Analysis of Operating Reserve Demand Curves in Power System Operations in the Presence of Variable Generation

Ibrahim Krad [1*], David Wenzhong Gao [2], Erik Ela [3], Eduardo Ibanez [4], and Hongyu Wu [5]

[1] National Renewable Energy Laboratory, Golden, USA
[2] Department of Electrical and Computer Engineering, University of Denver, Denver, USA
[3] Electric Power Research Institute, Knoxville, USA
[4] General Electric Energy Consulting, Schenectady, USA
[5] Department of Electrical and Computer Engineering, Kansas State University, Manhattan, USA

[*]ibrahim.krad@nrel.gov

Abstract: The electric power industry landscape is continually evolving. As emerging technologies such as wind, solar, electric vehicles, and energy storage systems become more cost-effective and present in the system, traditional power system operating strategies will need to be re-evaluated. The presence of wind and solar generation (commonly referred to as variable generation or VG) may result in an increase of the variability and uncertainty in the net load profile. One mechanism to mitigate this issue is to schedule and dispatch additional operating reserves. These operating reserves aim to ensure that there is enough capacity online in the system to account for the increased variability and uncertainty occurring at finer temporal resolutions. A new operating reserve strategy, referred to as flexibility reserve, has been introduced in some regions. A similar implementation is explored in this paper, and its implications on power system operations are analysed. This is achieved by studying the operational changes in a system both with and without this reserve product. Results show that flexibility reserve products can improve economic metrics, particularly in significantly reducing the number of scarcity pricing events, with minimal impacts on reliability metrics and production costs. The production costs increase with the inclusion of the flexible ramping product, although only by a small percent. This is most likely attributable to increased curtailment in VG generation—i.e., including the flexible ramping product resulted in the commitment of excess thermal capacity that needed to remain online at the expense of curtailing VG output.

1. Introduction

As emerging technologies continue to become more significant players in the power system, operating strategies will need to evolve that allow system operators to mitigate adverse effects while maximizing system benefits. Wind and solar generators, electric vehicles and distributed generation located throughout the distribution system have recently drawn significant attention. These technologies may increase the variability and uncertainty in the power system if not properly controlled and operated. Power system operators may need new and improved methods to maintain the real-time balance between electricity generation and consumption. Traditionally, system operators have utilized a combination of operating reserves [1]. These requirements are typically based on simple heuristics developed independently by each footprint, without any consensus on a universal methodology to calculate how

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much reserves the system operator must acquire. Although contingency reserves are typically designed with N-1 reliability in mind, there is still much discussion about how operating reserves are procured.

New operating reserve methodologies are explored to address the additional variability and uncertainty from variable generation (VG) resources. Methodologies to determine operating reserves in recent wind integration studies and operating practice were examined in [2], where simulation results were compared with different methods or data. A statistical approach to assess the impact of intra-hour wind power variability on the quantity of primary reserve provided by wind generators was proposed in [3], where three reserve allocation strategies were compared in case studies. Market implications of dynamic reserve policies for managing uncertainty from renewable resources and contingencies were examined in [4], where different policies were compared and a locational reserve pricing scheme was proposed. Reference [5] describes different assumptions and methods for calculating the amount of different types of reserves and how these methods have evolved over time. Reference [6] describes the relationship between operating reserve and wind generation and compared three methodologies for calculating regulating and flexibility reserve in systems with wind generation. A dynamic operating reserve requirement that was updated on an hourly basis to account for the variability of wind power was presented in [7], where the requirement was driven by probabilistic forecast errors as well as the short-term variability of wind power generation. Their analysis showed that there are significant opportunities to modify a static reserve requirement, and this modification could potentially reduce the cost per MWh of wind power injected. The authors of [8] proposed a dynamic reserve requirement methodology based on the probability of load shedding. The requirement was determined by considering the reliability requirements of the system throughout the entire year with respect to the number of allowable load-shedding incidents per year. Their analysis showed that increasing wind power generation in the system increases the need for operating reserves and that reserve requirements that consider longer temporal horizons typically result in requirements larger than those for shorter temporal horizons. A dynamic economic dispatch problem was formulated to simultaneously schedule energy and reserves utilizing an interior point algorithm in [9], where the model converged well with improved computational speed. The authors of [10] proposed an hourly, dynamic reserve requirement methodology based on risk indices, such as the loss of load probability. This formulation allows the system operators to examine the trade-off between acceptable risk levels and operating cost and decide on a reserve requirement that best suits the current operating needs of the system.

The industry is also interested in this new class of flexibility reserves. In [11], a framework was presented to determine the quantity of ramping reserves based on the standard deviation of ramping imbalance, i.e. the difference between scheduled and actual generation ramping rates. The authors of [12] developed a flexibility reserve methodology to address ramping concerns that can be integrated within the

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Midcontinent Independent System Operator's day-ahead market model. This method aims to prepare generation assets for variability and uncertainty in the net load. One of the potential benefits of this ramping product is the potential reduction in real-time scarcity events. The California Independent System Operator recently developed a proposal to incorporate a flexible ramping ancillary service [13]. This product was meant as a dynamic reserve requirement implemented via a multi-segment reserve demand curve to address potential net load ramping concerns. This was motivated by the fact that the commitment and dispatch of generators does not always account for the variability and uncertainty in the net load that occurs at finer temporal resolutions. This product was developed with the intention of curbing the system's reliance on regulating ancillary services and interchange flows during times of insufficient or over-generation. Another motivation is to reduce the volatility in the locational marginal prices (LMPs) by reducing the number of scarcity pricing events caused by insufficient ramping capacity. The basic idea is that including the flexible ramping service will provide a ramping margin on top of forecasted net load ramps in multi-interval unit commitment and economic dispatch.

