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Dynamic dimensioning approach for operating reserves: Proof of concept in Belgium

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ABSTRACT

This article discusses a new method for the sizing of operating reserves by electric power system operators. Operating reserves are used by system operators to deal with unexpected variations of demand and generation, and maintain a secure operation of the system. This becomes increasingly challenging due to the increasing share of renewable generation based on variable resources. This paper revisits the current sizing method applied in Belgium, which is based on a *static* approach that determines the required capacity once a year. The presented *dynamic* sizing method determines the required capacity on a daily basis, using the estimated probability of facing a system imbalance during the next day. This risk is estimated based on historical observations of system conditions by means of machine learning algorithms. A proof of concept is presented for the Belgian system, and demonstrates that the proposed methodology improves reliability management while decreasing the average capacity to be contracted. The method is compliant with European market design, and the corresponding regulatory framework, and is of particular interest for systems with a high share of renewable generation. For these reasons a gradual implementation in Belgium towards 2020 has been decided based on the results of this study.

1. Introduction

1.1. Context

In power system operations, the high-voltage System Operator[1] is responsible for maintaining the balance between injections and off-take in its control zone. Any divergence from this equilibrium results in frequency deviations which can, in extreme cases, disrupt the system by causing, among other effects, the disconnection of generation, demand, or even black-outs. In the liberalized European market, market players are represented by Balancing Responsible Parties (BRPs) who are individually responsible for maintaining a balanced portfolio of trading positions and physical injections/withdrawals of power. Similar to other TSOs, the Belgian TSO (Elia System Operator, hereafter referred to as Elia) has established a balancing mechanism according to which (1) market players are incentivized to maintain and restore the system balance and (2) the system operator manages remaining imbalances in the system by means of contracted and non-contracted power reserves supplied by Balancing Service Providers (BSPs).

Operating reserves represent capacity which can be activated in an up- or downward direction when requested by the TSO in order to restore the system balance. Under current European legislation, the System Operation Guidelines (SOGL) define Frequency Containment Reserve (FCR), automatic Frequency Restoration Reserve (aFRR) and manual Frequency Restoration Reserve (mFRR) (European Commission 2017a). These operating reserves are activated according to a certain hierarchy, as indicated in Fig. 1. FCR is activated automatically and on a continuous basis, and its set-point is adjusted up- or downwards as required so as to stabilize the system frequency in the synchronous area, e.g. Continental Europe. aFRR is activated automatically and on a continuous basis, and its set-point is adjusted up- or downwards so as to handle sudden imbalances in the control area, e.g. Belgium. mFRR can be activated manually upon the request of the system operator and can be used to address a major imbalance in the zone managed by the system operator. In Belgium, mFRR is activated after aFRR and remains activated until the cause of the system imbalance is resolved. In some

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[1] Electric power system operators are generally referred to as Transmission System Operators (TSOs) in Europe, and Independent System Operators (ISOs) elsewhere. This distinction in terminology, which relates to the separation of power system and power market operations, is irrelevant in this paper. Throughout the paper, 'TSO' is used with the understanding that the methodology proposed in the paper applies equally well in a TSO, as well as an ISO context.

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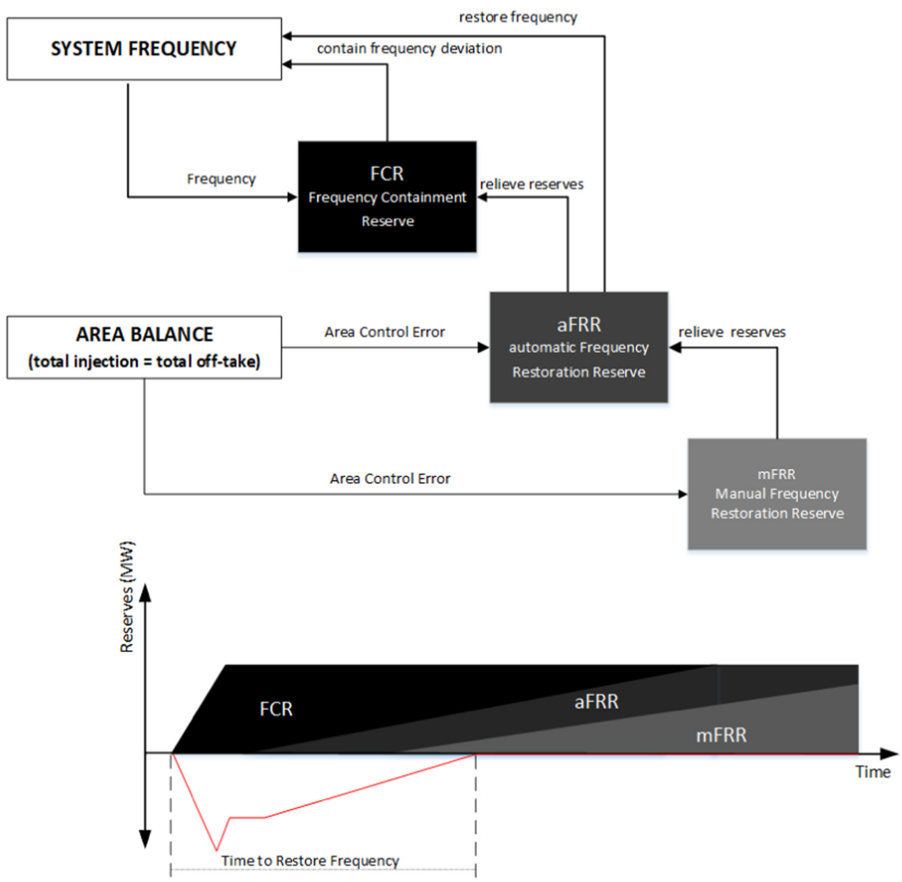

Fig. 1. Schematic overview of the activation of operating reserves in Belgium (based on the SOGL).

systems, FRR is supported with Replacement Reserves (RR), which are slower manually activated reserves meant to partially replace the FRR after 15 min. Generally, market parties are incentivized to restore their imbalance after 15 min, and this mechanism is specified as optional by the SOGL. It is therefore considered out of the scope of this paper. The reserve product characteristics and order of activation is described in the balancing rules, and is governed by European legislation, specifically the Electricity Balancing Guidelines (EBGL) (European Commission 2017b).

As inadequate reserve capacity increases the risk of resorting to emergency measures, such as demand shedding or the curtailment of generation, the TSO defines the minimum operating reserve capacity required to maintain the balance in the control zone so as to achieve a predefined reliability level. This reserve capacity requirement, and in particular the methodology of its determination, needs to be approved by the National Regulatory Authority (NRA), and this reserve capacity is subject to a set of minimum requirements described in the SOGL. In contrast, the FCR capacity which is needed for maintaining stable frequency is determined on the level of the synchronous area. The objective of this paper is to present system operators with a novel approach to size their FRR needs while remaining in line with the regulatory and legal framework. The method is based on a dynamic approach, whereby reserve needs are determined on a daily basis, based on the probability of facing system imbalances, with the goal of the method being to match reserves to the exact amount of reserve capacity which is needed in order to maintain reliability. A proof of concept which demonstrates the effectiveness of the proposed approach has been published by Elia (2017a).

1.2. Literature review

The sizing of operating reserves has been studied extensively in the literature, due to its significant impact on system reliability and market operation. Sizing decisions are driven by two major types of uncertainty in power system operations. The first type of uncertainty are *forced outages*, predominantly generation units and transmission line contingencies. The second type of uncertainty relates to *forecast and market errors*, such as demand, photovoltaic or wind power forecast errors, generator ramps, and set-point deviations related to the mismatch with day-ahead hourly and intra-day quarter-hourly market products.

