Swing Contracts with Dynamic Reserves for Flexible Service Management

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Abstract
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Keywords
Day-ahead market, Swing contract, Dynamic reserve zones, Flexible service provision, MILP optimization

Disciplines
Agricultural and Resource Economics | Controls and Control Theory | Industrial Organization | Power and Energy

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Swing Contracts with Dynamic Reserves for Flexible Service Management

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Abstract—The increasing penetration of variable energy resources in modern electric power systems requires additional flexibility in ancillary service provision to maintain reliable and efficient grid operations. However, full recognition and appropriate compensation of this flexibility is difficult to ensure within current power market designs due to rigidities in service definitions and requirements. For example, reserve requirements (RRs) are typically set in advance at administratively determined levels. If RRs are too large, wasteful expenditures result; and, if RRs are too small, high real-time costs are incurred for peak generation and/or load curtailment. To address these problems, this paper proposes a new mixed-integer linear programming (MILP) formulation for the optimal clearing of a day-ahead market based on swing contracts and a dynamic reserve method permitting the daily adaptive updating of reserve zones. Numerical examples based on a 5-bus test system are used to illustrate the effectiveness of the proposed new day-ahead market design.

Index Terms—Day-ahead market, swing contract, dynamic reserve zones, flexible service provision, MILP optimization

NOMENCLATURE

Sets and Indices

- $B$: Set of bus indices $b$
- $B(z) \subset B$: Subset of buses in reserve zone $z$
- $L \subset B \times B$: Set of transmission line indices $\ell$
- $L_O(b)$: Subset of lines $\ell$ originating at bus $b$
- $L_{E}(b)$: Subset of lines $\ell$ ending at bus $b$
- $M$: Set of indices $m$ for market participants with dispatchable resources
- $M(b) \subset M$: Subset of market participants with dispatchable resources at bus $b$
- $M(z) \subset M$: Subset of market participants with dispatchable resources in reserve zone $z$
- $S$: Set of net load forecast scenarios $s$
- $T$: Set of time period indices $t = 1, \ldots, T$
- $Z$: Set of reserve zone indices $z$

Parameters and Functions

- $A_m(t)$: Binary service offer indicator: 1 if $m$ in time period $t$ is within its contract service period; 0 otherwise
- $B(\ell)$: Inverse of reactance $X(\ell)$ (p.u.) for line $\ell$
- $c_m^0$: Availability price ($\$$) requested by $m$ for a swing contract that offers service availability
- $\%$: Reserve requirement percentage
- $E(\ell)$: End bus for line $\ell$
- $NL_b(t)$: Net load forecast (MW) for bus $b$ during $t$
- $O(\ell)$: Originating bus for line $\ell$

- $P_{m}^{\text{max}}$: Line flow limit (MW) for line $\ell$
- $P_{m}^{\text{min}}$: Lower power limit (MW) for $m$
- $P_{m}^{\text{max}}$: Upper power limit (MW) for $m$
- $R_{D,m}^{\ell}$: Ramp-down limit (MW/\Delta t) for $m$
- $R_{U,m}^{\ell}$: Ramp-up limit (MW/\Delta t) for $m$
- $S_o$: Positive base power (in three-phase MVA)
- $\Delta t$: Time-period length
- $A_1$: Imbalance penalty ($$/MW) for excess power supply
- $A_2$: Imbalance penalty ($$/MW) for a power supply deficit
- $\phi_m(t)$: Energy price ($$/MW/\Delta t$) as a simple form of performance payment method for real-time service offered in a swing contract

ISO Control Variables for SC DAM Optimization

- $p_m(t)$: Power output (MW) of $m$ in time period $t$
- $x_m$: Binary cleared contract indicator: 1 if the swing contract offered by $m$ is cleared; 0 otherwise
- $\theta_b(t)$: Voltage angle (radians) at bus $b$ in time period $t$

Solution Values Derived from SC DAM Optimization

- $\pi_m(t)$: Max available power output (MW) of $m$ during $t$
- $p_m(t)$: Min available power output (MW) of $m$ during $t$
- $P_{m}^{\ell}(t)$: Line power (MW) for line $\ell$ during $t$
- $RR_{D,m}^{\ell}(t)$: Lower spinning reserve requirement (MW) at reserve zone $z$ during $t$
- $RR_{U,m}^{\ell}(t)$: Upper spinning reserve requirement (MW) at reserve zone $z$ during $t$
- $v_m(t)$: Binary unit commitment indicator derived from $x_m$ and $A_m(t)$: 1 if $m$ is online in time period $t$; 0 otherwise
- $\alpha_\ell^0(t)$: Non-negative slack variable indicating excess power supply (MW) at bus $b$ during $t$
- $\alpha_\ell^1(t)$: Non-negative slack variable indicating a power supply deficit (MW) at bus $b$ during $t$

I. INTRODUCTION

The growing participation of variable energy resources (e.g., wind and solar power) in electric power markets has increased the importance of flexible service provision to ensure continual load-balancing capabilities. This, in turn, has increased the need for a level playing field for all potential service providers that includes appropriate compensation for flexibility in service provision.

