Uncertainty and Market Simulation Based Cost-Benefit Study for Dynamic Ramp Reserve Requirement

Bing Huang, *Member IEEE*, Christine Ross, *Member, IEEE,* Chen-Hao Tsai, *Member, IEEE*, Congcong Wang *Member, IEEE*.

***Abstract*—Wind and solar penetration have been increasing rapidly in the Mid-continent Independent System Operator (MISO) footprint in the past few years. In addition, extreme weather events have become more frequent. Market operations need additional margins and flexibility to manage the increasing uncertainty and variability. Over the years, MISO's co-optimized energy and ancillary service markets have been developed to include different reserve products to address the uncertainty in different timeframes. Historically, MISO has regulation reserve and contingency reserve to cover the real-time uncertainty and loss of generation in 4-sec to 5 minutes and 10 minutes time frames respectively. More recently, MISO implemented 10-min ramp capability products and 30-min short term reserve (STR). It becomes increasingly important to appropriately determine reserve product requirements. This paper focuses on the uncertainty component requirement of ramp capability product and introduces methods to enhance uncertainty management through improved requirement procurement. A systematic method is developed to generate clusters and samples from historical real-time market cases. A close-to-production real-time market rolling simulation tool is built to simulate the sample cases. A cost-benefit quantification framework is developed to select the optimal requirement in Normal and High Uncertainty conditions. Simulation results show system reliability is improved, and the annual production cost is estimated to be reduced by half million dollars with the recommended dynamic requirements.**

***Index Terms*—Ancillary services, dynamic reserve, market design, system reliability, flexibility.**

I. Introduction

In addition to the increase in renewable generation, extreme weather can significantly increase the system uncertainty and impose challenges to operation reliability. In December 2022, winter storm Elliot brought extreme cold temperatures that led to wide-spread electric generation outages coinciding with winter peak electricity demands, resulting in many U.S. RTOs declaring energy emergencies [1-4]. Managing increasing uncertainty and maintaining reliable power system operation is a very challenging problem. It has motivated numerous efforts to provide candidate solutions with different problem formulations.

A stochastic optimization formulation, such as a recent work presented in [5], allows stochastic scenarios and reserve to be co-optimized, enabling the solutions to be robust for different operating scenarios, and the need for an empirical reserve requirement is eliminated. However, the quality of the stochastic scenarios is unknown, and a stochastic optimization is computationally more expensive. Therefore, it has not been widely adopted in the electricity market.

Benchmarked with a stochastic unit commitment model, [6] illustrates that the ramp reserve can improve market efficiency, but a logical and proper tuning of the requirement is important to such success. Different reserve allocation models based on a deterministic estimation on the reserve requirement are proposed in [7]. An extended DC-Optimal Power Flow (DC-OPF) formulation is provided to explicitly represent ramping requirements that arise from the combined variability of the load and intermittent resources [8]. In addition to the variability portion studied, [9] proposes methods to procure ramp reserves with uncertainties that are captured through historical distributions from different sources such as renewable generation and generation outages.

The cost of reserve requirement with quantified uncertainty has been studied with probabilistic constraints. The cost of wind generation uncertainty is quantified as expected energy not supplied (EENS) using the probability distribution of the wind generation uncertainty [10]. A parametric analysis derives insights into the relationship between minimal generation cost and the ramp product requirements in a risk-limiting economic dispatch problem [11]. An adjustable chance constraints formulation is proposed to achieve reasonable trade-off between operational risks and reserve costs [12]. One challenge of the probabilistic constraint model is that it cannot be directly computed by existing commercial solvers. An equivalent tractable transformation is necessary, and it can be complicated to implement.

Another approach to determine the reserve requirement is based on the analysis of the historical uncertainty distribution. A linear mapping between a risk factor that is defined based on the net load forecast error and non-spin reserve requirement is presented in [13]. A Monte Carlo simulation-based optimization is used to determine the proper level of ramp uncertainty and corresponding to the ramp requirement [14]. Similarly, standard deviation and the mean value of the historical net load variation are used to determine ramp reserve requirements in [15]. A probabilistic method is proposed to quantify ramp reserve requirement based on the historical ramping data in [16].

B. Huang, C. Ross, C. Tsai, and C. Wang are with Midcontinent Independent System Operator, Inc. (MISO), Carmel, IN, 46032 USA.
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As part of MISO's centralized uncertainty platform effort, MISO adopted the methods in [17] to quantify net uncertainty from historical operational data. With the uncertainty distribution directly obtained from the historical data, assumptions on the uncertainty distribution can be avoided. Reserve requirements with different confidence levels can be directly given by the actual historical distribution.