Operating reserve sizing methods can be classified in static and dynamic methods. *Static* sizing methods, such as the one currently adopted by Elia (2013), are already compliant with the requirements defined in Art. 157 of the SOGL. The guidelines require that the sizing method for FRR in place has to be based on (1) a probabilistic methodology covering the imbalances for at least 99% of the time, taking into account historic system imbalance observations, and potential factors that can influence imbalance within the time period considered, and (2) the size of the dimensioning incident, i.e. the largest component failure, which acts as a minimum FRR requirement. Static sizing methods produce a reserve capacity target which remains constant over time (for example, in Belgium the aFRR and mFRR requirements are until today revisited on an annual basis), and were originally motivated by the dominant role of component failures, and simplicity of implementation. Specific literature focuses on the separation between aFRR and mFRR (Jost et al., 2015; De Vos et al., 2013; Maurer et al., 2009).

The large-scale integration of renewable resources has overturned this paradigm, since forecast errors have become an increasingly significant source of imbalances, as opposed to contingencies which pose a relative constant risk for imbalances. In particular, the largest contingency is often considered as the predominant risk that the system needs to be secured against, i.e. a nuclear generation outage of 1 GW in Belgium. In contrast forecast errors vary over time depending on various observable conditions: for example, renewable forecast errors resulting in a shortage may be systematically smaller in periods for which the renewable supply is forecasted to be very low, since there is little margin for error in over-estimating renewable supply under such conditions. This has motivated *dynamic* sizing (Bucksteeg et al., 2016; De Vos and Driesen, 2014), whereby the amount of reserve capacity is adapted according to observable conditions, e.g. the predicted wind power generation, such that the same target reliability is achieved as in static sizing.

Sizing methods can be further classified between *bottom-up* system modelling methods and *probabilistic methods. Bottom-up* system modelling methods employ unit commitment and economic dispatch models in order to determine how many units should be committed at the day-ahead scheduling stage in order to cope with system uncertainty in real-time (Dvorkin et al., 2015a, 2015b; Zhou and Botterud, 2014; Zhou et al., 2013; Bertsimas et al., 2013; Meibom et al., 2011; Papavasiliou et al., 2011; Ortega-Vazquez and Kirschen, 2009; Tuohy et al., 2009; Gooi et al., 1999). This decision is determined endogenously in unit commitment and economic dispatch models, with a typical objective of minimizing system costs associated to committing the resources up-front, and then dispatching them in real time in order to balance system disturbances (with outages and forecast errors being represented endogenously). By contrast, *probabilistic* methods focus on meeting a reliability target by determining a probability distribution function of capacity shortfall, and setting the operating reserve requirements at the quantile of the derived distribution which corresponds to the target reliability.

The simplest probabilistic methods rely on *heuristics* that relate the statistical parameters (e.g. the standard deviation) of the probability distribution of capacity shortfall to a certain reserve requirement (Holttinen et al., 2012). *Parametric* methods assume distributions, e.g. Levy alpha-stable (Bruninx and Delarue, 2014), gamma (Menemenlis et al., 2012) and Gaussian distributions (Maurer et al., 2009), on the sources of uncertainty and seek to fit the parameters of these distributions based on data. More advanced probabilistic sizing methods implemented in this article rely on *machine learning,* whereby the goal is to use kernel density estimation, k-nearest-neighbours (Ohsenbruegge and Lehnhoff, 2015), quantile regression based on artificial networks (Jost et al., 2016, 2015), and k-means (Bucksteeg et al., 2016) in order to predict system imbalances as a function of features.

This paper focuses on dynamic probabilistic methods, which, as argued in this paper, strike a favourable balance between capturing the complexity of future power system operations, and simplicity of implementation. On the one hand, heuristic sizing methods remain widespread in power systems, although they are unlikely to be adequate for tackling the increasing complexity and uncertainty that power systems with increasing decentral and renewable generation are coping with. Only very simplistic dynamic heuristic approaches are known, such as determining a spinning reserve capacity as percentage of the hourly load and/or wind forecast (GE Energy, 2010; Papavasiliou and Oren, 2013). Bottom-up approaches based on unit commitment models present an interesting alternative. These methods result in challenges that are well-known and have been discussed extensively in the literature, including scenario generation, scenario selection, and the resolution of the resulting large-scale problems within acceptable time frames (Papavasiliou and Oren, 2013; Papavasiliou et al. 2011a). There is growing scientific literature that demonstrates continuous improvements in reducing computation time for these methods by means of decomposition techniques that can be exploited to solve stochastic unit commitment models in reasonable time (Feng et al., 2015a, 2015b; Papavasiliou et al., 2015). Research has also focused on developing unit commitment models that include uncertainty but are less computationally intensive (Bruninx and Delarue, 2017; Pandžić et al., 2016). An appealing aspect of such models is that they are well suited for determining optimal reliability levels, by optimally trading off the procurement cost of reserves with the benefit of additional reliability (Telson, 1975). Consequently, this can also be used to determine a dynamic reserve capacity. However, such models require detailed information regarding the technical and cost characteristics of individual generators, including information related to fuel cost, start-up cost, minimum load cost, ramp rates, minimum up and down times. This should be contrasted to the minimal information employed in the proposed approach, which requires only power generator capacities in order to conduct simulations of outage risks. The collection of detailed data on a unit-level basis presents institutional challenges in European electricity markets, where resources are bid as portfolios, which implies that the transmission system operator may not have all the necessary data which is needed in order to formulate and solve a stochastic unit commitment model. This should be contrasted to US markets where individual generator data is typically available to the independent system operator, and can be used for formulating detailed stochastic unit commitment models.

1.3. Paper contribution and structure

This paper presents two contributions relative to the state of the art. Firstly, it presents the design of a mechanism for dynamic sizing of FRR, which is compliant with the European market framework. Secondly, a range of implementation methods are compared and tested in a proof of concept in Belgium for 2020 and 2027, taking into account a realistic operational context, including all known drivers for system imbalances.

Section 2 describes the dynamic sizing method considered in this study, including the machine learning methods, used in order to map the predicted system conditions to the system imbalance risk and the resulting FRR needs. Section 3 presents the assumptions and data used for this proof of concept on the Belgian system, while Section 4 discusses the results. Section 5 presents the conclusions and implications for the market and regulatory framework.

2. Dynamic sizing methodologies

2.1. The drivers of system imbalances

As the dimensioning of FRR requirements relies on predicting the risk for system imbalances, identifying the causes of system imbalances is the basis of designing an accurate probabilistic dimensioning method. System imbalances result in a deviation of the BRPs from their nominated position. Although the determination of the drivers of imbalances is challenging, and a substantial degree of idiosyncratic error cannot be explained by statistical analysis, it is possible to highlight some of the factors that contribute to imbalances. An overview is given in Fig. 2 and explains in further detail the factors that contribute to the two main categories of uncertainty which were identified in the literature review: (1) the forecast and market errors and (2) the power plant and transmission asset forced outages.

The market and forecast errors affect the BRPs' positions, which are scheduled to cover the forecasted net demand in their portfolio, taking into account variable renewable generation. Therefore, a forecast error in generation (i.e. wind and photovoltaic forecast errors) or in demand can result in a system imbalance, at least when the BRP is not able to cover this imbalance through intra-day trading or real-time adjustments in generation, storage or demand offtake, or through other bilateral trades. On top of these forecast errors, some errors due to the market design can also lead to *deterministic frequency deviation*, also referred to as *scheduled leaps* (Hirth and Ziegenhagen, 2015), which result from market deviations, i.e. the mismatch between the hourly granularity of the market products (in day-ahead as well as intra-day markets) and the continuous nature of operations. Finally, there remains also a part of the imbalance which cannot be explained from the factors of Fig. 2, and is referred to as *residual noise* or *idiosyncratic error*.