The contribution of this paper lies in analysing the economic and reliability implications of a dynamic operating reserve product that does not enforce a singular reserve requirement but rather offers the operator flexibility in reserve procurement on power system operations at multiple timescales. The intent of this reserve product is to prepare the system for real-time flexibility needs by dynamically modifying the operating reserve requirement based on real-time load, solar, and wind forecasts. The analysis is performed over several weeks and operational impacts are studied. Economic implications are measured via total system production costs and LMP. Of particular interest is the impact on scarcity prices. If there is not sufficient ramping capacity available in the system to meet an incremental increase in demand, then that interval would exhibit scarcity pricing. Reliability implications are measured based on the area control error (ACE), i.e., the imbalance between generation and consumption.

The rest of this paper is organized as follows: Section II details the flexible ramping product methodology, Section III describes the case study used in this analysis, Section IV provides the results, and Section V concludes the paper with final remarks.

2. Methodology and Determination of Reserve Requirements

The analysis performed in this study utilized the Flexible Energy Scheduling Tool for Integrating Variable generation (FESTIV) developed by the National Renewable Energy Laboratory (NREL). This is a steady-state power system operations simulation tool. FESTIV captures the entire scheduling process, from the day-ahead unit commitment through the generator automatic generation control (AGC). FESTIV simulates an integrated set of scheduling tools: security-constrained day-ahead unit commitment

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(DASCUC), security-constrained real-time commitment (RTSCUC), security-constrained real-time economic dispatch (RTSCED), and AGC. Each model is interconnected to subsequent models such that the outputs of one model serve as the inputs into the next. FESTIV is built in MATLAB and GAMS [14]-[15]. More details about the model can be found in [16].

The flexibility reserve requirements were implemented following the description provided in [13]. The requirements are calculated by examining the distribution of subhourly forecast errors for net load (load minus wind and solar). As described in [13], upper and lower bounds for these forecast errors are calculated for each hour of the day, on a monthly basis. Although the calculation and subsequent requirements change among the different models in FESTIV (DASCUC, RTSCUC, RTSCED), the demand curve has a similar behavior.

Fig. *1* (left) shows a diagram with the basic shape of the flexible reserve demand curve (FRDC). The demand is determined dynamically for each step in the simulation. The minimum flexibility reserve requirement (FRMIN) represents the expected ramp need of the system. A penalty cost is associated with the FRMIN. The demand curve is in place such that ramping capability above the FRMIN can be purchased when cost effective. There are a number of additional steps for increasing need with decreasing penalty costs. The last step is extended to the maximum flexible reserve value (FRMAX).

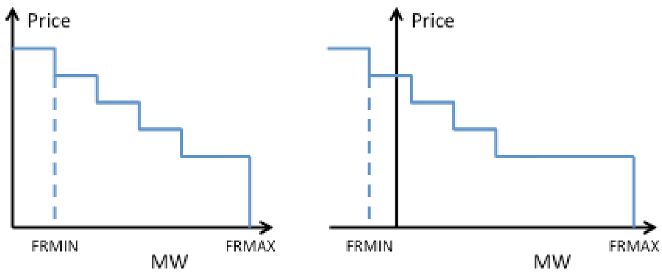

Fig. 1. Example flexible reserve demand curve

The optimization algorithm will select the reserve level on the demand curve where the marginal cost of providing the service is less than the penalty cost. The use of demand curves allows for the implementation of decreasing penalty costs, which provide more granularities to the optimization. Both upward and downward requirements are held in these simulations. In the event that FRMIN is negative for a given requirement, i.e. the expected change in the net load profile is opposite that of ramping need (Fig. 1, right) the supply curve is shifted, and FRMIN is set to zero. For example, if the change in the net profile is in the downward direction (negative), then the ramping need in the downward direction is positive and the ramping need in the upward direction is negative. In this case, rather than enforcing a negative requirement, the upward requirement is set to zero instead.

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Table 1 summarizes the different parameters that, along with FRMIN and FRMAX, determine the supply curves for each solution step. The goal was to match the methodology as closely as possible to that of [13] while making necessary changes due to differing systems and data availability.