In this paper, based on the quantified historical ramp uncertainty, we propose a cost-benefit analysis framework to determine the optimal requirement with a focus on the ramp capability reserve. The key research problem this paper addresses is how to determine ramp reserve requirement based on the trade-off between the cost of procured reserve and the benefit of production cost savings when the uncertainty materializes. The contributions of this work are summarized as follows. First, a holistic simulation-based framework is developed for reserve requirement optimization. A sequence of quantitative methods including k-means for the uncertainty-distribution based sample set preprocessing and requirement adjustments are systematically designed to optimize the choice of reserve requirement. Second, a high-fidelity production-grade real-time market simulation tool is developed. Third, case studies are performed using MISO system historical cases, and the results provide a realistic reference on uncertainty management in a system with significant and growing renewable penetrations. Although this work is focused on a ramp product, the framework and methods can be easily generalized for different types of reserves.

The rest of this paper is organized as follows. Section II presents the methodologies used to quantify historical ramp uncertainties. The definition of Normal/High Uncertainty condition and K-means sampling and weighting method is presented in Section III. The production engine based real-time market simulation tool is introduced in section IV. Simulation and results analysis are provided in section V. Section VI concludes the paper.

II. MISO Ramp Capability Reserve product and Ramp Uncertainty Quantification

Both MISO and California ISO (CAISO) have implemented ramp capability (RC) products in the energy and operating reserves markets. Different from other reserve products, ramp capability reserve is defined primarily to address the increasing uncertainty in the market operation [18],[19]. The goal of the ramp reserve design is to schedule additional amounts of flexible capacity and, ultimately, to incentivize investment in flexible generation. One characteristic of the RC reserve is that it is defined to designate capacity in the current market optimization interval to meet higher or lower than expected and unexpected net load in the subsequent intervals. Therefore, the units cleared for RC reserve are pre-positioned to be prepared for the upcoming changes in future. From the system operator point of view, procuring RC in a real-time market interval is equivalent to purchasing insurance to hedge against the uncertainty in the future interval. From generators who can provide the RC reserve, clearing of RC incurs opportunity cost which can be compensated by the RC price. The RC product can be defined in both up and down direction, in this paper we focus our discussion on the ramp capability up reserve.

Ramp capability reserve in MISO is defined as a system wide requirement, and it is designed to manage both the net load variations and uncertainties [18]. The variation component is designed to reflect the deterministic forecast of net load change in the subsequent interval, and the uncertainty component is designed to cover the deviation from the forecast. In MISO's design, at each real-time market economic dispatch that is sequentially performed every five minutes, ramp capabilities would be secured ten minutes in advance. Details of the formulation of the ramp capability reserve product can be found in [18].

Ramp reserve requirements at different confidence levels can be directly generated from the historical ten minutes uncertainty distribution. Leveraging the cascading unit commitment (UC) and economic dispatch (ED) processes with historical data in MISO, the aggregated net uncertainty including uncertainties from load, generation, renewable, Net Scheduled Interchange (NSI), can be acquired from the differences between the forecast in an earlier process and the forecast or realization in a later process. In this work, the methods developed in section III.A in [17] are applied to six years of production data to generate the 10-minute ramp uncertainty historical distribution. To reflect the seasonal and hourly variations, the reserve requirements of each confidence level is generated at hourly basis for each season.

III. K-means based sampling and weighting method

To study the cost of ramp reserve requirements at different confidence levels, a real-time market simulation, that is introduced in section IV, needs to be performed. Due to the time and resource limits, a small set of historical market cases need to be selected for simulation. To select sample cases and calculate weightings, a systematic method is developed and presented in this section. The goal is to balance the results across different historical system conditions and to avoid biases toward certain scenarios.

A. Normal and High Uncertainty Conditions

TABLE I. Definition of High/Normal Uncertainty Conditions

Conditions	Hourly Maximum Ramp Uncertainty	Number of Hours
High Uncertainty	>=97% of historical distribution	6606
Normal	<97% of historical distribution	49228

According to the current design in MISO's dynamic ramp reserve, the most granular requirement change is hourly. Therefore, the market operation time of each sample is one hour, and it contains twelve 5-minute RT-SCED cases. The ramp uncertainty of each 5-minute RT-SCED can be calculated by method introduced in II.B. The ramp uncertainty of an hour is marked as the highest 5-minute RT-SCED ramp uncertainty within that hour.