Currently, however, the appropriate compensation of service flexibility is hindered by rigid service definitions and provision requirements. For example, reserve requirements (RRs) are typically set in advance at administratively determined levels. If RRs are too large, wasteful expenditures result; and, if
RRs are too small, high real-time costs are incurred for peak generation and/or load curtailment.

In recent studies [2], [3] researchers have proposed a new swing-contract market design for electric power systems that facilitates flexible service provision. A swing contract allows a resource to offer a bundle of diverse power and ancillary services as ranges of values rather than as point values, thus permitting greater flexibility in their real-time implementation. A swing-contract market is a centrally-managed forward market that functions as a robust-control mechanism for the management of load and generation uncertainties. It permits dispatchable resources to offer services in flexible swing-contract form to ensure the availability of flexible service performance at a later date.

Subsequent studies [4]–[6] have demonstrated the practical feasibility of the swing-contract market design by developing and implementing Mixed Integer Linear Programming (MILP) formulations for the optimal clearing of swing contracts subject to standard system and reserve-requirement (RR) constraints. However, a difficulty with these optimization formulations is their reliance on exogenously specified RR levels. While service supply offers are permitted to take a flexible form, reserve demands are not. This suggests the desirability of modifying the swing-contract market design by replacing exogenously specified RR levels with some form of dynamic reserve method.

A dynamic reserve method is any process permitting the run-time adjustment of reserve demands for electric power market operations. Dynamic reserve methods currently under exploration include the adaptive updating of RR levels, reserve zones, reserve demand curves, and/or reserve deliverability status based on updated grid congestion conditions [7].

Dynamic reserve methods are particularly promising for dealing with potential power imbalances caused by high penetration of variable energy resources [8]–[12]. For example, [8] investigates whether the adaptive modification of a targeted reserve capacity over time based on expected system conditions can avoid expensive overestimation of RR with high levels of wind power. Ref. [9] proposes a heuristic rule to define dynamic reserve requirements: the reserve should be no less than 3% of load and 5% of forecasted renewable generation.

However, recent research has stressed the need to consider more carefully the effects of variable energy resources on the ability of market operators to predict network congestion, hence power transfer capabilities, in order to guarantee real-time reserve deliverability [13], [14]. To mitigate reserve deliverability problems, current U.S. ISO/RTO-managed day-ahead markets rely on pre-specified reserve zones to ensure the distribution of reserves across the transmission grid. A reserve zone is a portion of the grid that experiences relatively infrequent internal transmission congestion.

This paper proposes a new MILP formulation for the optimal clearing of swing contracts in an ISO-managed swing-contract day-ahead market (SC DAM) with dynamic reserve determination. Reserve zones and associated zonal RR requirements are adaptively adjusted each day to facilitate the balancing of net load, i.e., load minus non-dispatchable generation.

Section II describes the reformulation of the SC DAM optimization problem in [5] to incorporate reserve zones and associated zonal reserve requirements among the problem constraints. Section III explains our new proposed method for the dynamic adjustment of reserve zones and associated zonal reserve requirements. This adjustment is accomplished by means of a weighted average of shift factor differences, which in turn is based on a line-congestion risk index.

Performance testing of our new proposed dynamic reserve method in comparison with other proposed dynamic reserve methods is reported in Section IV. This testing is undertaken for a 5-bus test system consisting of a swing-contract DAM operating over a 5-bus transmission grid. Performance is measured in terms of expected energy costs and reserve delivery reliability. It is shown that our proposed method outperforms other methods in terms of these metrics. Section V concludes.

II. A SWING-CONTRACT MARKET DESIGN WITH DYNAMIC RESERVE DETERMINATION

A. An Illustrative Swing Contract

As detailed in [2]–[5], a swing contract (SC) is a contract that permits a resource to offer the availability of a collection of power paths with a wide range of specified services, such as start-up location, start-up time, power level, ramp-rate, duration, and volt/VAr support. For concreteness, as in [5], this study will focus on the following specific form of SC permitting a dispatchable resource to offer swing (flexibility) in power levels and ramp rates:

$$\text{SC} = [b, t_s, t_e, P, R, \phi]$$

where:

- $b$ = location where service delivery is to occur;
- $t_s$ = power delivery start time;
- $t_e$ = power delivery end time;
- $P = [P_{\text{min}}, P_{\text{max}}]$ = range of power levels $p$;
- $R = [-R^D, R^U]$ = range of down/up ramp rates $r$;
- $\phi$ = Performance payment method for real-time services.