Table 1 FRDC characteristics

	DASCUC	RTSCUC	RTSCED
Step Width [MW]	250	50	50
Segment Penalty Costs / Up Direction [\$/MW]	250 / 24, 15, 8, 2.5		
Segment Penalty Costs / Down Direction [\$/MW]	250 / 3.6, 2.25, 1.2, 0.375		

In order to calculate the price break points of the FRDC, a historic analysis on ramp error distributions was performed. Based on [13], the approximate probability of different groups of ramp errors are shown in column 2 of Table 2. Column 3 shows the midpoint of that group. Then, the expected cost of having a ramping violation based on the previous analysis was calculated using (1). This represents the cumulative cost of violation if only the minimum requirement is met for each step in the demand curve.

$$C_{vio} = \delta_{up} \sum_{k=n}^{5} \rho_k \cdot \left(R_{avg\ need} - R_{procured}\right) \tag{1}$$

In (1), δ_{up} is the upward violation penalty price (1000 \$/MW taken from [13]), ρ is the probability of a violation, R is the expected magnitude of the average violation ramp error not served based on historical data, and k indexes the steps in the demand curve. For example, the cost of a ramping violation in the second block of the FRDC is calculated as:

$$C_2 = 1000\ (0.008 \cdot (150 - 100) + 0.006 \cdot (250 - 100) + 0.005 \cdot (350 - 100)) = \$\ 2550 \tag{2}$$

The costs are shown in column 4 of Table 2. With these costs defined, the price of each block in the demand curve is calculated as incremental cost between blocks normalized by the magnitude of the block (i.e., width of the block). For example, the price of the first block is taken as (4950-2550)/100=24 \$/MW. These costs are summarized in column 5 in Table 2.

Table 2 Summary of demand curve break point calculations

Ramp Group [MW]	Probability, ρ	Average Need [MW]	Expected Cost [\$]	Demand Price [\$/MW]
0 – 100	0.010	50	4950	24
100 – 200	0.008	150	2550	15
200 – 300	0.006	250	1050	8
300 – 400	0.005	350	250	2.5
400+	0.000	–	0	0

With the upward FRDC breakpoints defined, the downward FRDC breakpoints are defined by scaling these prices. The downward penalty price as taken from [13], δ_{down}, is equal to 150 \$/MW. The downward FRDC prices are calculated using (3).

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$$D_{down} = D_{up} \cdot \frac{\delta_{down}}{\delta_{up}} \tag{3}$$

In (3), D represents the demand curve price and δ is the penalty price. The demand curves are decreasingly structured so that the optimizations only procure additional capacity over the minimum required if it is economically feasible to do so. The requirements are sectioned off into blocks in order to assign marginally increasing value to increasing excess capacity.

The description in [13] suggested a number of system factors that contribute to the determination of flexibility reserve requirements. In this paper, we consider the contribution of load and VG toward that requirement. We do not consider the impact of self-scheduling generators or interchange with other regions because neither is considered in our modeling. In the absence of many years of data to determine the requirements, as suggested in [13], data for one year was utilized.

FRMIN is calculated differently for each simulation step:

- DASCUC: Day-ahead flexibility requirements are calculated based on the hourly difference in net load (i.e., load minus VG generation). FRMIN is calculated based on the difference in day-ahead forecasts for each hour. FRMAX is calculated as the 97.5^{th} and 2.5^{th} percentiles for net load hourly ramps for each month and hour of the day for the upward and downward directions, respectively. It is a 60-minute product.
- RTSCUC: Intra-day unit commitment happens with a frequency of 15 minutes in the simulations. FRMIN is calculated as the difference between the forecast for each of the 5-minute RTSCED steps that correspond to each RTSCUC solution. FRMAX is calculated as the 95% confidence interval for FRMIN for each hour of the day within a month. Requirements are calculated for the binding and advisory intervals. It is a 5-min product.
- RTSCED: Real-time economic dispatch flexibility reserve requirements are based on the difference of each consecutive 5-minute forecasts for net load, both for the binding and advisory intervals. FRMIN values are calculated as the expected 5-minute ramps in the net load forecasts. Up and down FRMAX values are calculated to cover 95% of those differences. It is a 5-min product.

Fig. 2 shows plots of the maximum requirement for a single day for the week simulated in October in both the upward (upward ramps) and downward (downward ramps) directions. Although the actual requirements will change with every interval, each month exhibits similar trends, and the magnitude of the requirements at each temporal resolution is also comparable among months.0

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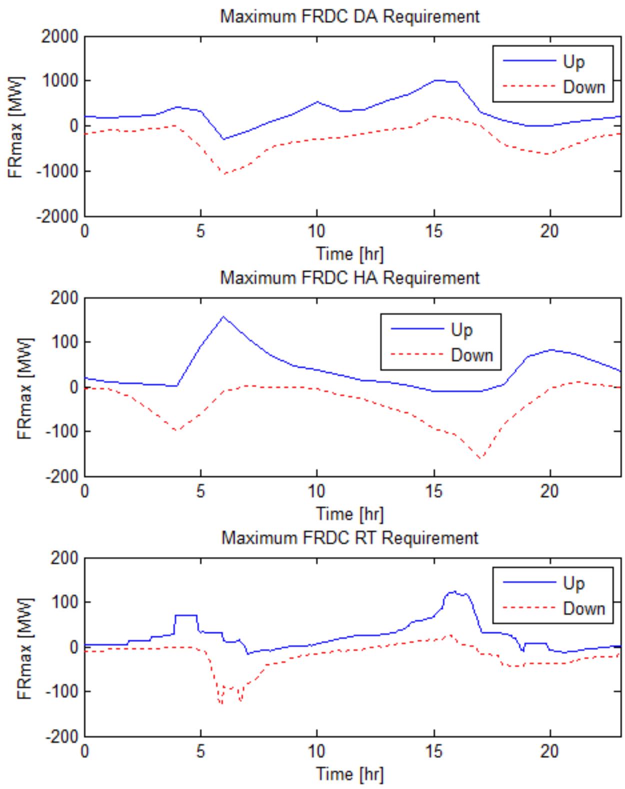

Fig. 2. Flexible reserve demand curve maximum requirements in October

3. Study Test Bed

The system studied in this analysis is a modified version of the IEEE 118-bus test system [17]. The system generation portfolio and transmission capacities were updated to better reflect current, available operation cost data. Namely, some coal generation was converted to combined-cycle generation, and plant operating characteristics such as ramp rates were updated to better capture current generation plant flexibility.

