Calibration of Operating Reserve Demand Curves using Monte Carlo Simulations

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***Abstract*—Scarcity pricing has been proposed to enhance investment in flexible assets through the use of an adder on real-time energy and the application of that adder on real-time reserve. We implement a Monte-Carlo simulator for obtaining statistically confident estimates of scarcity pricing adders which is motivated from the implementation of this mechanism in Belgium. The analysis is based on a multi-level, multi-horizon simulation of day-ahead and real-time operations in the Belgian market. The methodology relies on k-means clustering for selecting a set of representative day-ahead forecasts, followed by the generation of synthetic real-time load scenarios for simulating real-time operations.**

***Index Terms*—operating reserve demand curve, scarcity pricing, unit commitment, k-means**

I. Introduction

The European Union has the ambition of becoming climate neutral by 2050 [1], and the integration of renewable energy in the electricity sector will have to increase in order to achieve this goal. This increased integration of renewable energy has a two-fold effect: on the one hand, it increases the variability in the system and the need for flexible assets, and on the other hand it decreases their profitability by pushing them further down the merit order curve.

Scarcity pricing has been considered as an adaptation to market design for coping with this transition. Papavasiliou et al. [2], [3] have demonstrated the potential of the mechanism to restore economic viability for flexible assets. The mechanism takes the form of an adder that supplements the price of energy when reserve is scarce in the system. The adder is valued with an *Operating Reserve Demand Curve* (ORDC) based on the *value of lost load* (VOLL) and the *loss of load probability* (LOLP). Introducing flexibility in the procurement of reserve with an ORDC has been proposed in [4] and was later anchored to the loss of load probability by Hogan in [5].

The authors in [6] analyse the potential level of the adder in Belgium by investigating (i) the incentives created by different shapes of ORDCs on the dispatch and (ii) the resulting adder for the historical load that took place in 2018. Their investigation relies on a *simulator of the short-term operation* of the Belgian electricity market. The authors emulate the electricity market with 4 embedded optimization problems that commit and dispatch assets in sequence as the day unfolds.

The present work proposes to extend [6] to a *Monte-Carlo simulation* that enhances the statistical reliability of the results by exposing the simulated Belgian system to multiple years of uncertainty. The Monte-Carlo simulation is based on synthetically generated scenarios and it has an institutional motivation [7]. The present work, by improvement the statistical confidence of the results provided in [6], improves the ability for stakeholders to reach informed decisions regarding the implementation of scarcity pricing in Belgium.

The synthetic scenarios are obtained with a two-step process. The *k-means* algorithm is first applied on the net forecast flexible production, so as to cluster similar days together. A time series model is then used in order to generate synthetic real-time demand from the de-seasonalized clustered historical time series.

Clustering scenarios in order to reduce computational cost is a common practice in the literature on power system operations, and has been used in capacity expansion problems [8] and in market simulation [9]. This method groups together similar scenarios, in order to avoid redundant computation.

Synthetic data generation is receiving increasing attention with the rise of data-intensive methods such as reinforcement learning or deep learning [10]. Artificial data-sets are an efficient way to confront a system to a variety of conditions, and these methods have also also been applied to power system operations [11].

The contribution of this paper is a framework for assessing the incentives that are induced by a scarcity pricing mechanism in Belgium. This framework relies on a Monte-Carlo simulation of daily scenarios, with the aim of providing reliable estimations of the expected yearly adder that can be faced by potential investors. This analysis is used as a basis for supporting recommendations to the Belgian regulator for the roll-out of scarcity pricing in Belgium.

The paper is organised as follows: section II summarises the basics of scarcity pricing, section III characterizes the variants of ORDC considered for this analysis, section IV describes the model used in [12], section V describes our scenario generation process and VI presents and analyses the derived results. We conclude in section VII.