As illustrated in Fig. 1, the location $b$ in (1) refers to a particular bus or node of a transmission grid. The start and end times $t_s$ and $t_e$ denote specific calendar times expressed at the granularity of time periods of length $\Delta t$ (e.g., 1h, 1Min), with $t_s < t_e$. The power interval bounds $P_{\text{min}} \leq P_{\text{max}}$ can represent pure power injections (if $0 \leq P_{\text{min}}$), pure power withdrawals or absorptions (if $P_{\text{max}} \leq 0$), or bi-directional power capabilities (if $P_{\text{min}} \leq 0 \leq P_{\text{max}}$). The down/up limits $-R^D$ and $R^U$ for the ramp rates $r$ (MW/\Delta t) are assumed to satisfy $-R^D \leq 0 \leq R^U$.

The location $b$, the start time $t_s$, and the end time $t_e$ are all specified as single values in (1). However, the power levels $P$ and the down/up ramp rates $R$ are specified in swing form with associated ranges $P$ and $R$.

The performance payment method $\phi$ in (1) designates the mode of ex post compensation for actual real-time service performance. As detailed in [5], $\phi$ can take a wide variety of forms. For example, $\phi$ could specify a flat-rate price ($/\text{MWh}$) for down/up power delivery together with a “power-mileage” compensation for ramping based on power-path length.
An issuer \( m \) of a cleared swing contract \( SC_m \) is immediately paid its contract offer price \( c_m^{\alpha,m} \), which functions as a form of insurance premium to ensure real-time service availability. If \( m \) is subsequently dispatched to perform real-time services in accordance with \( SC_m \), compensation is paid to \( m \) for these services in accordance with the performance payment method \( \phi_m \) that \( m \) has included among the terms of \( SC_m \).

It is the responsibility of issuer \( m \) to guarantee the physical and financial feasibility of its offered swing contract \( SC_m \). With regard to physical feasibility, \( m \) must ensure it is able to fulfill the terms of \( SC_m \), if cleared. With regard to financial feasibility, \( m \) should make sure that its contract offer price \( c_m^{\alpha,m} \) is sufficient to cover all of the avoidable fixed costs (e.g., start-up and no-load costs) that \( m \) would incur to guarantee service availability in accordance with \( SC_m \). In addition, \( m \) should make sure that its performance payment method \( \phi_m \) is sufficient to cover all avoidable operational costs (e.g., fuel costs) that \( m \) would incur if called upon to provide real-time service performance in accordance with \( SC_m \).

C. SC DAM Optimization Formulation with Dynamic Reserve

Current U.S. ISO/RTO-managed DAMs use two optimizations to determine unit commitment, generation dispatch, and pricing solutions: namely, Security-Constrained Unit Commitment (SCUC) and Security-Constrained Economic Dispatch (SCED) [15]. SCUC is formulated as a mixed integer linear programming (MILP) problem, and SCED is typically formulated as a linear programming problem.

In contrast, a single MILP optimization process is used for the ISO-managed SC DAM in [3] to determine which SCs are cleared, hence which dispatchable market participants are obligated (committed) to ensure service availability for the following day. However, this optimization process assumes pre-specified system-wide down/up spinning reserve requirements without consideration of reserve deliverability.

In this paper we reformulate the SC DAM optimization problem developed in [3] to include the adaptive updating of reserve zones for spinning reserve. The goal of this reformulation is to achieve an SC DAM design that further reduces expected costs by improving reserve delivery reliability.

The reformulated SC DAM optimization is depicted in Fig. 2. In the remainder of this section we explain this reformulated optimization for an arbitrary day \( D \), taking as given a particular reserve zone specification. Note that the lower/upper zonal reserve requirements \( RR^L_z(t) \) and \( RR^U_z(t) \) associated with each reserve zone \( z \) in each time period \( t \) that appear in this reformulated optimization are endogenously determined as part of the optimal solution; hence, they depend on net load forecasts and other current system conditions. Our proposed procedure for undertaking the daily adaptive updating of the reserve zones \( z \) will be carefully explained in Section III.