Load, wind, and solar data were obtained based on available data for northern California from the Western Wind and Solar Integration Study Phase 2 report performed by NREL [18]. The characteristics of this new system are reflected in Table 3 - Table 5.

Table 3 Updated IEEE 118-Bus test system characteristics

System Characteristics	
Coal Capacity [GW]	2.30
Combined-Cycle Capacity [GW]	2.76
Combustion Turbine Capacity [GW]	2.52
Annual Solar Energy Penetration [%]	17.45
Annual Wind Energy Penetration [%]	16.98

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Table 4 Load and net-load data characteristics

	λ = Load Data		ζ = Net Load Penetration	
	mean(λ) [MW]	max(λ) [MW]	mean(ζ) [%]	max(ζ) [%]
January	3,625	4,452	22.5	71.5
April	3,145	3,713	37.5	92.3
July	4,725	6,552	22.2	57.6
October	3,300	4,019	33.2	93.5

Table 5 VG data characteristics

	ρ = Net Renewable Generation Data			
	std(ρ) [MW]	max 4-sec up ramp [MW]	max 4-sec dn ramp [MW]	avg. energy pen. [%]
January	554.15	12.23	18.42	22.55
April	840.35	14.96	16.44	37.47
July	798.19	13.13	11.65	22.22
October	742.27	15.55	18.43	33.18

In Table 5, the std() function represents the standard deviation of the net-load profile. The net-load profile is defined as the load profile minus all wind and solar generation profiles. The second column shows the largest ramp in the aggregated wind and solar generation profile in the upward direction. Similarly, the last column shows the largest downward ramp of the aggregated wind and solar generation profile.

The system was simulated for four weeks (one week each in January, April, July, and October) to capture the seasonal trends in load, wind, and solar profiles. To capture the effects of the ramp product, each week was simulated twice, once without the product to establish baseline results and once with it to measure its effects on efficiency and reliability metrics. Base case simulations contain traditional reserve capabilities such as contingency and regulation reserves in both upward and downward directions. This comparison is intended to extract the operational implications of updating traditional operating procedures, i.e. base case (no explicit flexibility ramping requirement), to a new procedure that does include a flexibility requirement in the form of a flexibility reserve demand curve.

4. Results

A summary of the simulation results are shown in Table 6. The production costs increase with the inclusion of the flexible ramping product, although only by a small percent. This is most likely attributable to increased curtailment in VG generation—i.e., including the flexible ramping product resulted in the commitment of excess thermal capacity that needed to remain online at the expense of curtailing VG output.

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Table 6 Overall summary of simulation numerical results

Case	Cost (million $)	Δ Cost	Number Of Price Spikes	Δ Number of Price Spikes	AACEE (MWh)	Δ AACEE	σ_{ACE}	Δ σ_{ACE}
January-Without FRDC	12.12	-0.06%	162	-96.3%	2357	-5.3%	26.7	-8.2%
January-With FRDC	12.11		6		2231		24.5	
April-Without FRDC	7.87	+4.4%	103	-75.8%	2851	+2.3%	35.3	-0.01%
April-With FRDC	8.22		25		2917		35.3	
July-Without FRDC	17.64	+0.12%	241	-58.1%	1447	-4.1%	16.9	-5.3%
July-With FRDC	17.66		101		1388		16.0	
October-Without FRDC	8.97	+3.8%	73	-89.0%	1960	+10.8%	23.8	+12.4%
October-With FRDC	9.31		8		2172		26.8	

The inclusion of the flexible ramping product helped to eliminate real-time scarcity events that were the result of insufficient ramping flexibility rather than energy shortage, and in some cases the number of scarcity events in the LMPs was reduced by as much as 96%. The flexible ramping product also helped to converge day-ahead and real-time prices. Fig. ***3*** shows the absolute difference between the load-weighted mean of the day-ahead and real-time LMPs. This helps shed some light on how well the day-ahead and real-time prices agree. Notice that among all weeks simulated, the differences between the day-ahead and real-time LMPs are reduced.