Forced outages occur when power plants such as nuclear or gas power units shut down unexpectedly. Following such an event, the missing generation contributes to the system imbalance. Imbalances

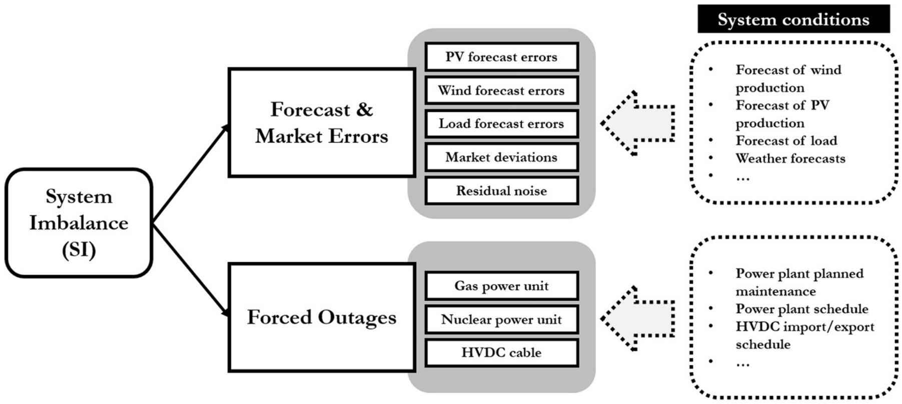

Fig. 2. System imbalance drivers and related system conditions that affect these imbalance drivers.

may also result from the unexpected loss of a transmission asset (e.g. an HVDC-interconnector) or demand, although the latter has a minor impact on grid operations due to the smaller magnitude of the disturbance. Therefore, outages related to the demand-side are typically not accounted for in reserve dimensioning in Belgium. Belgium is a relatively small system, and includes five 1-GW nuclear units. The peak demand of the system amounts to 13 GW. The installed capacity of wind power amounted to 2 GW in 2015, while the installed capacity of solar photovoltaic capacity amounted to 3 GW. Therefore, the potential impact of component failures (especially generator outages) is substantial, at least in comparison with large countries such as Germany, where imbalance is largely governed by renewable supply forecast errors.

2.2. Current static sizing methodology in Belgium

In its current ‘static’ method, Elia sizes the FRR needs of the system once a year, based on historical system imbalances. The process is illustrated in Fig. 3. The system operator develops a time series of simulated system imbalances for the next year. These simulated system imbalances are derived from historical system imbalances, which are corrected for forced outage events and for factors which represent future expected improvements in the management of system imbalance. The historical forecast errors of wind power and photovoltaic power generation are scaled up according to the projected future capacity roll-out of renewable resources in the Belgian system. A time series of forced outages is constructed by means of a Monte Carlo simulation, which accounts for all generating units larger than 100 MW based on their outage probability and duration.

The probability density functions of the two time series (simulated system imbalances and outages) are convoluted and the resulting shortfall density function is used for determining the FRR needs. This is achieved by sizing the FRR needs to a volume which achieves a pre-defined reliability level. In the case of Belgium the target reliability level for 2018 is 99.9%. The required FRR capacity is obtained as the corresponding quantile of the system imbalance probability density function. This methodology is combined with a deterministic approach which sets the minimum FRR capacity at the dimensioning incident level (N-1 criterion), i.e. the maximum deviation in a control area resulting from the most severe power plant outage.

Until 2018, Elia has only dimensioned and procured upward reserve capacity, although the aFRR is used in both directions. For 2018, Elia determined a total FRR capacity requirement of 1190 MW. It is noted that Elia prepared a downward dimensioning compliant with SOGL for 2019. The FRR needs are covered with different sources of FRR capacity, including reserve sharing with other TSOs, aFRR (contracted secondary reserve) and mFRR (contracted tertiary reserves). In 2018, the

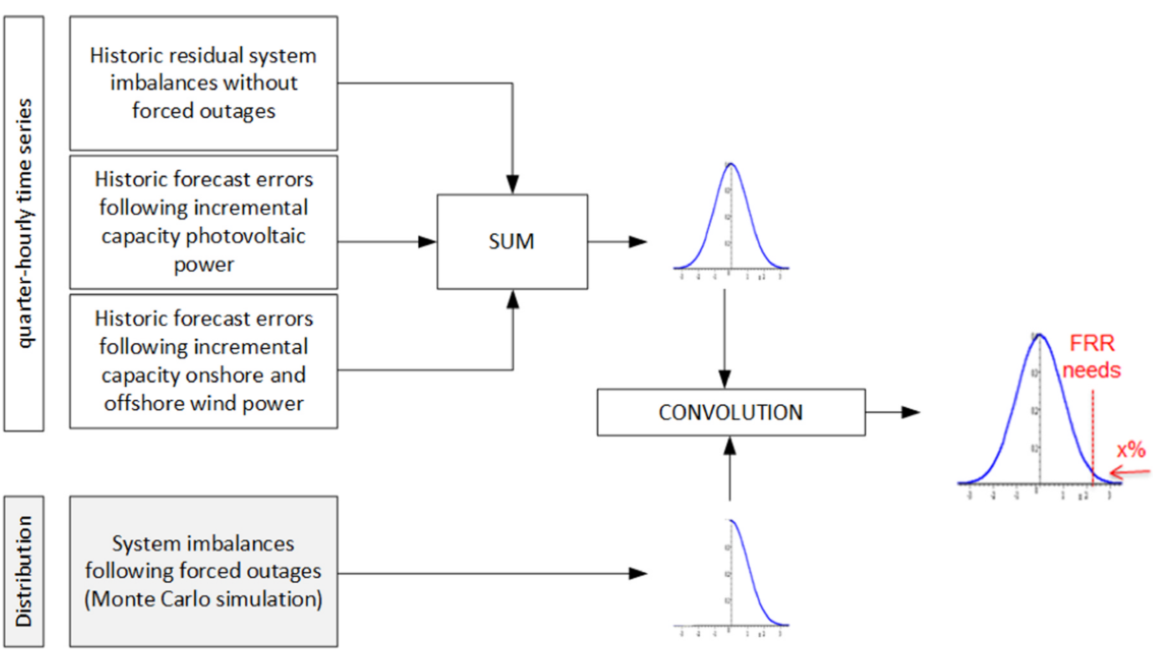

Fig. 3. Schematic representation of the static sizing method implemented in Belgium.

aFRR volume amounted to 139 MW, the contracted upward mFRR volume amounted to 830 MW. In 2017, the contracted volume of aFRR amounted to 143 MW, the contracted volume of upward mFRR amounted to 730 MW, and the procurement cost can be determined at approximately 70 million Euro. This procurement cost is estimated based on average volumes and prices published on the website of the TSO.

The current methodology is sensitive to extreme conditions, e.g. the forecast errors of an offshore wind park on very windy days, and such conditions impose high operating reserve requirements. However, since extremely risky conditions are only valid under specific circumstances, the FRR requirements are overestimated for a large part of the year, resulting in oversizing and therefore inefficient procurement. Although the increasing reserve needs resulting from the integration of variable renewable generation are correctly reflected by the current static sizing method, under static reserve sizing the reserved capacity is required to be available throughout the year, even during conditions with lower imbalance risk. Since this weakness of the present static sizing methodology is expected to increase in future years as increasing amounts of renewable generation capacity are connected to the system, static sizing methods are currently scrutinized by practitioners and academics (Papavasiliou and Oren, 2013).