Following [5, Section 5.2], eight simplifying assumptions are made for clarity of exposition. First, the SC DAM takes place on day \( D \) in order to plan for net load balancing on day \( D+1 \). Second, the 24-hours of day \( D+1 \) are represented by \( T = \{1, \ldots, 24\} \) with \( \Delta t = 1h \). Third, all loads are fixed (must-serve) loads that do not provide dispatchable services. Fourth, all loads are serviced by Load-Serving Entities (LSEs). Fifth, an LSE’s demand bid at any bus \( b \) for any hour \( t \) consists of a price-insensitive power demand (MW) reflecting the LSE’s load forecast at that bus for that hour. Sixth, each market participant \( m \) with dispatchable resources offers a single swing contract \( SC_m \) into the SC DAM, where \( SC_m \) takes form (1). Seventh, the performance payment method \( \phi_m \) appearing within \( SC_m \) takes the form of a collection of flat-rate energy prices \( \phi_m(t) (/MWΔt) \), one price for each hour \( t \in T \). Eighth, only spinning reserve requirements for normal load balancing purposes are considered.

Given these assumptions, the objective of the ISO managing the day-D SC DAM is to minimize total cost (\$) over \( T \) by appropriate selection of the ISO control variables listed in the Nomenclature, subject to system and zonal reserve requirement constraints.

1) Total cost minimization objective:

\[
\begin{align*}
\min & \quad \sum_{m \in M} c_m^{\alpha,m} x_m + \sum_{t \in T} \sum_{m \in M} \phi_m(t) |p_m(t)| \Delta t \\
& + \sum_{b \in B} \sum_{t \in T} \alpha_b^+(t) + \sum_{b \in B} \sum_{t \in T} \alpha_b^-(t)
\end{align*}
\]

Total cost is the summation of SC availability cost, expected
performance cost, and imbalance penalty cost. The latter cost proxies the additional cost that would be incurred for peak generation purchase and/or load curtailment if the SC DAM dispatch schedule is unable to ensure real-time balance between power supplies and power demands (loads).

2) Unit commitment constraints:

\[ v_m(t) = x_m A_m(t), \forall m \in M, t \in T \]  

The unit commitment \( v_m(t) \in \{0, 1\} \) for each market participant \( m \in M \) for each hour \( t \) of day D+1 is determined by two variables: the cleared contract indicator \( x_m \in \{0, 1\} \); and the service offer indicator \( A_m(t) \in \{0, 1\} \). The indicator \( A_m(t) \) is a derived value, calculated by the ISO from the information provided within SC\(_m\). For example, suppose SC\(_m\) specifies that services can be provided by \( m \) during the time interval \([s_t, s_m] = [10, 19]\) on day D+1. Then \( A_m(t) = 1 \) if \( t \in \{10, \ldots, 19\} \) and \( A_m(t) = 0 \) if \( t \in \{1, \ldots, 9, 20, \ldots, 24\} \). Participant \( m \) is committed to be available for service provision during hour \( t \) of day D+1 if and only if both \( x_m \) and \( A_m(t) \) in (5) equal 1.

3) Voltage angle limits:

\[ \theta_v(t) = 0, \forall t \in T \]  

\[ -\pi \leq \theta_b(t) \leq \pi, \forall b \in B, t \in T \]  

Constraints (4) determine the voltage angle specification at a designated angle reference bus \( r \) for all hours \( t \), and constraints (5) impose voltage angle limits at all buses for all hours \( t \).

4) Line power transmission constraints:

\[ P_L(t) = S_0 B(t) \left[ \theta_O(t) - \theta_L(t) \right], \forall \ell \in L, t \in T \]  

\[ -P_L^{\text{max}} \leq P_L(t) \leq P_L^{\text{max}}, \forall \ell \in L, t \in T \]  

5) Power balance constraints at each bus:

\[ \sum_{m \in M(b)} p_m(t) + \sum_{\ell \in E(b)} P_L(t) = NL_b(t) + \sum_{\ell \in E_O(b)} P_L(t) + \alpha_b^+(t) - \alpha_b^-(t), \forall b \in B, t \in T \]  

6) Market participant capacity constraints:

\[ \underline{p}_m(t) \leq p_m(t) \leq \overline{p}_m(t), \forall m \in M, t \in T \]  

\[ \overline{p}_m(t) \leq P_m^{\text{max}} v_m(t), \forall m \in M, t \in T \]  

\[ p_m(t) \geq P_m^{\text{min}} v_m(t), \forall m \in M, t \in T \]  

7) Market participant ramp-up and ramp-down constraints:

\[ p_m(t) - p_m(t - 1) \leq R_L^u \Delta t v_m(t - 1) + P_m^{\text{max}} [1 - v_m(t - 1)], \forall m \in M, t = 2, \ldots T \]  

\[ p_m(t - 1) - p_m(t) \leq R_L^d \Delta t v_m(t) + P_m^{\text{max}} [1 - v_m(t)], \forall m \in M, t = 2, \ldots T \]  