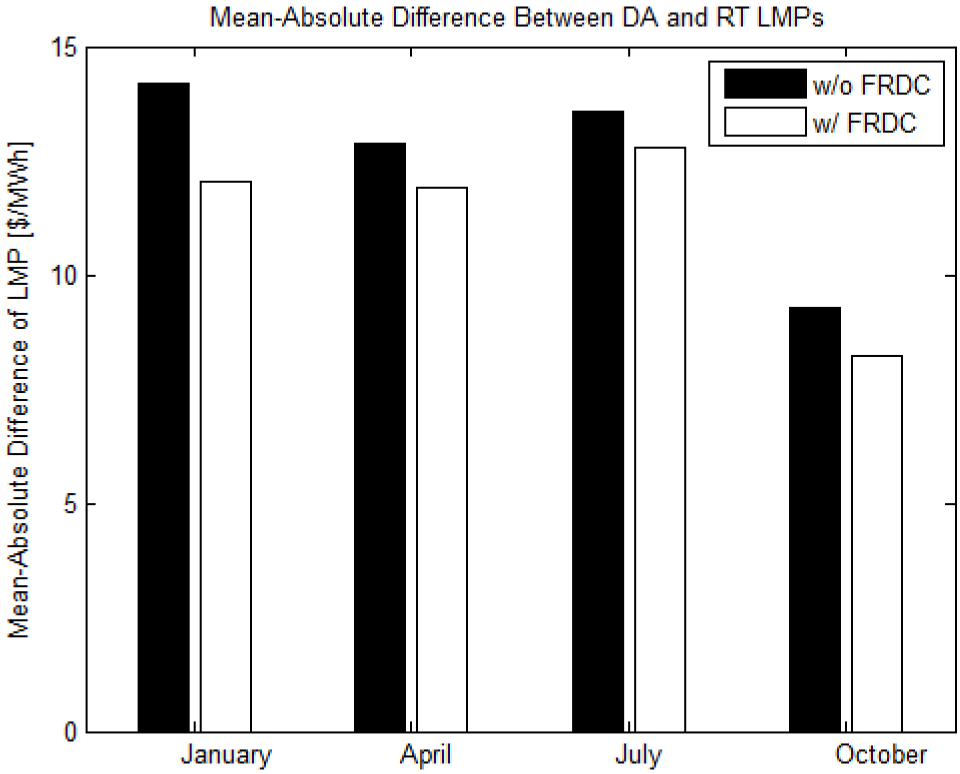

Fig. 3. Mean-absolute difference between day-ahead and real-time electricity prices

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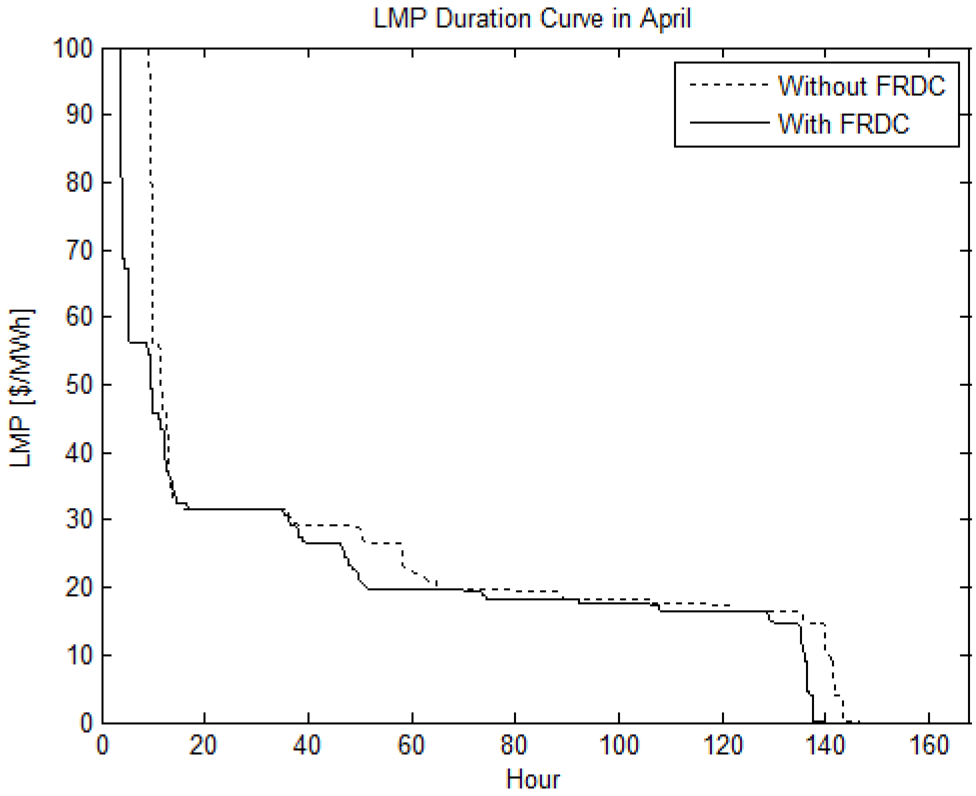

Fig. 4. Electricity price duration curve for April

The significant wind and solar curtailment occuring in the system leads to more instances with an LMP of 0 $/MWh. This is shown in the LMP duration curve in Fig. 4. The amount of VG curtailment is shown in Table 7. Notice that the amount of time with scarcity prices is noticably reduced and the amount of curtailment as shown by zero prices increases.

