxGeneration0s:
    g[i]["0"][t] + sr[i][t] <= unit[i].Pmax * u[i]["0"][t];

forall(i in avunits)
  initialRamp0:
    -unit[i].RD <= g[i]["0"]["H01"] - unit[i].Go <= unit[i].RU;

forall(t in periods, i in avunits : t!="H01")
  ramplimits0:
    -unit[i].RD <= g[i]["0"][t] - g[i]["0"][prev( periods,t)] <= unit[i].RU;

forall(i in avunits)
  initialStartup:
    x[i]["0"]["H01"] - y[i]["H01"] == u[i]["0"]["H01"] - unit[i].Uo;

forall(t in periods, i in avunits : t != "H01")
  startupSequence:
    x[i]["0"][t] - y[i][t] == u[i]["0"][t] - u[i]["0"][prev( periods,t)];

forall(t in periods, i in avunits)
  x[i]["0"][t] + y[i][t] <= 1;

forall(i in avunits, T in 1..24 : unit[i].Uo == 1 && T <= (unit[i].UT-
unit[i].UTo) )
  u[i]["0"][item( periods,T-1)] == 1;

forall(t in periods, i in avunits, T in 1..23-ord( periods,t) : T <=
(unit[i].UT-1) )
  x[i]["0"][t] <= u[i]["0"][next( periods,t,T)];

```

```

    forall(i in avunits, T in 1..24 : unit[i].Uo == 0 && T <= (unit[i].DT-
unit[i].DTo) )
        u[i]["0"][item( periods,T-1)] == 0;

    forall(t in periods, i in avunits, T in 1..23-ord( periods,t) : T <=
(unit[i].DT-1) )
        y[i][t] <= 1 - u[i]["0"][next( periods,t,T)];

    forall(t in periods, s in states, i in avunits: s != "0" && i == gOut[s] )
        g[i][s][t] == 0;

    forall(t in periods, s in states, i in noresunits: s != "0" && i != gOut[s] )
        u[i][s][t] == u[i]["0"][t];

    forall(t in periods, s in states, i in noresunits: s != "0" && i != gOut[s] )
        g[i][s][t] == g[i]["0"][t];

    forall(t in periods, s in states, i in resunits : s!="0" && i != gOut[s] )
        status_k:
        u[i][s][t] - u[i]["0"][t] >= 0;

    forall(t in periods, s in states, i in resunits : s!="0" && i != gOut[s] )
        startup_k:
        x[i][s][t] == u[i][s][t] - u[i]["0"][t];

    forall(t in periods, s in states, i in resunits: s != "0" && i != gOut[s] )
        minGeneration_k:
        g[i][s][t] >= unit[i].Pmin * u[i][s][t] ;

    forall(t in periods, s in states, i in resunits: s != "0" && i != gOut[s] )
        minGeneration_spk:
        g[i][s][t] >= g[i]["0"][t] - unit[i].Pmax * ( 1 - u[i]["0"][t] );

    forall(t in periods, s in states, i in resunits: s != "0" && i != gOut[s] )
        maxGeneration_k:
        g[i][s][t] <= unit[i].Pmax * u[i][s][t];

    forall(t in periods, s in states, i in resunits : s!="0" && i != gOut[s] )
        ramplimitsk:
        g[i][s][t] - g[i]["0"][t] <= unit[i].RR * 10 * u[i][s][t];

    forall(t in periods, s in states, i in resunits, T in 1..23-ord( periods,t) :
T <= (unit[i].DT-1) && s != "0")
        y[i][t] <= 1 - u[i][s][next( periods,t,T)];

    forall(t in periods, s in states, i in resunits: s!= "0" && i != gOut[s] )
        spReserve:
        sr[i][t] >= g[i][s][t] - g[i]["0"][t] - unit[i].Pmax * ( 2 - u[i][s][t] -
u[i]["0"][t] );

    forall(t in periods, i in resunits)
        spReserveLimits:
        sr[i][t] <= Rmax[<i,t>] * u[i]["0"][t];

    forall(t in periods, s in states, i in resunits: s!= "0" && i != gOut[s] )

```



```

    nsReserve:
    nr[i][t] >= g[i][s][t] - unit[i].Pmax * u[i]["0"][t];

    forall(t in periods, i in resunits)
    nsReserveMaxLimit:
    nr[i][t] <= ( unit[i].Pmin + Rmax[<i,t>] ) * ( 1 - u[i]["0"][t] );
}