8) Zonal reserve requirement constraints:

\[ \sum_{m \in M(z)} [\overline{p}_m(t) - p_m(t)] \geq RR_L^z(t), \forall t \in T, z \in Z \]  

\[ \sum_{m \in M(z)} [p_m(t) - \underline{p}_m(t)] \geq RR_L^z(t), \forall t \in T, z \in Z \]

Constraints (14)-(15) represent each reserve zone’s upper and lower RR constraints for each hour \( t \). Constraints (16)-(17) represent system-wide RR constraints for each hour \( t \). Constraints (18)-(19) provide dynamic reserve requirements for different reserve zones: the upper and lower reserve requirements for a reserve zone \( z \) should be no less than \( d\% \) of the summation of forecasted net load for that zone.

As in [5], the system inherent reserve range for hour \( t \) can be calculated as a function of the solution for the SC DAM optimization: \( SIRR(t) = [RR_L^{\text{min}}, RR_L^{\text{max}}(t)] \), where \( RR_L^{\text{max}}(t) = \sum_{m \in M} \overline{p}_m(t), \forall t \in T \)  

\[ RR_L^{\text{min}}(t) = \sum_{m \in M} \underline{p}_m(t), \forall t \in T \]  

III. DYNAMIC RESERVE ZONE UPDATING METHOD

A. Overview

One promising approach for improving reserve delivery reliability is the adaptive updating of reserve zones based on system conditions, including net load uncertainties. Previous researchers have proposed various metrics for this purpose, such as electrical distance (ED) [16], power transfer distribution factors (PTDFs) [17], and weighted averages of PTDF differences [13].

The ED metric cannot be used to determine reserve zones for the SC DAM optimization proposed in Section IIC, since voltage magnitudes for this optimization are assumed to be 1 (p.u.). Also, a PTDF is a “what if” construction that does not reflect actual system conditions, especially line congestion.

Perhaps for these reasons, ref. [13] instead proposes a dynamic reserve zone specification method involving the use of a weighted average of PTDF differences, where the weights are adaptively updated to reflect current system conditions. However, since this method is formulated for a standard AC optimal power flow optimization, it cannot be directly applied to our SC DAM optimization.

In this section we propose a modified version of the dynamic reserve method developed in [13] that can be used to generate daily updated reserve zone specifications for the SC DAM. Our method differs from [13] in two principle respects: (i) use of a different similarity metric (based on a line congestion risk index) to measure the similarity of buses and bus subsets; and (ii) use of a hierarchical clustering method instead of a k-mean

A power transfer distribution factor PTDF(\( \ell, \Delta p, b_s, b_k \)) measures the change in power flow on a power line \( \ell \) resulting from a power increment \( \Delta p \) injected at a source bus \( b_s \) and withdrawn at a sink bus \( b_k \) [18].
algorithm to partition the set of grid buses into reserve zones based on bus and bus-subset similarity.

More precisely, our proposed dynamic reserve method consists of four steps to be carried out immediately prior to the operation of the SC DAM on the morning of each day D. These four steps are as follows:

Step 1: Use Monte Carlo simulations to construct a set of net load forecast scenarios;
Step 2: Use off-line preliminary optimizations to determine power line dual variable solutions, and use these solutions to construct line congestion risk indices;
Step 3: Use these indices to construct a matrix WA whose components consist of weighted averages of shift factors; and
Step 4: Use a hierarchical clustering algorithm based on WA to partition the set of buses into reserve zones for use in the day-D SC DAM.

These four steps will now be more carefully explained.

B. Construction of Net Load Forecast Scenarios

Net load is load minus non-dispatchable generation. This section explains our method for generating a set $S$ of net load forecast scenarios. Each scenario takes the form $s = \{NL_b(t) \mid b \in B, t \in T\}$, where the terms $NL_b(t)$ are the net load forecasts appearing in our SC DAM optimization formulation in Section II-C.

For concreteness, we assume all non-dispatchable generation consists entirely of wind power. The net load forecasts $NL_b(t)$ can thus be represented as follows:

$$NL_b(t) = \hat{p}_b^L(t) - \hat{p}_b^W(t), \quad \forall b \in B, t \in T,$$

where $\hat{p}_b^L(t)$ denotes LSE forecasted load (if any) at bus $b$ for hour $t$ and $\hat{p}_b^W(t)$ denotes the ISO’s forecasted wind power generation (if any) at bus $b$ for hour $t$.