Table 7 VG curtailment in GWh

	Without FRDC	With FRDC
January	13.19	15.02
April	28.18	32.38
July	11.19	11.35
October	20.85	25.43

Table 8 shows the direction of accumulated ACE for each case. Notice that including the flexibility reserve product increases the amount of ACE in the positive direction while reducing the amount of ACE in the negative direction. This behavior is expected. The negative ACE is reduced because there is additional ramping capacity available in the system that can be used to help meet the demand that is otherwise unserved due to ramping constraints. However, since the flexible ramping products typically resuts with extra thermal generator commitments, this can have an adverse effect when the wind and solar generation ramp up rapidly over a short period of time. Thermal generators that are online can not back down fast

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enough or are already operating at minimum generation levels. This results in periods of time where the total generation exceeds the demand and extra positive ACE is accumulated as shown in Table 8.

Table 8 Breakdown of accumulated ACE in MWh

Case	Postive ACE	Negative ACE
Jan—Without FRDC	1298	1060
Jan—With FRDC	1416	815
Apr—Without FRDC	1972	879
Apr—With FRDC	2074	844
Jul—Without FRDC	704	744
Jul—With FRDC	712	676
Oct—Without FRDC	1200	761
Oct—With FRDC	1465	707

Table 9 summarizes the behaviour of the thermal generation fleet for all scenarios. The utilization factor is the average output of the thermal generation fleet with respect to the total thermal capacity. The next result is the average number of thermal generators online per dispatch interval. The next result is the average time a thermal generator remains online after it is turned on, measured in hours. The final result is the average number of thermal generator start-ups. In general, the flexible ramping product results in higher utilization of the thermal generation fleet. Thermal units are turned on slightly more frequently, once turned on, they remain online for longer periods of time, additional units are committed, and they operate at slightly higher set points.

Table 9 Results summarizing generator behaviour

Case	Utilization Factor, μ	$\Delta\ \mu$	Online Generators, γ	$\Delta\ \gamma$	Online Time per Startup, τ	$\Delta\ \tau$	Thermal Startups, σ	$\Delta\ \sigma$
January-Without FRDC	0.287	+2.0%	13.59	+8.2%	27.89	+24.4%	6.48	-36.2%
January-With FRDC	0.292		14.69		34.69		4.13	
April-Without FRDC	0.204	+2.0%	9.63	+15.1%	29.67	-6.1%	3.94	+33.8%
April-With FRDC	0.209		11.09		27.85		5.28	
July-Without FRDC	0.355	+3.26%	17.78	+7.1%	39.69	+4.5%	2.96	+2.6%
July-With FRDC	0.367		19.03		41.50		3.04	
October-Without FRDC	0.214	+7.20%	10.40	+14.6%	27.66	+11.9%	4.00	+4.2%
October-With FRDC	0.230		11.92		30.94		4.17	

Fig. *5* compares the LMPs among the cases to the flexible ramping product and the cases without flexible ramping product for all weeks simulated. If the inclusion of the flexible ramping product had no impact on LMPs, then all of the data points (LMPs) would fall on the diagonal (also plotted for reference). Any data point that falls below the diagonal implies that the flexible ramping product reduces the average LMP at that particular bus, and vice versa for all data points that fall above the diagonal. In general, the

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inclusion of the flexible ramping product increased the LMPs at nearly all buses for all weeks considered. In October, the opposite effect was observed. This could be due to the excess thermal generation committed during the valley times of the net load profile. Even though VG output was curtailed, thermal generators operating at their minimum output levels could not be turned off, thus resulting in significant excess thermal capacity online and the accumulation of positive ACE.

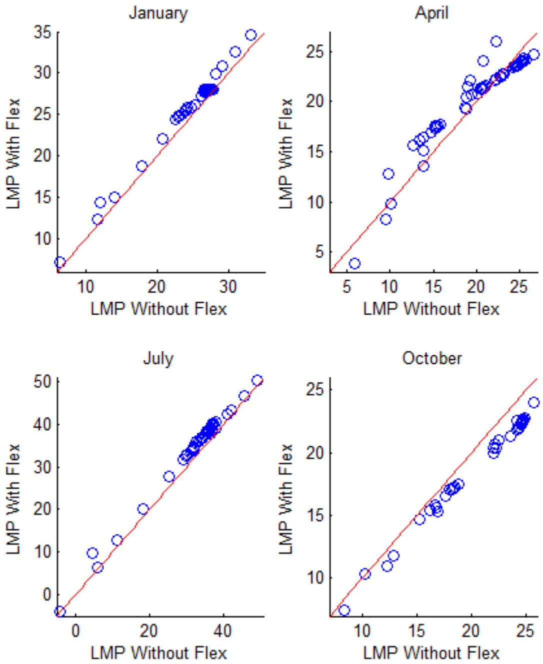

Fig. 5. Real-time electricity price comparison among all cases

Fig. ***6*** shows the difference in available 5-minute ramping capacity in the January simulation. A positive value means that there was more ramping capacity available without the flexible ramping product. Conversely, a negative value means that there was more ramping capacity availabe with the flexible ramping product. It is noticed that over the course of the entire week, there is generally more ramping capacity available when the flexible ramping product is included. This is expected since the flexible ramping product typically results in committing extra thermal generators which translates directly to the extra ramping capacity. Similar behavior occurred thoughout the week and among all other weeks as well.