// post-processing results

tuple result {
    string periods;
    string avunits;
    float status;
    float dispatch;
    float spreserve;
    float nsreserve;
}

{result} LocReserve = { <t,i,u[i]["0"][t],g[i]["0"][t],sr[i][t],nr[i][t]> | t in
periods, i in avunits };

```

Appendix D Part II Test System Data

The following technical data for the six-bus test system of Part II was taken from [15] and complemented as necessary.

Table 30. Test System Bus Data

Bus Number	Type	Vb (kV)	Vmax (pu)	Vmin (pu)
1	generation	230	1.07	0.95
2	generation	230	1.07	0.95
3	generation	230	1.07	0.95
4	load	230	1.07	0.95
5	load	230	1.07	0.95
6	load	230	1.07	0.95

Table 31. Test System Branch Data

Line Number	From Bus	To Bus	R (pu)	X (pu)	Bc (pu)	Cont. Rating (MVA)	STE Rating (MVA)
T01	1	2	0.10	0.20	0.04	100	125
T02	1	4	0.05	0.20	0.04	100	125
T03	1	5	0.08	0.30	0.06	100	125
T04	2	3	0.05	0.25	0.06	60	75
T05	2	4	0.05	0.10	0.02	60	75
T06	2	5	0.10	0.30	0.04	60	75
T07	2	6	0.07	0.20	0.05	60	75
T08	3	5	0.12	0.26	0.05	60	75
T09	3	6	0.02	0.10	0.02	60	75
T10	4	5	0.20	0.40	0.08	60	75
T11	5	6	0.10	0.30	0.06	60	75

Table 32. Test System Load Data

Period	L4 (MW)	L5 (MW)	L6 (MW)	Total (MW)
1	84	83	83	250
2	70	70	70	210
3	64	63	63	190
4	60	60	60	180
5	67	67	66	200
6	77	77	76	230
7	90	90	90	270
8	104	103	103	310
9	110	110	110	330
10	107	107	106	320
11	100	100	100	300
12	90	90	90	270

Table 33. Test System Generation Data

Generator Number	Bus Number	Pmax (MW)	Pmin (MW)	Qmax (MVar)	Qmin (MVar)	Ramp (MW/h)	Min Up Time (h)	Min Dn Time (h)
G1	1	200.0	50.0	150	-100	90	2	4
G2	2	150.0	37.5	150	-100	150	1	1
G3	3	180.0	45.0	120	-100	120	2	2

Table 34. Test System Generation Cost Data

Generator Number	Pmax (MW)	a (\$/MW ²)	b (\$/MW)	c (\$/h)	StartUp (\$)	Reserves (\$/MW-h)
G1	200.0	0.00533	11.669	213.10	300	4.00
G2	150.0	0.00889	10.333	200.00	150	3.00
G3	180.0	0.00741	10.833	240.00	100	3.00

Table 35. Test System Initial Conditions

Generator Number	Time on (+/- h)	Status on (1/0)	Power (MW)
G1	4	1	90
G2	2	1	90
G3	2	1	90

Appendix E Part II Programming Codes

The following is the OPL programming code used to implement the simulations of Chapter 8 with CPLEX. All input and output data was stored and handled in MS Access relational databases.

E.1 Centralized Energy and Reserve Scheduling

```
// DETERMINISTIC NETWORK CONSTRAINED UNIT COMMITMENT WITH GLOBAL SPINNING RESERVES

// Data & Parameters

{string} periods=...;           // hourly periods ID
{string} units=...;            // generating units ID
{string} nodes=...;           // electrical nodes (buses) ID
{string} lines=...;           // transmission lines ID

float base=...;                // base power (MVA)

tuple unitData {
    string bus; float Pmax; float Pmin; float Rmax; float RP;
    int UT; int DT; int IT; int Uo; float Go;
    float c2; float c1; float c0; float SuC; float ReC;
}

tuple busData {
    string Type;
    string kV;
}

tuple branchData {
    string fromN;
    string toN;
    float Xpu;
    float Fmax;
}

tuple busTime {
    string bus;
    string time;
}

unitData unit[units]=...;
busData node[nodes]=...;
branchData line[lines]=...;
{busTime} busTimes=...;
float Dem[busTimes]=...;
```