In consistent with MISO's risk tolerance across different reserve products, 97% percentile of historical ramp distribution is defined as the Normal condition and the top 3% of the distribution is considered as High Uncertainty condition. Based on this criterion, the historical RT-market operating hours can be divided into two groups as shown in Table I.

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B. K-means Clusters and Weighting

Only a limited number of hours can be simulated and thereby samples need to be carefully selected to represent full spectrum of the impact from ramp reserve requirements to the market. It is noted that high ramp uncertainty does not necessarily lead to a tight system operating condition which can also been affected by the availability of flexible capacity in the system. Therefore, the same ramp requirement may result in very different market outcomes even within the same uncertainty condition group introduced in Table I.

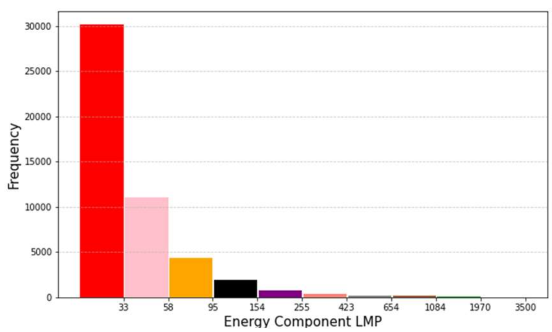

Figure 1. Normal Clusters.

The energy component (EC) of the Location Marginal Price (LMP) that is the Lagrange Multiplier of the energy balance constraints in each RT-SCED case, can serve as a good representation of the system operating condition. Therefore, each historical real-time market hour can be marked with the maximum EC-LMP of the 5-minute RT-SCED solution within that hour. K-means method can then be applied using the single feature EC-LMP to create clusters for each of the two groups in Table I. Ten clusters are generated for each group and shown in Fig. 1 and Fig. 2. The x-axis is marked with the range of EC-LMP for all clusters that are shown as the bars in different colors. The height of each bar is marked on y-axis indicating the frequency/size of the cluster. One sample hour is selected from each cluster. The weight of sample/cluster n is calculated:

$$W_n = \frac{|Cluster_n|}{\sum_{n\in\mathcal{N}}|Cluster_n|}, \forall n \in \mathcal{N}. \quad (1)$$

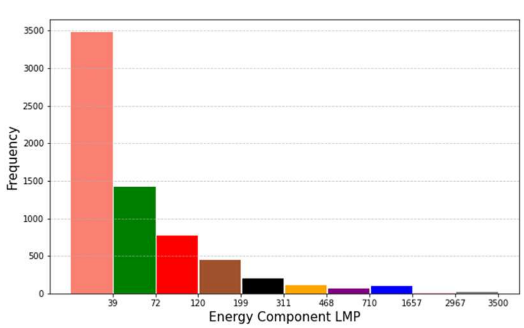

Figure 2. High Uncertainty Clusters.

Shown by the frequency of each cluster in both Fig. 1 and Fig. 2, the system price is relatively low in majority of time. Cluster at lower EC-LMP have much more weights in the Normal condition group in Fig. 1 compared to the High Uncertainty group in Fig 2. In addition, the clusters at lower EC-LMP still have more weight compared to the clusters with higher EC-LMP even in the High Uncertainty group shown in Fig.2. That indicates the system condition is not tight most of the time even with a high ramp uncertainty.

IV. High Fidelity Automated RT-SCED Rolling Simulation

There are twelve 5-minute RT-SCED cases in each of the sample hour. MISO's RT-SCED engine solves single interval standalone market optimization, taking the starting point of generators and transmission flows from the projection of the state estimation (SE). In the rolling simulation, the generator and the active power part of transmission starting points are updated from the previous solutions instead of SE. It is assumed all generators following MISO's dispatch signals exactly and the reactive power changes do not dramatically change the flow and the set of binding transmission constraints in the RT-SCED remains the same in the simulation. The pre-process and case preparation to achieve the rolling simulation is written in Python 3.11. Using a server with 16 vCPUs and 64 GB RAM, it takes on average 1 minute to prepare a single RT-SCED case ready for a rolling simulation. It is noted that transmission flow update involves manipulation of a large volume of data and files and a parallel processing module is developed in this work to reduce the process time to on average 40 seconds.