II. Scarcity Pricing and ORDCs

Scarcity pricing based on ORDCs is a market design adaptation that aims at accurately valuing energy and reserve in periods of scarcity. The mechanism uses an operating reserve demand curve which depends on the LOLP and VOLL in order to approximate the intrinsic stochasticity of an economic dispatch in the context of a deterministic market clearing model. This ORDC can be interpreted as the incremental value derived by a system operator for holding additional reserve capacity which increases the security of the system. It is defined in (1) as a demand curve depending of the loss of load probability as a function on the reserve capacity that is available in the system (r), the value of losing load and a proxy of the marginal cost of the marginal unit (MC).

$$V^R(r) = LOLP(r) \cdot (VOLL - MC) \tag{1}$$

Under co-optimization of reserve and energy, the ORDC is the explicit demand curve of the system operator for procuring reserve which is introduced in the objective function of a multi-product auction model. The price of reserve and energy are directly obtained from the dual variables of the co-optimized problem.

In the absence of co-optimization, the ORDC is used in order to compute an ORDC adder. The outcome of co-optimization is then emulated by remunerating the available reserve capacity in the system with the adder, and balancing energy with the energy price of the non-cooptimized problem supplemented by the adder.

III. Variants of ORDC

The formulation of the ORDC in (1) is based on a number of assumptions. This work aims at quantifying the effect that these assumption may have on the cost of operating the system and on the level of the resulting adders.

We consider three sets of assumptions, that are further explained hereunder.

1) VOLL at 8300 €/MWh versus 13500 €/MWh: The Federal Planning Bureau of Belgium has estimated VOLL for Belgium at 8300 €/MWh [13]. The value of 13500 €/MWh has been considered as the current bidding limit on imbalance prices [14].

2) Pre- or Post-Activation: This variant corresponds to whether balancing capacity is measured before or after the imbalance of a given imbalance period is cleared.

3) Independent or Correlated 7.5-minute imbalance increments: Formula (1) can be generalized for different types of reserve, depending on their activation time. For Belgium, energy and reserve would be priced over 15-minute periods. This generalization would take the form of distinct ORDCs for the two 7.5-minute periods. The first ORDC would remunerate generators providing reserve that can be made available in 7.5 minutes and would be dependent on the $LOLP$ after 7.5 minutes. The second ORDC would remunerate generators providing reserve that can be made available in 15 minutes and would be dependent on the $LOLP$ after 15 minutes. These different loss of load probabilities are parametrized using the distribution of the historical imbalances of the system after 7.5 minutes and 15 minutes. The assumption of independent versus correlated imbalance increments concerns the assumed correlation between the two 7.5-minute imbalance increments that form the full 15-minute imbalance. Independently correlated 7.5-minute increments would imply a higher standard deviation than correlated ones, and as such would produce wider ORDC.

Depending on these assumptions, the ORDC will be more or less wide and this will influence the willingness of the system operator to procure reserve. With a wide ORDC, the system operator procures reserve more conservatively, however this higher reliability is expected to come at a higher operating cost. Narrow ORDCs are expected to result in lower operating cost, but would provide less reliability to the system operator. Our analysis quantifies this tradeoff between incurring non-negligible fixed costs for a higher level of reliability versus operating the system at a lower cost with a higher risk of shedding load.

IV. Short-term Simulation Model

The objective of the short-term simulation model is to capture the decision process of a system operator faced with the revelation of uncertainty in an idealized representation of system operation based on a unit commitment and economic dispatch model. This uncertainty can correspond to variability in production or demand and the response of the system operator will be dependent on the ORDC that is selected.

The model that we develop is composed of 4 optimization problems that are solved in sequence as the day unfolds. A schematic overview of the simulator is presented in figure 1. Assets are scheduled in one of the four modules, depending on their reactivity and inertia.

1) Inelastic assets cannot modify their scheduled production and are dispatched in the *day-ahead unit commitment* problem, which is solved once in the day ahead.
2) Slow balancing assets need one or two hours to start up, but are very reactive once online. They are committed in the *intermediate rolling window unit commitment*, that is solved every 6 hours over a 24-hour scheduling window. They are dispatched in the *real-time economic dispatch*. CCGTs comprise the bulk of the slow balancing assets.
3) Fast balancing assets are expensive but can be started in less than 15 minutes. They are committed in the *pre-real time rolling window unit commitment*, which is solved every 15 minutes with a 1-hour scheduling window. Fast balancing assets include emergency generators and demand response.