```

float pi= 3.141592654;

// Decision variables

dvar float+ g[units][periods];           // generation variable
dvar float+ r[units][periods];           // reserve variable
dvar boolean u[units][periods];          // commitment variable
dvar float+ x[units][periods];           // start up variable
dvar float+ y[units][periods];           // shut down variable
dvar float theta[nodes][periods] in -pi..pi; // node voltage angles

// Expressions

dexpr float EnergyCost = sum(t in periods, i in units) ( 2*(unit[i].c2*g[i][t]^2)/2 +
unit[i].c1*g[i][t] + unit[i].c0*u[i][t] );
dexpr float StartUpCost= sum(t in periods, i in units) unit[i].SuC * x[i][t];
dexpr float ReserveCost= sum(t in periods, i in units) unit[i].ReC * r[i][t];
dexpr float TotalCost= EnergyCost + StartUpCost + ReserveCost;

// Model

minimize TotalCost;

subject to {

    forall(t in periods)
        swingbusAngle:
            theta["01"][t] == 0 ;

    forall(t in periods, l in lines)
        anglelimits:
            -pi/2 <= theta[line[l].fromN][t]- theta[line[l].toN][t] <= pi/2;

    forall(t in periods, n in nodes)
        DCnodalBalances:
            sum(i in units: unit[i].bus == n) ( g[i][t] / base ) -
            sum(l in lines: line[l].fromN == n) ( ( theta[n][t] -
theta[line[l].toN][t] ) / line[l].Xpu ) -
            sum(l in lines: line[l].toN == n) ( ( theta[n][t] -
theta[line[l].fromN][t] ) / line[l].Xpu ) == ( Dem[<n,t>] / base ) ;

    forall(t in periods, l in lines)
        DCmaxFlows:
            ( -line[l].Fmax / base ) <= ( theta[line[l].fromN][t] - theta
[line[l].toN][t] ) / line[l].Xpu <= ( line[l].Fmax / base ) ;

    forall(t in periods, i in units)
        spinningReserve:
            sum ( i in units) r[i][t] >= ( g[i][t] + r[i][t] ) ;

    forall(t in periods, i in units)
        minGeneration:
            g[i][t] >= unit[i].Pmin * u[i][t];

    forall(t in periods, i in units)

```

```

    maxGeneration:
    g[i][t] + r[i][t] <= unit[i].Pmax * u[i][t];

forall(t in periods, i in units)
    maxReserve:
    r[i][t] <= unit[i].Rmax * u[i][t];

forall(i in units)
    initialRamp:
    -unit[i].RP <= g[i]["H01"] + r[i]["H01"] - unit[i].Go <= unit[i].RP;

forall(t in periods, i in units : t!="H01")
    rampLimits:
    -unit[i].RP <= g[i][t] + r[i][t] - g[i][prev( periods,t)] <= unit[i].RP;

forall(i in units)
    initialStartup:
    x[i]["H01"] - y[i]["H01"] == u[i]["H01"] - unit[i].Uo;

forall(t in periods, i in units : t != "H01")
    startupSequence:
    x[i][t] - y[i][t] == u[i][t] - u[i][prev( periods,t)];

// min up time constraints

forall(i in units, T in 1..12 : unit[i].Uo == 1 && T <= (unit[i].UT-
unit[i].IT) ) // IT > 0
    u[i][item( periods,T-1)] == 1;

forall(i in units, t in periods : ord( periods,t)+1 >= unit[i].UT )
    sum ( T in ord( periods,t)-unit[i].UT+1 .. ord( periods,t) )
x[i][item( periods,T)] <= u[i][t];

// min down time constraints

forall(i in units, T in 1..12 : unit[i].Uo == 0 && T <=
(unit[i].DT+unit[i].IT) ) // IT < 0
    u[i][item( periods,T-1)] == 0;

forall(i in units, t in periods: ord( periods,t)+1 >= unit[i].DT )
    sum ( T in ord( periods,t)-unit[i].DT+1 .. ord( periods,t) )
y[i][item( periods,T)] <= (1 - u[i][t]);
}

// post-processing results

tuple result {
    string periods;
    string units;
    float status;
    float dispatch;
    float reserve;
    float capacity;
}

```