2.3. General design and implementation of the dynamic sizing methodology

System imbalance drivers are highly dependent on system conditions. If a power plant is in maintenance during a given period, it does not make sense to account for its potential outage during this period. Thus, the risk of forced outage is not uniform over time. Similarly, if the forecasted wind production for a given period is close to zero, the forecast error can only be such that the generation has been underestimated. Therefore, also the forecast and market error risks are not constant over time.

Dynamic sizing aims at adjusting FRR needs to the expected system conditions of the next day (e.g. forecast wind power and photovoltaic generation, power plant schedules). Specifically, dynamic sizing aims at leveraging the *system conditions* which are illustrated in Fig. 2 in order to predict the risk of a system imbalance. In order to obtain the required up- and downward FRR needs as presented in Fig. 4, the computation of dynamic sizing requirements is conducted day-ahead before market closure. Although it should preferably be conducted as close as possible to real-time, European market design and regulations constrain the methodology. In contrast to other market designs that are encountered worldwide, the majority of European energy and reserve markets are operated by separate entities, which implies that reserves are procured before market closure, so as to ensure their availability. In practice, this means that the dimensioning of reserves has to occur several hours before the day-ahead market closes, in order to facilitate the required calculations, validations and tendering procedures.

As in the static sizing approach, dynamic sizing aims at estimating the probability density corresponding to the *forecast and market error* risk, which is then convoluted with the estimated probability density function of *forced outage risk*. The risk of forced outages is treated separately because forced outages are rare events which implies that the outage risk density function of the portfolio of units in Belgium cannot be captured with only a few years of historical data. Recalling that the target reliability level for 2018 in Belgium is 99.9%, the FRR needs are determined as the 99.9% percentile of the resulting convoluted distribution.

The difference between static and dynamic sizing is that dynamic sizing uses day-ahead forecasted system conditions in order to estimate the probability distribution of the imbalance risk: on the one hand, machine learning algorithms are used to estimate the forecast and market error risk while the forced outage risk relies on a Monte Carlo simulation with estimated schedules of generation and transmission assets.

- Regarding the forecast and market errors, these are assumed to be driven on the one hand by the day-ahead forecasts of demand and renewable production (since these influence the corresponding forecast errors) and on the other hand by scheduled leaps, which were described previously. In addition to these drivers, general information such as “hour of the day”, “day of the week” or weather forecasts are also exploited by the dynamic method. Machine learning algorithms are leveraged to map these forecast system conditions to a certain probability distribution. The machine learning algorithm involves two steps: a training (or learning) step and a prediction step which corresponds to the “training” and “sizing” step in Fig. 4. The learning step consists of “feeding” the algorithm with historical data which are used to compute the parameters of the algorithm. The prediction step consists of using the trained algorithm to make prediction on a new data set.
- Regarding outage risk, since the dimensioning is conducted before the day-ahead market closure, the exact schedule of units is not known. In this study, the main system conditions that are considered as drivers of outage risk are the maintenance schedules of power plants and the scheduled import/export flow in the relevant HVDC-interconnector. The dynamic sizing approach uses this information as input to the Monte Carlo simulator such that the resulting probability distribution of capacity shortfall due to outages corresponds to the actual risk of the system on the day of operations. More specifically, the Monte Carlo simulator uses a list of power plants as

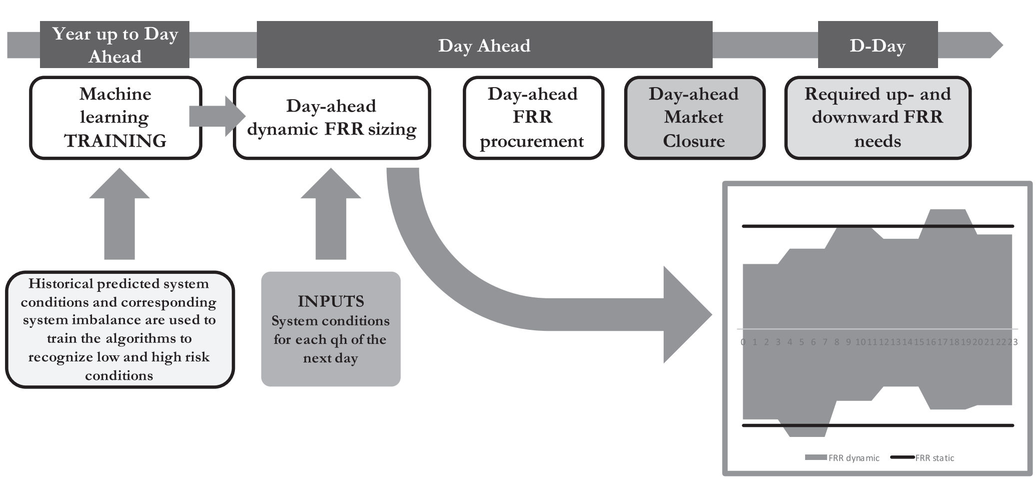

Fig. 4. Illustration of a possible daily profile of dynamic FRR needs.

input. Each of these plants is associated with a "probability of outage", an "outage impact" (i.e. the impact of the outage on the imbalance, which is assumed to be equal to the nominal power of the asset) and an "outage impact duration" (i.e. not the duration of the outage itself, which can last several months, but the lapse of time for which the outage impacts the imbalance). All the power plant outages are assumed to be independent. The Monte Carlo tool simulates hundreds of years, using an hourly time step, and produces the outage risk probability distribution as output.

Considering this general methodology, three dynamic dimensioning approaches have been considered and tested in this study. The first approach which is considered is a semi-dynamic approach, later denoted as outage-only (OO) approach. This sizing approach treats the forced outage imbalance driver dynamically, as described above, while it treats the forecast and market error risk statically. Additionally, two fully dynamic methods are considered in order to predict the risk of a system imbalance for each time step of the next day. Each time step is treated separately, i.e. as an isolated problem, without explicit intertemporal relations. Nevertheless, consecutive periods are indirectly correlated as the input features of the algorithm (e.g. wind or solar production) are themselves correlated. Both dynamic methods treat forecast and market errors, as well as forced outage risks dynamically. Their differences are related to the machine learning approach used for determining the interrelation between the system conditions and the distribution of the forecast and market error risk. Several machine learning approaches have been proposed in the recent literature to tackle this problem. These are included in our methodology and compared on the case study of Belgium:

- The first machine learning method applied is the "k-means" algorithm, which is a popular machine learning clustering method. The idea of applying k-means to the problem of dynamic sizing is to divide the space of system conditions into different scenarios, and to associate a different distribution of forecast and market error risk to each scenario. The objective of k-means clustering is to split n observations into k clusters such that each observation belongs to the cluster with the nearest mean. Mathematically, this means that the sum of squares of the distances of the observations from the corresponding cluster centres is minimized, i.e. the objective is to minimize, where $(x_1, x_2,...,x_n)$ is the set of observations and $(S_1, S_2,...,S_k)$ is the set of the clusters, with μ_i indicating the center of cluster S_i. For each of the cluster centres, the distribution of imbalances is obtained using a non-parametric probabilistic estimator, namely kernel density estimation (Bucksteeg et al., 2016).
- The second machine learning method applied is the so-called "knn" (k nearest neighbours) algorithm. The idea of applying the k-nearest-neighbours method to dynamic sizing is to predict system imbalances as a function of features, and to use the k-nearest-neighbour algorithm in order to detect the k past observations which are nearest to the one characterizing the present operating interval. The reserve capacity is then sized as the weighted sum of these k observations. Mathematically, this amounts to of finding the k observations $S = (x_1^*, x_2^*,...,x_n^*)$ among n observations $D = (x_1, x_2,...,x_N)$ such that $\|x_i^* - y\|^2 \leq \|x_j - y\|^2\ \forall\, x_i^* \in S,\, x_j \in D\,/\,S$, where y is the forecast system condition for tomorrow.
- Neural networks are another popular family of machine learning algorithms that have been considered for this study. A neural network can be used in order to derive non-linear regression functions. These functions, in turn, can be used in order to predict a certain quantity, for instance the system imbalance. The backpropagation function of a neural network can be tuned so as to estimate a quantile of this quantity, for instance the 99.9% quantile of the system imbalance. In that case, the neural network would directly estimate the FRR needs by predicting the 99.9% reliability percentile of the imbalance. In contrast to the encouraging findings that have been reported in the literature for the German power system (Jost et al., 2015), the approach is less appropriate for the Belgian system because the role of outages risk is dominant in Belgium. It is therefore crucial to convolute forecast and market risk with outage risk in order to obtain a precise sizing method. This convolution requires computing the complete distribution of the "forecast and market risk", and not only a quantile. For this reason, the approach of neural networks is less appropriate to the methodology of this study. Furthermore, some further tests have been conducted, isolating the forecast and market risk to avoid the convolution step and to test the neural network performances. These tests did not reveal superiority of the approach for the case study of Belgium which is considered in this paper. In contrast, it is a promising method for larger systems, such as Germany, where individual unit outages have a less dominant role on imbalance risk. In such systems, where forced outages do not need to be considered separately, neural networks have been considered as a promising dynamic sizing approach (Jost et al., 2015).

3. Proof of concept in Belgium: scenarios and assumptions

The dynamic FRR sizing methods are compared to the benchmark static FRR sizing method in a proof of concept representing four scenarios for Belgium for 2020 (before the phase-out of nuclear capacity in Belgium[2]) and 2027 (after the phase-out of nuclear capacity). In order to train, test and implement the algorithms described in Sections 2.2 and 2.3, a database is developed for 2015, 2016 and 2017, which represents historically observed system imbalances, as well as the corresponding day-ahead predicted system conditions (predicted before day-ahead market closure). These system conditions include the offshore and onshore wind power generation, the solar photovoltaic generation, the total demand and several weather parameters such as irradiation, wind speed and temperature for every quarter-hour. In order for the results to represent the FRR needs in 2020 and 2027 as accurately as possible, the historic system imbalances are extrapolated by means of the same method as presented in the static approach discussed in Section 2.2, i.e. using the forecast errors of the incremental capacity of renewable generation which is presented in Table 1. The dynamic sizing methods are trained on the data of 2015 and the first half of 2016, and are then tested against the data of the second half of 2016 and the first half of 2017 (where the data from these years has been extrapolated to represent the conditions of 2020 and 2027, as explained in Section 2.2).

The *Reference* scenario represents Belgium in 2020. It is assumed that in 2020 BRPs exhibit a similar ability to anticipate system imbalances as observed in the past. An analysis of historical data shows that the ability of BRPs to mitigate system imbalances improves by 4.5% every year. A sensitivity is conducted on this factor by also considering 0% and 7% annual improvement rates. These are referred to as a *Low* and *High Market Balancing* scenario, and they correspond to the assumed capability of BRPs to anticipate system imbalances to a lesser or greater extent, respectively. It is noted that for the actual deployment of a dynamic sizing method these extrapolations become less relevant, since the dynamic sizing is conducted close to real-time, and not multiple years in advance. Instead, these assumptions are used for the comparison of the performance of the alternative sizing methods in the proof of concept.

Finally, a *Post-Nuclear* scenario corresponding to 2027 is investigated. In this scenario it is assumed that the nuclear units of Belgium have been replaced by conventional gas-fired power plants,

[2] The current legal framework foresees a phase-out of nuclear capacity in Belgium between 2022 and 2025, however 2 GW of the total 5.8 GW are planned to be decommissioned in 2022 and 2023. At the time of writing, a political agreement is being drafted concerning the scenarios, costs and required mechanisms to replace this capacity.

Table 1
Historic and projected installed capacity of renewable energy sources in Belgium.

	2012[a]	2016[a]	2020[a]	2027[b]
Onshore wind [MW]	1005	1580	2663	3542
Offshore wind [MW]	380	713	2205	2312
Photovoltaics [MW]	2051	3101	4966	4966

[a] Elia (2017b).
[b] Elia (2016).

Table 2
Overview of assumptions regarding training frequency, resolution and lead time in the Proof of Concept.

	Training Frequency	Resolution	Lead Time
OO	Yearly	4-h	Day-Ahead
KMEANS	Monthly		
KNN	Daily		

and additional renewable generation capacity has been added to the system, as indicated in Table 1. In this post-nuclear scenario, the annual improvement factor of BRPs is assumed to evolve by 4.5% until 2020, and by 1% after 2020. The post-nuclear scenario analyses the behaviour of a dynamic sizing method after all nuclear units are replaced by six 400 MW CCGT units. The objective is to verify the effect of this transition and not to make an appraisal regarding the required capacity to replace the nuclear units, which subject to policy discussion.

Looking forward to the conditions of the Belgian power system in 2020 and 2027, a new imbalance driver is accounted for in the study, which contributes to the forced outage risk. This driver is the HVDC-interconnector between Belgium and the United Kingdom (referred to as NEMO-link), planned to be commissioned in 2019. This transmission asset results in a shortage or excess of power if a forced outage occurs during periods when the interconnector is importing or exporting power, respectively. It is accounted for in the Monte Carlo analysis of the forced outages. A representative schedule for 2020 and 2027 is used, based on historic price differences between Belgium and the United Kingdom. The schedule is then extrapolated to 2020 and 2027. The forecasting scheduled flow on the NEMO-link utilizes price forecasts. This forecasting is required because in actual operations the NEMO-link schedule will only be known after the sizing of the FRR needs has already taken place, since the flow over the interconnector is determined by the day-ahead market, which clears after reserve has been sized.

The proof of concept is conducted by running the proposed sizing methods against data over a full year. The chosen dynamic sizing methods are implemented on a rolling basis. The evaluation accounts for practical considerations, including (1) the frequency by which the algorithms are re-trained with updated historical data, and the frequency by which the optimal set of parameters is re-computed; (2) the sizing resolution of the dynamic needs, which is related to the FRR product length; and (3) the lead time which determines how much time in advance the sizing is conducted. An overview of the assumptions made for each method is given in Table 2.[3]

4. Results and discussion

This section presents the results of the proof of concept for 2020, and compares the three dynamic sizing methods with the current static sizing approach. The section discusses two main advantages of dynamic sizing relative to static sizing: (1) an average reduction of the reserve needs while (2) ensuring a better reliability management. Furthermore, this section discusses the relation between the profile of reserve needs and the corresponding system conditions. Finally, the robustness of the results is investigated with respect to scenarios with low and high reserve needs for 2020, and with respect to a post-nuclear scenario in 2027.

4.1. Reliability

Table 3 presents the average reliability level of each of the two full dynamic methods for 2020. The average reliability criterion expresses the amount of periods during which the determined reserve capacity covers the system imbalance during the test period. It is found that static sizing results in a 99.93% reliability, which meets the predefined reliability criteria of 99.90%. The three dynamic sizing methods exhibit similar reliability levels, which renders them acceptable in terms of meeting the reliability targets of Elia. Since this is the paramount performance criterion of any sizing method, it is necessary that any sizing method that would be considered for implementation meet the target reliability level set by the system operator.