The model simulates the limitations of the different recourse actions at the disposal of the system operator and a complete characterization of the model can be found in [6] and [12].

V. Scenario generation

The objective of the synthetic generation process is to create artificial scenarios based on the historical scenarios. In order to reproduce a sequenced operation planning, scenarios are formed, in our framework, by sampling a real-time realisation of load, which depends on an associated day-ahead forecast. The day ahead-forecast is used as input to the day-ahead unit

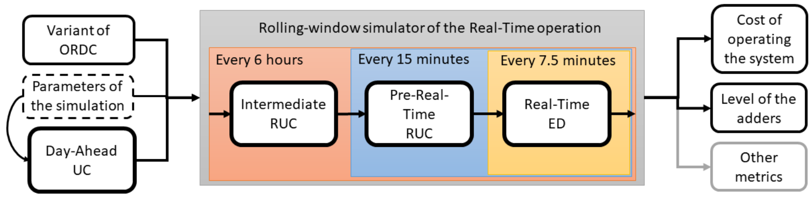

Fig. 1. Sequence of models in our simulator of short-term operation.

commitment module of the simulator. The goal is to obtain an initial position of the day. The real-time scenario updates the forecast of the real-time operation as the day unfolds. The scenario generation process should include a diversity of day-ahead load forecasts, that lead to different initial positions and a diversity of real-time load realisations that follow the aforementioned day-ahead load forecast.

The synthetic generation process based on the historical day-ahead and real-time load profiles is summarized hereunder.

1) The historical time series are divided by season, in order to account for the seasonality of the ORDC.
2) K clusters of days are created by clustering the historical day-ahead demand forecast using the k-means algorithm.
3) Synthetic forecast errors are generated from a time series model of the historical forecast error for a given cluster.
4) Synthetic real-time scenarios are generated by sampling day-ahead forecasts, and combining them with the generated forecast errors.

The remainder of the section will describe the day-ahead clustering and the real-time scenario generation.

A. Clustering of Day-Ahead Scenarios

The clustering is performed on the day-ahead net flexible production. The goal is to cluster together days that would produce similar initial positions. This initial position includes a pumped-hydro storage target that should be followed in real time, as well as inelastic production. Similar days are expected to follow similar flexible generation profiles. The clustering is performed on profiles that are 3 days long, in order to match the horizon of the simulator.

Loyd's algorithm is modified in order to introduce pre-selected days of interest in the clustering, following [8]. This ensures that the most extreme days are represented, and decreases the smoothing effect that clustering might have on the results. Such days of interest include (i) the day with the highest demand (Maximum value day) and (ii) the day with the highest difference between the maximum and minimum in the net load of the day (Maximum difference day).

The algorithm used to create K clusters from the set of historical scenarios $\mathcal{X}$ is described hereunder.

1) **Initialisation:**
   a) Take p pre-selected days as centers $c_1, \dots, c_p$.
   b) For $k \in \{p+1, \dots, K\}$, take $x \in \mathcal{X}$ as a new center c_k with probability $\frac{D(x)^2}{\sum_{x\in\mathcal{X}} D(x)^2}$ with $D(x)$ being the distance between x and the closest centre that has already been selected.
2) **Clustering:** For $k \in \{1, \dots, K\}$ set the cluster $\mathcal{C}_k$ to be the set of scenarios $x \in \mathcal{X}$ that are closer to c_k than they are to c_j for $j \neq k$. Distances are measured using the Euclidean distance.
3) **Update:** For $k \in \{p+1, \dots K\}$, set c_k to be the centroid of all scenarios in $\mathcal{C}_k$:
$$c_k \leftarrow \frac{1}{|\mathcal{C}_k|} \sum_{x \in \mathcal{C}_k} x. \tag{2}$$
4) Repeat steps 2 and 3 until the clusters $\mathcal{C}_k$ for $k \in \{1, \dots, K\}$ no longer change, and measure the quality of the clustering as the sum of the distance between the scenarios and the centroid of their cluster:
$$d = \sum_{k\in\{1,\dots K\}} \sum_{x\in\mathcal{C}_k} (x - c_k)^2. \tag{3}$$

The full algorithm is repeated 20 times and the best clustering is selected based on its measured quality. The *k-means++* [15] algorithm is implemented in the initialization step 1.a), in order to reduce the number of runs of the full algorithm. This initialization ensures an efficient spread of the initial centers.