```
{result} NCUC_Reserves = { <t,i,u[i][t],g[i][t],r[i][t],g[i][t]+r[i][t]> | t in
periods, i in units };
```

E.2 Distributed Generation Energy and Reserve Scheduling

```
// PRICE BASED UNIT COMMITMENT WITH ENERGY AND RESERVES

// Data & Parameters

{string} periods=...; // hourly periods ID
{string} units=...; // generating units ID

tuple unitData {
    string bus; float Pmax; float Pmin; float Rmax; float RP;
    int UT; int DT; int IT; int Uo; float Go;
    float c2; float c1; float c0; float SuC; float ReC; float ACmax;
}

tuple genTime {
    string gen; string time;
}

unitData unit[units]=...;
{genTime} genTimes=...;
float priceEne[genTimes]=...;
float priceRes[genTimes]=...;

// Decision variables

dvar float+ g[units][periods]; // generation variable
dvar float+ r[units][periods]; // reserve variable
dvar boolean u[units][periods]; // commitment variable
dvar float+ x[units][periods]; // start up variable
dvar float+ y[units][periods]; // shut down variable

// Expressions

dexpr float ProfitG1 = sum (i in units, t in periods : i == "G01" )
( priceEne[<i,t>]*g[i][t] + priceRes[<i,t>]*r[i][t] - unit[i].SuC*x[i][t]
- 2*(unit[i].c2*g[i][t]^2)/2 - unit[i].c1*g[i][t] - unit[i].c0*u[i][t] -
unit[i].ReC*r[i][t] );
dexpr float ProfitG2 = sum (i in units, t in periods : i == "G02" )
( priceEne[<i,t>]*g[i][t] + priceRes[<i,t>]*r[i][t] - unit[i].SuC*x[i][t]
- 2*(unit[i].c2*g[i][t]^2)/2 - unit[i].c1*g[i][t] - unit[i].c0*u[i][t] -
unit[i].ReC*r[i][t] );
dexpr float ProfitG3 = sum (i in units, t in periods : i == "G03" )
( priceEne[<i,t>]*g[i][t] + priceRes[<i,t>]*r[i][t] - unit[i].SuC*x[i][t]
- 2*(unit[i].c2*g[i][t]^2)/2 - unit[i].c1*g[i][t] - unit[i].c0*u[i][t] -
unit[i].ReC*r[i][t] );
```



```

dexpr float Profit= ProfitG1 + ProfitG2 + ProfitG3;

// Model

maximize Profit;

subject to {

    forall(t in periods, i in units)
        minGeneration:
            g[i][t] >= unit[i].Pmin * u[i][t];

    forall(t in periods, i in units)
        maxGeneration:
            g[i][t] + r[i][t] <= unit[i].Pmax * u[i][t];

    forall(i in units)
        initialRamp:
            -unit[i].RP <= g[i]["H01"] + r[i]["H01"] - unit[i].Go <= unit[i].RP;

    forall(t in periods, i in units : t!="H01")
        rampLimits:
            -unit[i].RP <= g[i][t] + r[i][t] - g[i][prev( periods,t)] <= unit[i].RP;

    forall(i in units)
        initialStartup:
            x[i]["H01"] - y[i]["H01"] == u[i]["H01"] - unit[i].Uo;

    forall(t in periods, i in units : t != "H01")
        startupSequence:
            x[i][t] - y[i][t] == u[i][t] - u[i][prev( periods,t)];

// min up time constraints

    forall(i in units, T in 1..12 : unit[i].Uo == 1 && T <= (unit[i].UT-
unit[i].IT) ) // IT > 0
        u[i][item( periods,T-1)] == 1;

    forall(i in units, t in periods : ord( periods,t)+1 >= unit[i].UT )
        sum ( T in ord( periods,t)-unit[i].UT+1 .. ord( periods,t) )
x[i][item( periods,T)] <= u[i][t];

// min down time constraints

    forall(i in units, T in 1..12 : unit[i].Uo == 0 && T <=
(unit[i].DT+unit[i].IT) ) // IT < 0
        u[i][item( periods,T-1)] == 0;

    forall(i in units, t in periods: ord( periods,t)+1 >= unit[i].DT )
        sum ( T in ord( periods,t)-unit[i].DT+1 .. ord( periods,t) )
y[i][item( periods,T)] <= (1 - u[i][t]);