We also assume the load forecast error $e_b^L(t)$ and the wind power generation forecast error $e_b^W(t)$ are uncorrelated random variables governed by mean-zero normal distributions for each $b \in B$ and $t \in T$. The standard deviations for the net load forecast errors can thus be expressed as:

$$\sigma_{NL}^b(t) = \sqrt{\sigma_b^L(t)^2 + \sigma_b^W(t)^2}, \quad \forall b \in B, t \in T.$$  \hfill (23)

In (23), $\sigma_b^L(t)$ denotes the standard deviation of the load forecast error $e_b^L(t)$ and $\sigma_b^W(t)$ denotes the standard deviation of the wind power forecast error $e_b^W(t)$. Hence, the net load forecast $NL_b(t)$ has a mean-zero normally-distributed forecast error $e_b^{NL}(t)$ with standard deviation $\sigma_{NL}^b(t)$.

We then use Monte Carlo simulation to generate multiple net load forecast scenarios $s$ as perturbations about a base net load scenario taken to represent true expected net load.

C. Line Congestion Risk Index Calculation

Transmission lines that are frequently congested are generally referred to as critical lines. In the SC DAM optimization formulation developed in Section II-C, the dual variables (‘‘shadow prices’’) corresponding to the lower and upper inequality constraints in (7) for line power flows indicate the congestion status of the transmission lines. In this section we explain how the solution values for these dual variables can be used to construct a ‘‘line congestion risk index’’ for each line $\ell \in L$ that indicates the degree to which line $\ell$ is critical.

First, we construct a set $S$ of net load forecast scenarios $s$ using the method described in Section II-B. Second, for each scenario $s \in S$, we solve the SC DAM optimization problem in Section II-C assuming the set $B$ of all grid buses constitutes a single reserve zone. Third, we record the resulting 0-1 unit commitment solution values $v_m^r(t)$. Fourth, we re-solve the SC DAM optimization problem for each scenario $s \in S$, taking as given the unit commitment solution values $v_m^r(t)$. Finally, we record the resulting dual variable solution values $\lambda_{1,s}^\ell(t)$ and $\lambda_{2,s}^\ell(t)$ corresponding to the lower and upper line power inequality constraints in (7).

The line congestion risk index for each line $\ell \in L$ is then calculated as follows:

$$w_{\ell} = \frac{\sum_{s \in S} \sum_{t \in T} \max \{ |\lambda_{1,s}^\ell(t)|, |\lambda_{2,s}^\ell(t)| \}}{|T| \cdot |S|}. \tag{24}$$

By construction, the larger the value of $w_{\ell}$, the more likely it is that line $\ell$ will experience congestion, conditional on the set $S$ of net load forecast scenarios.

D. Weighted Average of Shift Factor Differences

Let $SF_{\ell,i} = SF(\ell, 1\text{MW}, i, b_r)$ denote the shift factor that measures the change in power flow on line $\ell$ when $1\text{MW}$ of power is injected at bus $i$ and withdrawn at a fixed reference bus $b_r$; cf. footnotes 1 and 2. Given any two buses $i$ and $j$, we construct a weighted average of shift factor differences for these buses as follows:

$$WA_{ij} = \frac{\sum_{\ell \in L} \sum_{t \in T} w_{\ell} |SF_{\ell,i} - SF_{\ell,j}|}{|L|}, \tag{25}$$

where the weights $w_{\ell}$ in (25) are the line congestion risk indices given by (24). Finally, the matrix whose components are given by $WA_{ij}$ is denoted by WA.

E. Hierarchical Clustering Method for Reserve Zone Partition

The well-known hierarchical clustering method developed by [20] proceeds as follows. Consider a finite set $N$ consisting of $N \geq 2$ elements for which the dissimilarity between any two elements $i$ and $j$ in $N$ is measured by some designated dissimilarity metric $d(i, j)$. The dissimilarity between any two disjoint subsets of $N$ can then be measured in a variety of ways: e.g., via average dissimilarity calculated as the average dissimilarity between any element of one subset and any element of the other subset.

Start with a partition $P(N)$ of $N$ into $N$ disjoint subsets, each subset containing a single element. Find a pair of subsets in $P(N)$ whose dissimilarity to each other is at least as small as between any other two subsets in $P(N)$ and merge these two subsets; this results in a partition $P(N - 1)$ of $N$ into
N − 1 disjoint subsets. Repeat this process until one obtains P(1), a “partition” of \( N \) into one subset \( N \).

At each stage of this clustering process, by construction, the dissimilarity between the two merged subsets is non-decreasing. If the goal is to obtain a partitioning of \( N \) into subsets that display internal element similarity and between-subset dissimilarity, a natural place to stop the process is at a point where the dissimilarity between the next two subsets to be merged exhibits a sharp increase.