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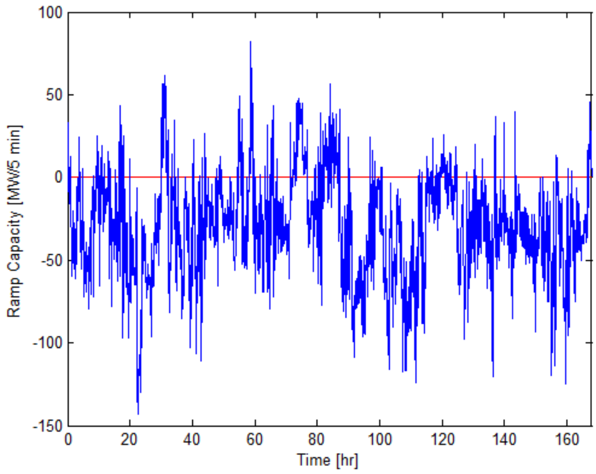

Fig. 6. Available ramping capacity for the block in January

Fig. *7* compares the amount of real time market infeasibilities across all weeks considered with and without the flexible ramping product.

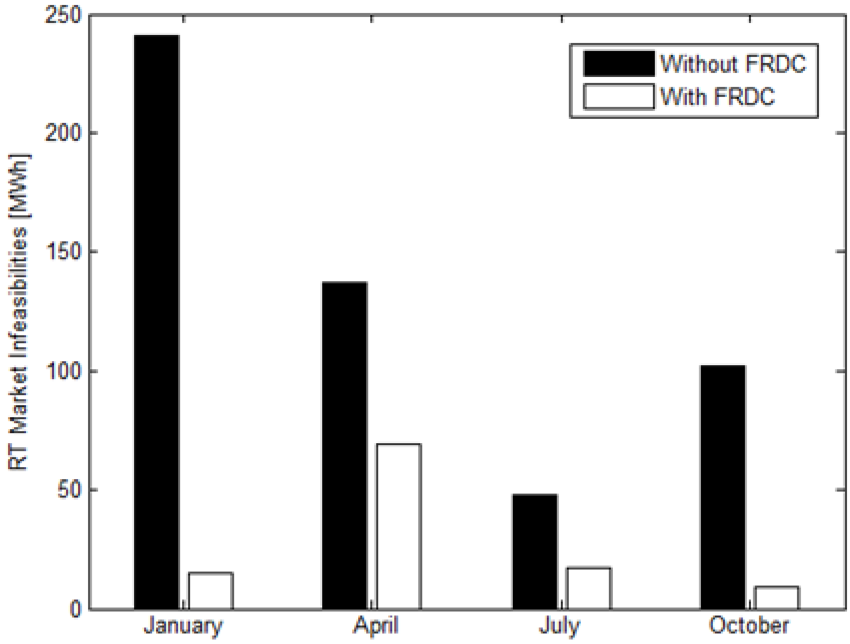

Fig. 7. Real time market infeasibilities for all weeks considered

The flexible ramping product is able to substantially reduce the amount of real time market infeasibilities across all cases. This is because the flexible ramping products necessitates the commitment of additional thermal generation. This excess capacity offers greater ramping flexibility and thus the system is able to avoid infeasible market solutions that are the result of inflexible generation portfolios.

The amount of wind and solar generation in the system does significantly impact operations. Fig. *8* shows the instantaneous renewable energy penetration in the October simulation week. Also shown in Fig. 8 is the absolute ACE in energy (AACEE) for this week for both cases considered, with and without the flexible ramping product. The AACEE is the integral of the absolute value of the ACE throughout the week. This metric gives some insight into how well the system is balanced throughout the simulation.

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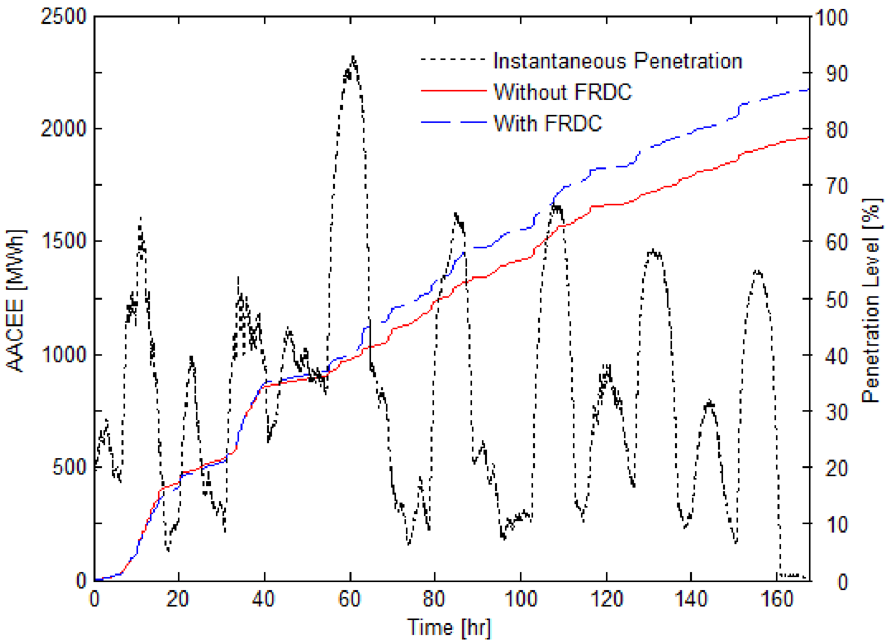