}

// post-processing results

```

```

tuple result {
    string periods;
    string units;
    float status;
    float energy;
    float reserve;
    float capacity;
}

{result} PriceUC_R = { <t,i,u[i][t],g[i][t],r[i][t],g[i][t]+r[i][t]> | t in periods,
i in units };

```

```
// DETERMINISTIC NETWORK CONSTRAINED MARKET CLEARING WITH GLOBAL SPINNING RESERVES
```

```
// Data & Parameters
```

```

{string} periods=...; // hourly periods ID
{string} units=...; // generating units ID
{string} nodes=...; // electrical nodes (buses) ID
{string} lines=...; // transmission lines ID

```

```
float base=...; // base power (MVA)
```

```

tuple unitData {
    string bus; float Pmax; float Pmin; float Rmax; float RP;
    int UT; int DT; int IT; int Uo; float Go;
    float c2; float c1; float c0; float SuC; float ReC;
}

```

```

tuple busData {
    string Type;
    string kV;
}

```

```

tuple branchData {
    string fromN;
    string toN;
    float Xpu;
    float Fmax;
}

```

```

tuple busTime {
    string bus;
    string time;
}

```

```

tuple offerData{
    float Pene; float Emin; float Emax;
    float Pres; float Rmin; float Rmax;
}

```

```

}

tuple genTime {
    string gen; string time;
}

unitData unit[units]=...;
busData node[nodes]=...;
branchData line[lines]=...;
{busTime} busTimes=...;
float Dem[busTimes]=...;
{genTime} genTimes=...;
offerData offer[genTimes]=...;
float pi= 3.141592654;

// Decision variables

dvar float+ g[units][periods]; // generation variable
dvar float+ r[units][periods]; // reserve variable
dvar boolean u[units][periods]; // accepted-offer variable
dvar float theta[nodes][periods] in -pi..pi; // node voltage angles

// Expressions

dexpr float MarketCost = sum(t in periods, i in units) ( offer[<i,t>].Pene*g[i][t] +
offer[<i,t>].Pres*r[i][t] );

// Model

minimize MarketCost;

subject to {

    forall(t in periods)
        swingbusAngle:
            theta["01"][t] == 0 ;

    forall(t in periods, l in lines)
        anglelimits:
            -pi/2 <= theta[line[l].fromN][t]- theta[line[l].toN][t] <= pi/2;

    forall(t in periods, n in nodes)
        DCnodalBalances:
            sum(i in units: unit[i].bus == n) ( g[i][t] / base ) -
            sum(l in lines: line[l].fromN == n) ( ( theta[n][t] -
theta[line[l].toN][t] ) / line[l].Xpu ) -
            sum(l in lines: line[l].toN == n) ( ( theta[n][t] -
theta[line[l].fromN][t] ) / line[l].Xpu ) == ( Dem[<n,t>] / base ) ;

    forall(t in periods, l in lines)
        DCmaxFlows:
            ( -line[l].Fmax / base ) <= ( theta[line[l].fromN][t] - theta
[line[l].toN][t] ) / line[l].Xpu <= ( line[l].Fmax / base ) ;

    forall(t in periods, i in units)

```

```

    spinningReserve:
        sum(i in units) r[i][t] >= ( g[i][t] + r[i][t] ) ;

forall(t in periods, i in units)
    eneMin:
        g[i][t] >= offer[<i,t>].Emin * u[i][t] ;

forall(t in periods, i in units)
    eneMax:
        g[i][t] <= offer[<i,t>].Emax * u[i][t] ;

forall(t in periods, i in units)
    resMin:
        r[i][t] >= offer[<i,t>].Rmin * u[i][t] ;

forall(t in periods, i in units)
    resMax:
        r[i][t] <= offer[<i,t>].Rmax * u[i][t] ;

forall(t in periods, i in units)
    capMax:
        g[i][t] + r[i][t] <= ( offer[<i,t>].Emax + offer[<i,t>].Rmin ) ;
}

// post-processing results

tuple result {
    string periods;
    string units;
    float status;
    float dispatch;
    float reserve;
    float capacity;
}

{result} MC_Reserves = { <t,i,u[i][t],g[i][t],r[i][t],g[i][t]+r[i][t]> | t in
periods, i in units };

```