Notice that the centers of the pre-selected clusters are not updated in step 3). This reduces the quality d of the clustering, but ensures the representativeness of the extreme days.

B. Generation of Real-Time Scenarios

The generation of synthetic real-time scenarios is a four-step processes.

1) A time series model is produced for each cluster of days based on the historical time series of the forecast error. This model decomposes the time series into a seasonal component, a trend component and a residual component using the *Seasonal and Trend decomposition using Loess* (STL) [16].
2) Synthetic residuals are obtained by simulating episodes of the deseasonalized residual component with an ARIMA model.
3) Synthetic forecast errors are obtained by combining the simulated residuals with the seasonal and trend component of the STL model.
4) Real-time scenarios are finally generated by adding the synthetic forecast errors to sampled days of the cluster.

VI. Case Study

The input data that are used for the Monte-Carlo simulator are the historical load, renewable production and import / export of electricity for Belgium from 2016 to 2018. The results are used for supporting the Belgian regulatory authority for a market design proposal for the implementation of scarcity pricing in Belgium.

We first assess the extent to which the generated synthetic scenarios are representative, and we then discuss the accuracy improvement and the insights that are provided by the Monte-Carlo simulation in relation to the value of the adder.

A. How Representative are the Synthetic Scenarios?

Figs. 2a and 2b display the cumulative probability for a cluster of 30 days of (a) the forecast error generated by the time series model and (b) the real-time load produced by our method for a cluster of 30 days. Both figures show that the synthetic sceanrio generation method is valid even tough it tends to slightly underestimate the most extreme forecast errors.

B. Accuracy improvements provided by the Monte-Carlo simulation

The level and confidence interval of the historical and simulated yearly mean adder for 2016, 2017, 2018 and for the aggregate 3-year interval for every variant are illustrated in Fig. 3. Table I presents the highest and lowest accuracy improvement provided by the Monte-Carlo simulation on the confidence intervals of the different variants of ORDC. The simulations are performed over 10 years of artificial scenarios.

The most notable improvements on the confidence interval brought by the Monte-Carlo simulation are observed in 2017 for the correlated variants and for the independent variants with the VOLL at 8300. These variants produce a notably higher mean adder than their simulated counterparts, and this behaviour is not exhibited by the independent variants with the VOLL at 13500 €/MWh. Most of this increase in the yearly mean adder is driven by a historical scenario that produces a mean daily adder of more than 150 €/MWh. The more conservative variants in 2017 are not affected by this outlier scenario, because of their more conservative commitment. The confidence interval of the adder from 2016 to 2018 decreases by 30 to 69% depending on the variants.

The accuracy improvement lies at approximately 33% for 2016. This corresponds to a 0.33 to 0.51 €/MWh narrower confidence interval. For 2018, two variants exhibit no improvement or almost no improvement in their confidence interval due to the influence of extreme scenarios, which suggest the need for a larger number of samples. The remaining variants exhibit an improvement that ranges from 25 to 46%. This corresponds to a confidence interval that is 0.14 to 0.59 €/MWh narrower.

The yearly mean adder analysis can also be conducted by simulating over artificially generated years that would be similar to the historical years. Artificial years can be generated by iterating over the days of a particular historical year and

TABLE I
MINIMUM AND MAXIMUM ACCURACY IMPROVEMENT ON THE CONFIDENCE INTERVAL PROVIDED BY THE MONTE-CARLO SIMULATION.

		2016	2017	2018	2016-2018
Mininum	[€/MWh]	0.3321	0.5480	-0.0388	0.2101
	[%]	33.2	48.9	-6.5	29.9
Maximum	[€/MWh]	0.5082	2.4469	0.5916	0.7288
	[%]	36.6	86.9	46.0	69.1

replacing them with artificially generated scenarios based on the characteristics of the original day. Experiments are performed by sampling the artificial scenario in ways. In the first approach, the clustering method samples the artificial scenario in the pool of scenarios built from the cluster to which the original day belongs. In the second approach, the "historical-day" method samples the artificial scenario in the pool of scenarios built with the day-ahead forecast of the original scenario. The pool used for the sample of the "historical-day" method is actually a subset of the pool used for the clustering method and so we expect the latter method to produce artificial years that are more diverse than those of the former method.