To show the accurate cost-benefit from the reserve requirement changes, four major components are included in the calculation of the production cost from the objective function of each RT-SCED. They are energy and reserve offer cost from generators, the system violation penalty cost and reserve scarcity cost. MISO's RT-SCED demand curve is used to calculate the reserve scarcity cost.

V. Simulation Results and Discussion

Based on the distribution of the historical ramp uncertainty discussed in section II, RC requirements with different confidence levels of each hour in every season can be obtained. In this study, RC requirements at 14 different confidence levels range from 86% to 99% are simulated with each sample hour. One sample is selected from each of the 10 clusters from each of the Normal and High Uncertainty groups. The total runtime to complete all the simulations for this study is about 120 hours. The ramp requirement framework proposed in this paper is designed to be performed offline and it can be repeated at a cadence based on how often the historical uncertainty distribution significantly changes with the newly added production data.

A. Simulation Results of Individual Samples

In the base case study, the production cases of the selected sample are resolved in the RT-SCED rolling simulation using the current production RC requirement value. The uncertainty component of the current RC requirement is a static value derived to represent 86% confidence level of all hours and seasons in the historical distribution.

The total RC up requirements of sample #1 are shown in Figure 3. Notice that this is the total RC up requirement that includes both the variability and uncertainty components.

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Compared to the base case RC up requirements shown in red triangles and labeled as 'Current RC Requirement,' it is observed that the requirement with 86% and 87% confidence level are lower than the current static value. That is due to the hourly and seasonal variations in the proposed ramp uncertainty requirement.

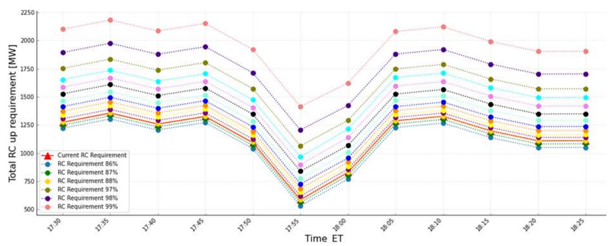

Figure 3. Total RC Up Requirment, Sample 1.

The system EC-LMP of sample #1 is shown in Figure 4. It can be observed that the higher RC up requirement may moderately increase the price when the base case price is low, but it can significantly reduce the price spikes. Compared to the 18:20 base case price spike, it is observed that 94% confidence level reduces the price the most. The price changes for sample 1 in Fig. 4 are mainly driven by the generation and reserve costs. This example shows an appropriate RC requirement which can effectively pre-position the unit and save system operation cost.

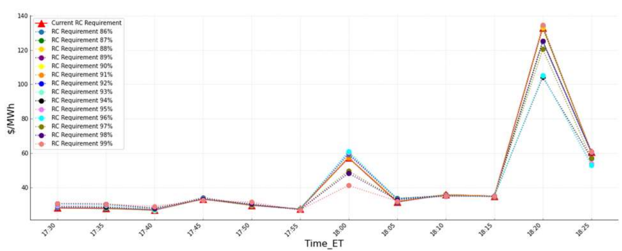

Figure 4. Energy Component LMP, Sample 1.

The increased RC up requirement can also reduce shortages in other reserve products. Results of sample hour 2 are shown in Figure 5. The regulation reserve, which is the 5-minute reserve product at MISO, runs into shortages in two consecutive intervals at 06:45 and 06:50 in base case shown as the solid red line. It is observed that RC up requirements that are higher than 93% confidence level reduce the regulation reserve shortages.

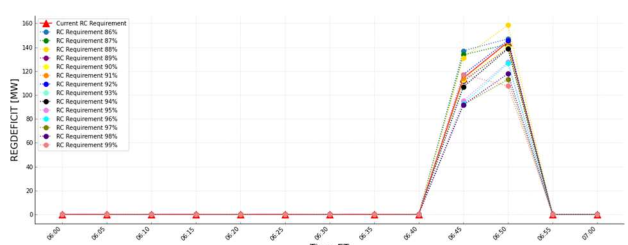

Figure 5. Regulation Reserve Shortage, Sample 2.

B. Production Cost Comparison

In the last subsection, the impact of different levels of RC Up requirement on RT-SCED is shown in a few examples. All the impacts are translated into production cost as introduced in section IV. In this section, the impact of different RC requirement to the hourly production cost is compared.