In order to better illustrate the adaptiveness of the dynamic sizing methods, indicator "reliability in high risk" and "reliability in low risk" is presented in Table 4, which compares the average reliability in the 20% periods with the highest reserve needs with the 20% periods with the lowest reserve needs.[4] This comparison indicates whether a sizing the method is capable of adapting the reserve sizing to the corresponding risk of the system under varying system conditions.

Note that this indicator makes especially sense for the fully dynamic methods. Indeed, similar reliability levels in high or low risk of the semi-dynamic method (*Outage-Only*, abbreviated *OO*) and the static method are expected. This is due to the fact that the outage-only method is only aiming to reduce the reserve needs during periods when a maintenance of one or more large assets in the scale of a Gigawatt (e.g. the nuclear generating units or the NEMO link) is taking place, or to reduce the reserve needs in accordance to the import / export schedule of the NEMO link. Consequently, this has no impact on managing better the reliability in high or low risk.

The results demonstrate that the dynamic sizing methods are able to identify the risk level and increase the reliability of the system during high-risk periods by foreseeing more reserves compared to the static approach. On the other hand, dynamic sizing reduces the reserve needs during the low-risk periods, lowering the reliability to the pre-defined level while avoiding to oversize during these periods, in contrast to static reserve. For the kmeans method, dynamic sizing results in a constant reliability of 99.89% and 99.91% for *upward* reserve needs

[3] A more regular training interval ensures that the algorithm is acting using the most recent information, while it requires more effort in terms of computational time as well as validation of the results by the utility that employs the algorithm. Therefore, the choice has been made to compare the two machine learning algorithms on different training frequencies. In contrast, the resolution is fixed in each method at 4 h. This is motivated by the fact that reserve capacity products in Belgium is likely to evolve towards 4-h products. The lead time for

(*footnote continued*)
training the algorithm is fixed in each method to one day ahead, which is dictated by the fact that reserve procurement is currently conducted before the closure of the day-ahead market in Belgium.

[4] As the reserve needs determined by the KMEANS and the KNN methods are not the same, the sets of "high-risk" and "low-risk" periods identified by these methods do not exactly coincide. Therefore, Table 4 makes a distinction between the reliability during high-risk and low-risk periods between static sizing and KMEANS, where high and low risk is determined according to the FRR needs determined by the KMEANS method. This corresponds to the second and third column of the table. Table 4 also compares the reliability of static sizing and KNN in high-risk and low-risk periods, where high and low risk are defined according to the FRR needs of the KNN method. These numbers are reported in fourth and fifth column of the table.

Table 3
Average reliability of the three methods for the 2020 reference scenario.

	STATIC	OO	KMEANS	KNN
AVERAGE	99.93%	99.91%	99.90%	99.89%

during high and low-risk periods, respectively, and results in 99.90% and 99.89% for *downward* reserve needs during high and low-risk periods. In contrast, static sizing oversizes in low-risk periods with 99.96% and 99.97% reliability for up- and downward reserve needs, respectively, while it under-sizes in the high-risk periods with 99.86% and 99.87% in up- and downward reserve needs. As can be observed in Table 4, the knn method exhibits a similar adaptive behaviour and achieves a stable reliability over time by adapting the sizing of reserves to the predicted level of risk in the system.

These results demonstrate that dynamic sizing methods achieve the target reliability level of 99.9% by adjusting the sizing so that this target reliability level is met instantaneously, meaning that the reliability of the system is 99.9% at any given moment in time. By contrast, the static sizing method achieves an average reliability level of 99.9%, by oversizing reserves in periods of low risk, and under-sizing reserves in periods of high risk. Therefore, although the average reliability is indeed consistent with the requirements of the system operator, this is not necessarily the case at any given moment in time.

The results of Table 4 show the reliability in high risk for a target average reliability level of 99.9%. In order to demonstrate that differences in reliability levels among the different sizing methods are statistically meaningful, the different sizing methods are tested for different levels of target reliability. Concretely, Fig. 5 presents the reliability and its confidence interval - achieved on the test set - of the dynamic approach and the static approach for different levels of target reliability. In this analysis, the forced outages are removed in order to test for the effectiveness of adapting to "forecast and market errors". It is found that the difference in reliability increases substantially when reducing the target reliability levels, e.g. 99.0%. The results demonstrate that the benefits of the dynamic treatment of the "forecast and market errors" increase with lower reliability levels. Fig. 5 shows that this effect is more pronounced for upward reservation than for downward reservation, This analysis supports the fact that the reliability differences achieved by the machine learning methods are statistically relevant.

4.2. Reserve capacity needs

4.2.1. Full dynamic methods in the reference scenario 2020

Table 5 compares the average, minimum and maximum reserve requirements of dynamic sizing methods to the requirements of static sizing for the "reference scenario 2020". The table further presents the difference between the average requirements of the dynamic and static methods, referred to as dynamic potential and indicated in the table as

Table 4
Comparison of the KMEANS, KNN and static methods on their reliability level and corresponding FRR needs for the high and low risk periods.

		KMEANS		KNN	
		Static (Reliability, FRRneed)	KMEANS (Reliability, FRRneed)	Static (Reliability FRRneed)	KNN (Reliability, FRRneed)
UPWARD FRR NEEDS	High Risk	99.86%; 1417 MW	99.89%; 1457 MW	99.84%; 1417 MW	99.84%; 1463 MW
	Low Risk	99.96%; 1417 MW	99.91%; 1304 MW	99.96%; 1417 MW	99.91%; 1271 MW
DOWNWARD FRR NEEDS	High Risk	99.87%; 1251 MW	99.90%; 1362 MW	99.96%; 1251 MW	99.98%; 1384 MW
	Low Risk	99.97%; 1251 MW	99.89%; 1053 MW	99.97%; 1251 MW	99.92%; 1025 MW