Fig. 8 Comparison of the Absolute Area Control Error in Energy and instantaneous penetration of wind and solar generation

Notice that throughout the beginning of the simulation, the flexible ramping product has minimal impact on the system imbalance. However, starting around the third day, the wind and solar generation profiles ramp up significantly for an instantaneous penetration of more than 90%. Thermal generators are backed off as much as possible in order to accommodate the spike in wind and solar generation. However, these generators cannot be turned off due to minimum generation time constraints and must remain online. This results in slight over-generation occurring during this time period and this effect is more exaggerated with the additional online thermal generators due to the flexible ramping product. This is seen in Fig. 8 where the two plots begin to deviate around hour 63. This helps corroborate the behaviour described in Table 8.

The commitment of additional thermal generators can also help partially mitigate transmission congestion in the system. The bar graph in Fig. 9 shows the number of congested intervals aggregated over all transmission lines per five minute interval with loading in excess of 95% rated capacity.

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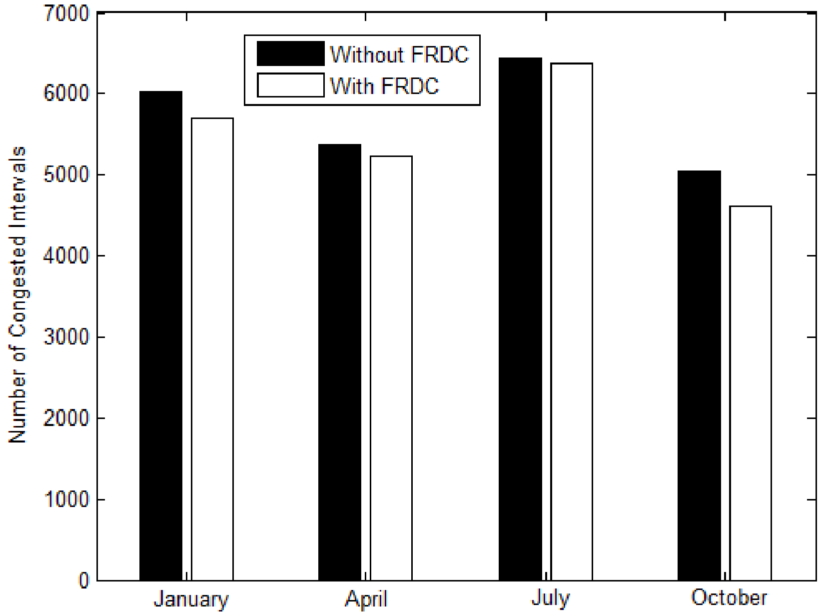

Fig. 9. Number of intervals with transmission lines experiencing at least 95% load of rated capacity

The utilization of the flexible ramping product resulted in committing more thermal generators that were more dispersed throughout the network. This is what caused the reduction in intervals exhibiting transmission congestion.

5. Conclusion

This paper presents the analysis of a flexibility reserve ancillary service product and its impact on various efficiency and reliability metrics. The flexible ramping product increases production costs and ACE. This is most likely due to the flexible ramping product necessitating the commitment of excess thermal generation, which resulted in the curtailment of wind and solar resources. The commitment of excess thermal generation to meet additional flexibility requirements may result in the curtailment of wind and solar generation, particularly during the valley times in the net load profile, if it resulted in additional thermal capacity commitments during the same time frame. The loss of this zero-cost resource resulted in an increase in the total system production cost while forcing slower thermal units to be online, which resulted in the accumulation of more ACE. This ACE was in the positive direction due to the combination of wind and solar generation ramping up quickly and thermal generators not being able to back off as fast and having to remain online to satisfy minimum run-time requirements and/or reliability requirements. The inclusion of the ramping product helps the convergence of real-time LMPs. It also helps eliminate scarcity pricing events that occur as a result of insufficient ramping capacity. The flexible ramping product can also help reduce transmission congestion if the commitment of extra thermal generators helps the distribution of the generation portfolio across a larger transmission footprint.

The purpose of this study was to begin understanding the operational implications of high renewable futures and new reserve requirement methodologies. What we have seen is that there are some benefits and

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some drawbacks for these techniques and the final decision is in the hand of the operator. However, these new flexibility reserve techniques are valuable specifically for their ability to reduce the number of scarcity pricing events. While these events can help small market participants whose business plan revolves around leveraging these large pricing discrepancies for arbitrage, they are symptoms of an inefficient market and could open the door for players to try to gain and exert market power.

Potential future work should revolve around assessing the benefits of the purposed flexibility reserve demand curves in energy futures containing high levels of wind and solar generation capacity. Under greater variability and uncertainty, it becomes even more critical to ensure reliable system performance and the benefits from this type of operating strategy could be even more profound.

6. Acknowledgment

NREL's contribution to this work was supported by the U.S. Department of Energy under Contract No. DE-AC36-08-GO28308 with NREL.

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