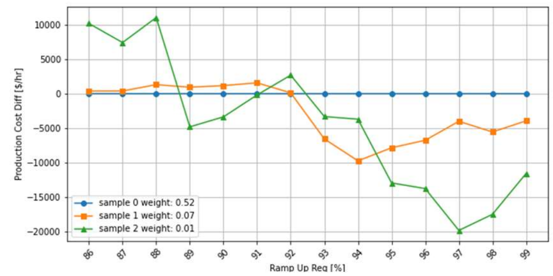

Figure 6. Production Cost Comparison of High Uncertainty Sample 0,1,2.

For a concise illustration, the hourly results of 3 out of 10 total samples in the High Uncertainty condition are shown in Fig. 6. The weight of each sample is shown in the label. The production costs of each sample hour with different Ramp Up Requirement that is marked on x-axis are compared to the base case and only the difference is shown on the y-axis. A positive number shows a cost increase and a negative number indicates a reduction. It is observed that minimum production cost for sample 1 is 94% confidence level. The minimum production cost for sample 2 is at the 97% confidence level.

Sample 0 is selected from the biggest cluster in the High Uncertainty Condition shown in Fig. 2 thereby has the highest weight. A flat line indicates that in more than half of the time in High Uncertainty group, the system is sufficient with ramp capacity such that different RC up requirement does not make any difference even with a very high ramp uncertainty. Different RC requirements have a larger impact on the production cost in Sample 1 and Sample 2. However, their small weights indicate the operating conditions with price spikes or significant reg shortages are rare.

C. Weighted Production Cost Comparison

Hourly production costs from all different samples are summed with their weights for both normal and high uncertainty conditions with results shown in Fig. 7. For normal hours, it can be observed that the weighted production cost is increasing with higher ramp up requirements. During normal hours, when the chance of extreme events is low, the procured reserve is deployed less often. Therefore, a higher requirement increases the overall system production cost. The lowest production cost occurs with the lowest requirement at 86% confidence level. Compared to the base case RC requirement, which is a static value at 86% of historical distribution on all hours, the simulated requirement at 86% confidence level that varies by hour and season can reduce the production cost by a small amount. In high uncertainty conditions, there are more extreme events, and the benefits of a higher RC up requirement materialize more often and that outweighs the cost of the procurements. The weighted production cost reaches the minimum with RC up requirement at 96% confidence level. An even higher RC up requirement would further increase procurement costs, but the benefit does not materialize enough and make it a less economic choice.

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The weighted results in Fig. 7 show recommendations balance different system conditions represented by different samples. Based on the results in Fig. 7, the RC up requirement (uncertainty component) recommendation for Normal and High Uncertainty conditions are 86% and 96% of the historical ramp uncertainty distribution respectively. Using the ratio of number of hours between normal and high uncertainty hours in Table I, the estimated annual production cost saving with the recommended RC requirement is $509,832.

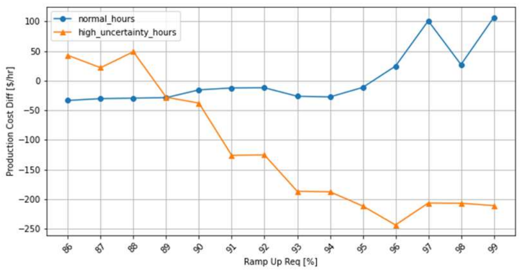

Figure 7. Weighted Production Cost Comparison.

It is noted that operational knowledge is applied to screen the sample case selection after the k-means method and that process is necessary to guarantee the high quality of the sample and the robustness of the study. A small sensitivity test is performed on k value in k-means method and results are robust to a different k value. It is noted that a larger k would generate more clusters and samples and therefore increases the accuracy of the sample representation. In this work, k=10 is selected given the project timeline and internal resources limit.

VI. Conclusion and Future Work

In this paper, a production-grade simulation-based framework is developed for reserve requirement optimization. Based on the current historical ramp uncertainty quantification data, the RC up requirement that minimizes the weighted system production costs are recommended for Normal and High uncertainty conditions separately. MISO is currently developing processes to dynamically switch between Normal and High Uncertainty RC up requirements based on the assessment on the system condition during market operations.

It is noted that MISO solves single interval real-time dispatch markets with a ramp reserve product looking ahead for 10 minutes [18]. This paper shows the value of ramp requirement optimization. However, due to the short look ahead window, the improvement can be limited in higher uncertainty levels due to the growing renewable penetration. Other pre-position options such as enhanced uncertainty reserve designs and look-ahead dispatch market need to be explicitly explored to provide strategic recommendations on uncertainty management in the energy market.

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