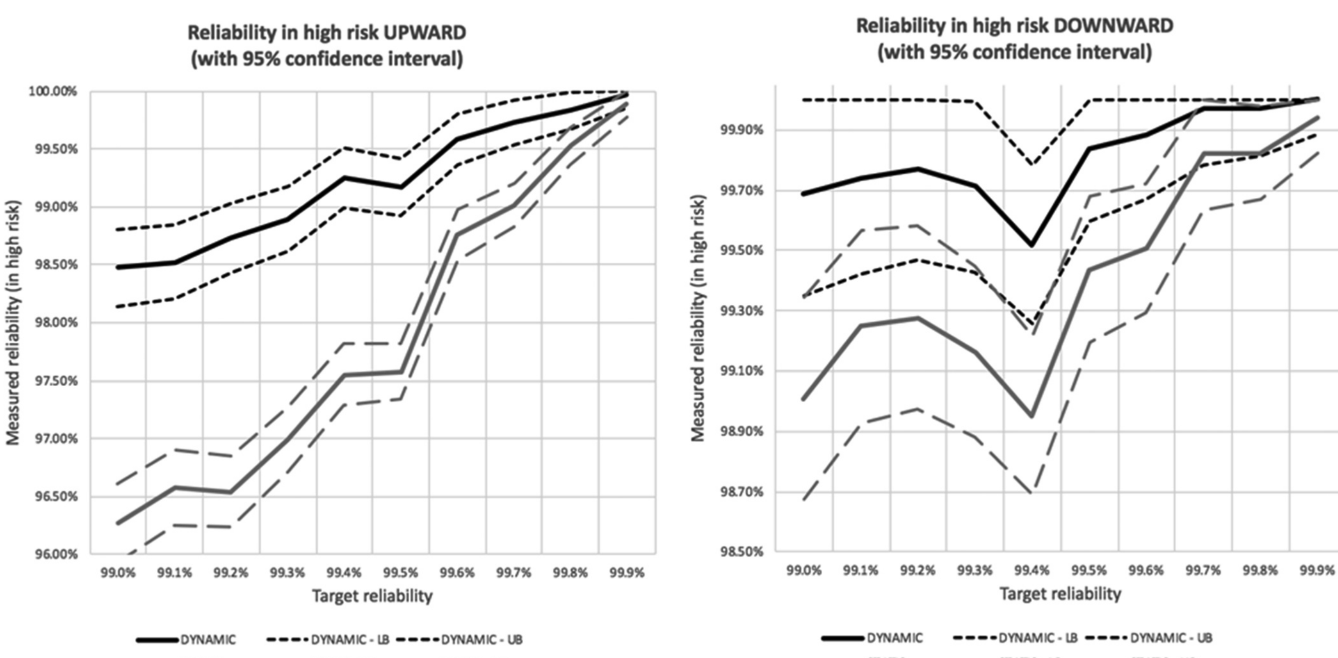

Fig. 5. Reliability in high risk for KMEANS vs static sizing, with a 95% confidence interval (UB and LB are the upper and lower bounds of the 95% confidence interval of the reliability achieved by the model in high risk). Note that a classical confidence interval is the normal interval. However, the normal interval behaves badly when p is close to 0 or 1, which is the case here (p is between 99% and 99.9%). Therefore, the Jeffreys interval has been used instead (Brown et al., 2001).

Table 5
Average, minimum, maximum reserve requirements, dynamic potential (Δ) and dynamic spread (expressed in MW).

	Upward					Downward				
	Avg	Max	Min	Δ	Spread	Avg	Max	Min	Δ	Spread
STAT	1417			–	–	1251			–	–
KMEANS	1365	1616	1270	52	346	1204	1593	794	47	799
KNN	1353	1616	1208	64	407	1205	1693	698	46	995
OO	1387	1418	1364	30	53	1237	1252	1140	14	112

Δ. Finally, the table presents the spread, which is the difference between the maximum and minimum reserve requirements over the simulation period.

The delta between both averages, which represents the potential for dynamic methods to reduce reserve requirements, demonstrates that the full dynamic sizing methods reduce average reserve needs by 52–64 MW for upward reserve, and by 46–47 MW for downward reserve needs.

Nevertheless, the spread between the minimum and maximum reserve needs and the duration curves in Fig. 6 demonstrate that there are large differences between the requirements in periods with high and low risks. This spread can amount up to 346–407 MW for upward, and 799–995 MW for downward reserve needs. The larger spread for downward reserves is due to the fact that the downward reserve requirement varies strongly as a function of the import or export state of the NEMO cable, which can swing by + 1 GW or − 1 GW depending on whether the cable is in import or export mode. By contrast, upward reserve requirements are driven by the capacity of the nuclear units, which amounts to 1 GW for the largest units. Since at least one nuclear unit is always scheduled in any given day, the upward requirement exhibits variations of lower magnitude throughout the year.

The duration curves of the FRR requirements (Fig. 6) demonstrate that the FRR requirements determined by the dynamic sizing methods are more commonly lower than those of static sizing. Concretely, up to 85% of the time, the upward reserve requirements of dynamic methods are lower than those of static methods, and 80% of the time the downward reserve requirements are lower for dynamic methods. Obviously, this also results in periods where the FRR needs increase above the static sizing benchmark. Regarding downward FRR requirements, it can be seen that FRR requirements below 1 GW occur only rarely, i.e. 2.6% of the time for KNN and 2.3% of the time for KMEANS. This is explained by the fact that the NEMO interconnector is only rarely scheduled in import, and exceptionally high renewable production conditions are required for achieving downward reserve levels below 1 GW.

The duration curves show that the two full dynamic methods (kmeans and knn) exhibit a similar behaviour. However, differences are observed in terms of extreme high or low FRR requirements, especially on the downward side. Indeed, Table 5 demonstrates that the minimum downward FRR requirements for kmeans amount to 794 MW, while the requirements of knn may be as low as 698 MW. Similarly, the maximum downward FRR requirements for kmeans amount up to 1593 MW, while the requirements of knn reach up to 1693 MW. This is a result of their parametrization and an interesting area of future research is to develop a hybrid method combining the features of each model.

4.2.2. Semi-dynamic methods in the reference scenario 2020

The outage-only method exhibits a lower potential for reducing FRR needs, up to 30 MW on the upward direction, and 14 MW on the downward direction. The moderate potential compared to the full dynamic methods is confirmed by observing the spread between the minimum and maximum reserve requirements, which is limited to 53 MW. Concretely, the minimum upward requirement amounts to 1364 MW, while the maximum upward requirement amounts to 1418 MW. This is due to the fact that upward reserve in Belgium is mainly driven by renewables and by the nuclear power plants. Since the outage-only method does not manage the imbalance resulting from renewable resources dynamically (i.e. the forecast and market errors are not treated dynamically), and since nuclear capacity in Belgium serves base load and therefore does not exhibit a notably dynamic schedule, there are very few opportunities for the outage-only method to reduce upward requirements.

By contrast, insofar as downward reserve requirements are concerned, the outage-only method exhibits a larger spread of 112 MW, since FRR requirements are mainly driven by renewable forecast errors and the NEMO interconnector schedule. The NEMO interconnector is expected to be scheduled in export mode 85% of the time, and in import mode 15% of the time. This provides opportunities for the outage-only approach. Indeed, when the NEMO interconnector is scheduled in import, the downward FRR requirements are reduced to 1140 MW (this corresponds to the minimum value in the last row of Table 5), compared to 1252 MW (this corresponds to the maximum value in the last row Table 5). By contrast, static sizing requirements remains constantly at a value of 1251 MW. These results demonstrate that a dynamic method based on the outage risk may have its merits, at least when large contingencies with respect to the demand and the installed renewable capacity are present.

Although the potential of the outage-only method in reducing upward requirements remains limited, some additional reduction in reserve requirements are possible when rare but scheduled events are accounted for. Such event include the planned maintenances of large

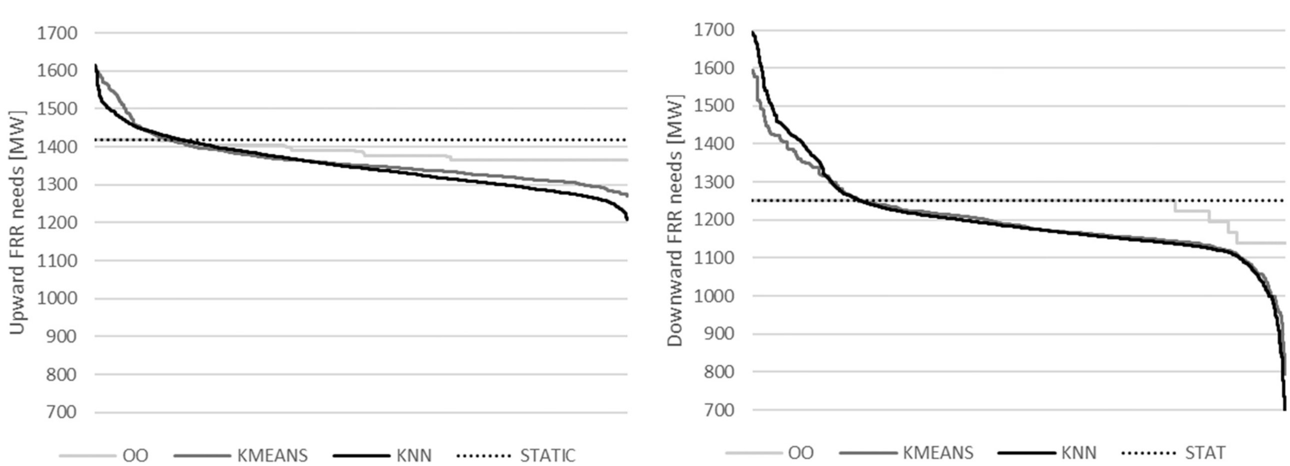

Fig. 6. Duration curve of upward (left) and downward (right) FRR requirements for the 2020 reference scenario.