In the current study, this hierarchical clustering method is applied to the set \( B \) consisting of all grid buses in order to partition \( B \) into reserve zones. The dissimilarity between any two buses \( i \) and \( j \) in \( B \) is measured by \( W_{A_{i,j}} \), and the dissimilarity between any two disjoint bus subsets is measured by the average dissimilarity of their bus elements. A sharp increase in subset dissimilarity is used to determine the point at which the clustering process is halted.

IV. COMPARATIVE PERFORMANCE SIMULATION STUDY

A. Overview

This section reports findings from a simulation study undertaken to test the ability of dynamic reserve methods to enhance the performance of the basic swing-contract day-ahead market (SC DAM) design presented in Section II. Three different methods for adaptive reserve-zone updating are considered: the PTDF method proposed in [17]; the weighted PTDF difference method proposed in [13]; and our modified version of [13], presented in Section III, that makes use of line congestion risk indices and hierarchical clustering.

The five-bus test system used for this study, adapted from [21], is depicted in Fig. 3. The grid consists of five buses B1-B5 and six transmission lines L1-L6. The participants include: five dispatchable thermal generation units G1-G5 located at buses B1, B3, B4, and B5; one non-dispatchable wind farm located at bus B3; and three LSEs servicing load at buses B2, B3, and B4. The designated reference bus is B4.

All simulations were carried out on the Iowa State University Condo cluster, whose individual blades consist of two 2.6 GHz 8-Core Intel E5-2640 v3 processors and 128GB of RAM. Pyomo 5.3.0 was used to formulate and solve the SC DAM optimization problem; CPLEX Python API 12.6 was employed as the MILP solver.

B. Configuration of the Five-Bus Test System

The time step for the SC DAM was set at \( \Delta t = 1h \), and the planning horizon \( T \) was specified to be 24 hours. The reserve requirement percentage \( \Delta G\% \) was set at \( 5% \). The imbalance penalties for excess and deficit power were set at \( \Lambda_1 = 1000$/MW and \( \Lambda_2 = 1000$/MW. The positive base power \( S_o \) was set equal to 100 MVA. The physical characteristics of the six transmission lines are given in Table I.

Wind power at bus B3 was simulated as a normally distributed power output with a standard deviation of 10% from expected value. Hourly load was simulated as a normally distributed power demand with a standard deviation of 2% from expected value. Simulated hourly load was distributed across buses B2, B3, and B4 as 40%, 30%, and 30% of total load, respectively.

The Monte Carlo procedure explained in Section III-B was used to construct a set \( S \) consisting of 1000 net load forecast scenarios \( s \), each 24 hours in length, for the five-bus test system. The net load at a particular bus during a particular hour equals load (if any) minus non-dispatchable wind power generation (if any). For the five-bus test system, net load is always zero at B1 and B5 since only thermal generation is present. Consequently, each scenario \( s \in S \) designates net load forecasts only for buses B2, B3, and B4. An illustrative scenario is depicted in Fig. 4.

The swing contracts submitted into the SC DAM by G1-G5 all take form (1); hence, swing (flexibility) is offered in the performance of the basic swing-contract day-ahead market scenario is depicted in Fig. 4.

The swing contracts submitted into the SC DAM by G1-G5 all take form (1); hence, swing (flexibility) is offered in power and ramp-rate levels. These swing contracts are shown in Table I.

For our dynamic reserve-zone updating method proposed in Section III, the bus dissimilarity matrix \( W_{A} \) with components (26) was calculated to be

\[
W_{A} = \begin{pmatrix}
0 & 0.1837 & 0.2543 & 0.4457 & 1.0720 \\
0.1837 & 0 & 0.0706 & 0.2650 & 0.8914 \\
0.2543 & 0.0706 & 0 & 0.1955 & 0.8219 \\
0.4457 & 0.2650 & 0.1955 & 0 & 0.6278 \\
1.0720 & 0.8914 & 0.8219 & 0.6278 & 0
\end{pmatrix}
\]

Hierarchical clustering based on \( W_{A} \) was then used to partition the set of five buses into two reserve zones, as shown in Fig. 5.
TABLE II
SWING CONTRACTS (SCS) SUBMITTED BY THE FIVE SC DAM PARTICIPANTS WITH DISPATCHABLE GENERATION