Fig. 4 presents the mean adder of artificial years generated by both methods based on 2018. This graph allows us to conclude that simulating the system based on historical day-ahead data is more accurate than clusters based on the net day-ahead flexible production.

VII. Conclusion

We perform a Monte-Carlo simulation of Belgian system operations in order to test the performance of scarcity pricing based on ORDC against a range of uncertain conditions. This process allows us to increase the statistical reliability of our indicators for the efficiency of different variants of operating reserve demand curves in the context of the discussion for introducing scarcity pricing in Belgium.

Our Monte-Carlo simulation is performed in a nested simulator of the short-term operation of the Belgian electricity market. Scenarios are created by combining historical day-ahead load with synthetic forecast errors generated from the residual component of the clustered time series of forecast errors.

By exposing the simulator to more diverse scenarios, we manage to improve the accuracy of the confidence interval on the level of the adder by 30 to 69% for the period between 2016 to 2018.

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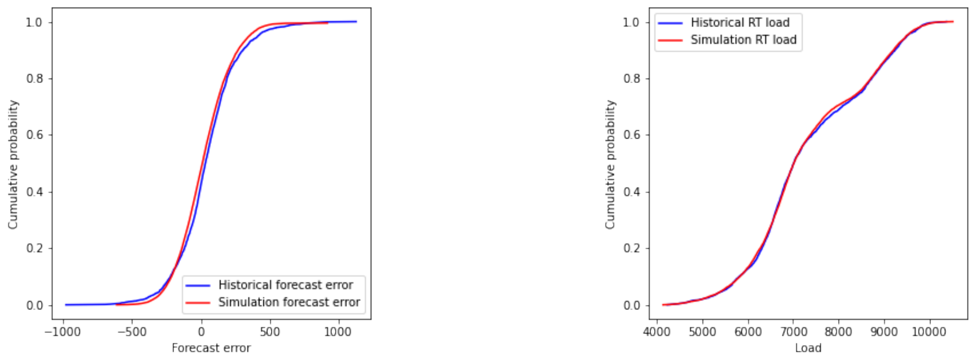

(a) (b)

Fig. 2. Cumulative probability of (a) forecast error and (b) real-time load of the historical and simulated scenarios for a cluster with 30 days.

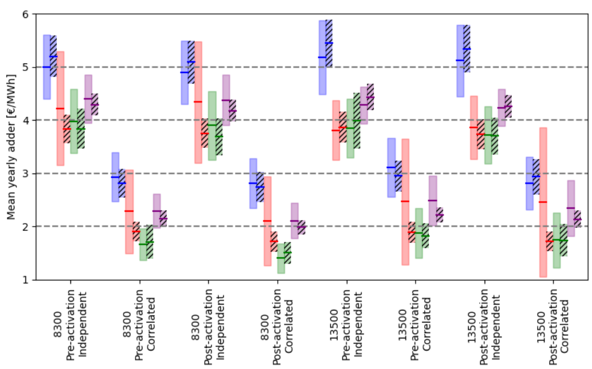

Fig. 3. Comparison of the yearly mean adder for the historical (full bar) and simulated (hatched bar) scenarios for 2016 (blue), 2017 (red), 2018 (green) and for 2016 to 2018 (purple)

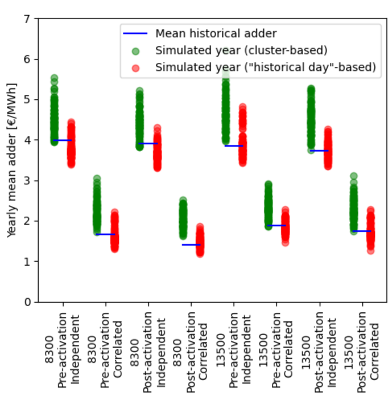

Fig. 4. Comparison of the historical yearly mean adder with artificially generated years based on the cluster or on the "historical day" method for 2018.

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