<table>
<thead>
<tr>
<th>Gen Units</th>
<th>Thermal Service Period ([t_{\text{rs}}, t_{s}])</th>
<th>Power Range ([P^{\text{min}}, P^{\text{max}}]) (MW)</th>
<th>Ramp Rate Range ([-R^D, R^U]) (MW/h)</th>
<th>Available Price (c^o) ($)</th>
<th>Performance Price (\phi) ($/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>[5, 24]</td>
<td>[10, 110]</td>
<td>([-32, 32])</td>
<td>1500</td>
<td>14</td>
</tr>
<tr>
<td>G2</td>
<td>[1, 20]</td>
<td>[10, 100]</td>
<td>([-50, 50])</td>
<td>1700</td>
<td>15</td>
</tr>
<tr>
<td>G3</td>
<td>[1, 24]</td>
<td>[50, 520]</td>
<td>([-104, 104])</td>
<td>2000</td>
<td>25</td>
</tr>
<tr>
<td>G4</td>
<td>[4, 20]</td>
<td>[20, 200]</td>
<td>([-60, 60])</td>
<td>1800</td>
<td>30</td>
</tr>
<tr>
<td>G5</td>
<td>[1, 24]</td>
<td>[40, 600]</td>
<td>([-120, 120])</td>
<td>1600</td>
<td>10</td>
</tr>
</tbody>
</table>

Fig. 4. An illustrative net load forecast scenario for the five-bus test system.

Fig. 5. Reserve zones for the five-bus test system as determined by hierarchical clustering.

C. Key Findings

Expected cost outcomes were calculated for the SC DAM operating under three different methods for the adaptive updating of reserve zones: namely, the PTDF method proposed in [17]; the weighted PTDF difference method proposed in [13]; and our new dynamic reserve method proposed in Section III. As explained with care in Section II-C, expected cost for the SC DAM is the summation availability cost, performance cost, and penalty cost for power supply excesses or deficits in real-time operations.

Expected cost comparisons are presented in Table III. These comparisons indicate that our new dynamic reserve method results in the lowest expected cost.

Fig. 6. The unit commitment determined by the SC DAM optimization using our proposed new dynamic reserve method.

Under our method, the SC DAM optimization solution clears the SCs submitted by G1, G2, G3, and G5; however, the SC submitted by G4 is not cleared. The only information communicated by the ISO back to G1-G5 is their unit commitment status, i.e., whether or not their SC was cleared. However, the SC DAM optimization solution also results in a dispatch schedule for next-day operations that the ISO can use as a planning device. The unit commitment and dispatch schedule, shown in Fig. 6 and Fig. 7, respectively, reveal that the ISO anticipates using G5 as a base-load unit due to its relatively low performance cost.

Fig. 7. The dispatch schedule determined by the SC DAM optimization using our proposed new dynamic reserve method.

TABLE III
EXPECTED COST UNDER THREE DIFFERENT DYNAMIC RESERVE METHODS

<table>
<thead>
<tr>
<th>Method</th>
<th>Reserve Zones</th>
<th>Cleared SCs</th>
<th>Expected Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>[17]</td>
<td>Z1: Bus 2, 3, 4</td>
<td>G1 G2</td>
<td>$187,877.68</td>
</tr>
<tr>
<td></td>
<td>Z2: Bus 1, 5</td>
<td>G3 G5</td>
<td></td>
</tr>
<tr>
<td>[13]</td>
<td>Z1: Bus 2, 3</td>
<td>G1 G2</td>
<td>$186,113.18</td>
</tr>
<tr>
<td></td>
<td>Z2: Bus 1, 5</td>
<td>G3 G5</td>
<td></td>
</tr>
<tr>
<td>Our</td>
<td>Z1: Bus 1, 2, 3, 4</td>
<td>G1 G2</td>
<td>$183,611.70</td>
</tr>
<tr>
<td>method</td>
<td>Z2: Bus 5</td>
<td>G3 G5</td>
<td></td>
</tr>
</tbody>
</table>
optimization solution resulting under our method. By construction, only Reserve Zone 1 has non-zero forecasted net load. Fig. 8 depicts this forecasted net load in Reserve Zone 1 under our proposed new dynamic reserve method.

As seen in Fig. 8, zonal forecasted net load is well covered by the endogenously determined zonal reserve ranges resulting from the SC DAM optimization under our proposed dynamic reserve method. In particular, the width of these zonal reserve ranges is typically wider than minimally required by the $d\%$ reserve requirement percentage and varies over time in response to anticipated system conditions.

V. CONCLUSION

This paper proposes a swing-contract day-ahead market (SC DAM) optimization formulation that incorporates a new dynamic reserve method for the adaptive updating of reserve zones and zonal reserve requirements. The optimization formulation is expressed as a mixed integer linear programming (MILP) problem and solved using a standard MILP solver. Comparative simulation studies are carried out for an SC DAM operating over a five-bus transmission grid to test the effectiveness of our new proposed dynamic reserve method. Expected cost outcomes indicate that our method results in lower expected costs of operation for the SC DAM than the dynamic reserve methods proposed in [17] and [13].

REFERENCES