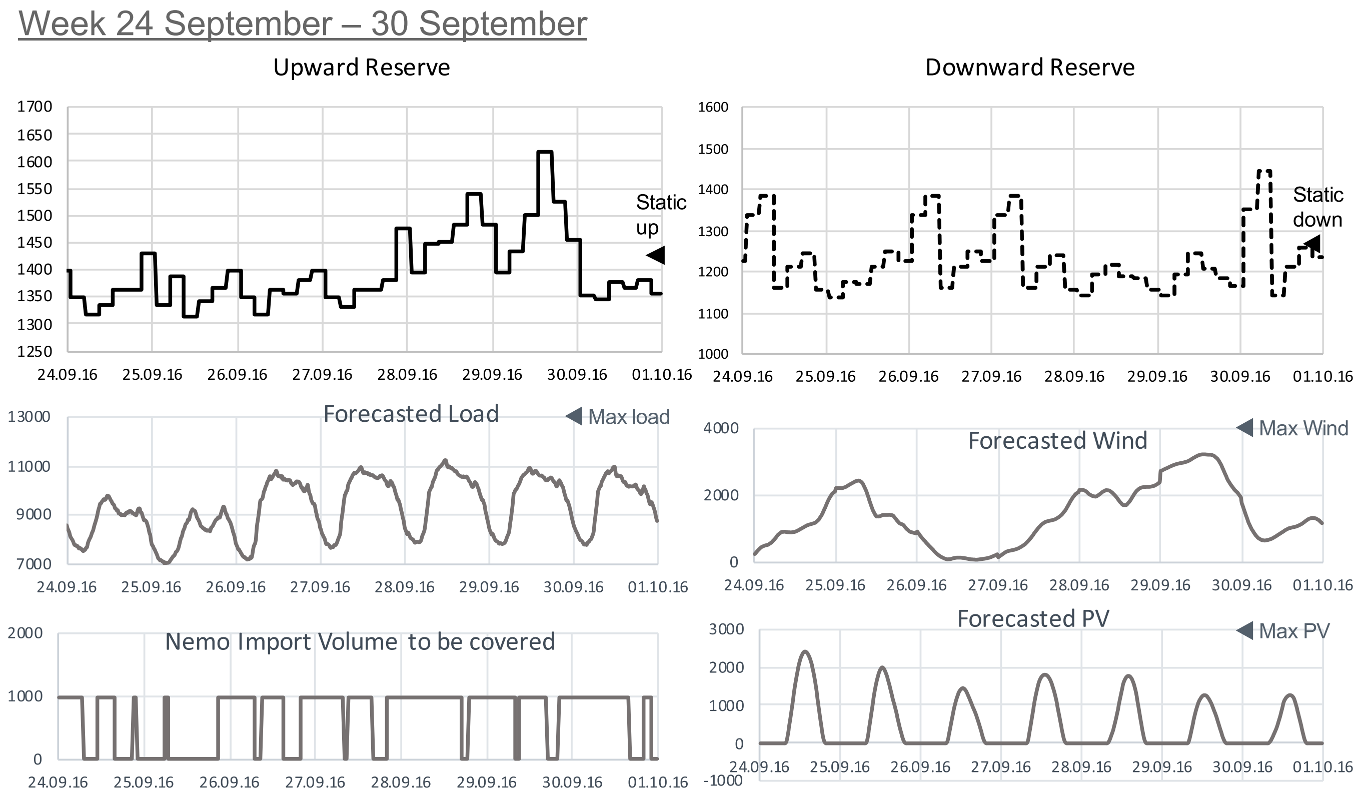

Fig. 7. Example of dynamic sizing on a given typical week for the kmeans method.

power plants, or the maintenance of the NEMO interconnector. These events permit temporary reductions in reserve requirements using the outage-only method. A separate analysis of the outage risk demonstrates that the reserve requirements are mainly impacted when at least one or two nuclear units with capacity level in the order of 1 GW are simultaneously in maintenance (for instance following unexpected events). Following the decreasing importance of outage risk in the future evolution of the Belgian electric power system, the outage-only method will not be suitable for a stand-alone implementation in the long term. However, despite its lower potential for achieving volume reductions, due to its lower complexity relative to fully dynamic methods, it is considered favourably by Elia as an easily implementable first step towards dynamic sizing in Belgium, which would serve as a potential first step for a TSO wishing to move smoothly from static to dynamic sizing.

4.3. Reserve capacity profile

In order to demonstrate the intuitiveness of the results, an example of the dynamic reserve sizing decisions is provided in Fig. 7, where reserve requirements are illustrated for a typical week. The figure demonstrates how the method increases the upward reserve needs during high wind production forecasts (perceiving a high risk for a forecast error resulting in a potential shortage), and reducing the upward reserve needs during low wind conditions and night (perceived as less risky). Another trend is presented in the downward profile, where FRR requirements are increased when facing low wind generation and vice versa. Such analysis of the system parameters provides an intuitive explanation of the evolution of FRR requirements under the dynamic methods.

The consistency of the dynamic methods can be further validated by studying the correlation between the historic FRR needs and the system conditions. Fig. 8 provides an overview of these correlations for the up- and downward FRR needs during the testing period for the kmeans method (correlations are similar to knn method):

- *Renewables*. It is shown that FRR requirements are strongly correlated with the expected renewable generation. Higher predicted renewable generation results in higher upward FRR needs, while downward FRR needs decrease. High renewable forecasts increase the risk of over-forecasting wind power and vice versa for under-forecasting. Further analysis demonstrates that this trend is mainly driven by offshore wind generation following its regionally concentrated nature.
- *Time of the day and demand*. It can be observed that the highest upward FRR requirements occur during day time (expressed by the percentage of day-hours). This is related to the expected demand: a high demand generally results in higher upward FRR requirements while a low demand results in greater downward FRR requirements. This is likley related to the schedules of flexible power plants (high demand results in high output schedules of power plant which may result in less remaining upward flexibility for market players to balance their portfolio which in its turn can result in higher shortage imbalance risk and higher upward FRR requirements; and vice versa for downward FRR requirements). Furthermore, analysis demonstrates that the ramping rate of the demand increases the downward impacts FRR requirements which can be explained by an effect of higher demand variability on the ability of market players to maintain their portfolio in balance, while this is not the case for the upward FRR requirements. Such correlations will be subject to further investigation when gaining further experience with the model
- *NEMO-link*. It is observed that the minimum downward FRR requirements only occur when the NEMO-link is predicted to be in import (where the outage risk does not need to be covered). Similarly, the minimum upward FRR requirements occur only when the NEMO-link is predicted to be in export. However, for moderate to high up- and downward FRR needs, the impact of the NEMO-link is less clear.

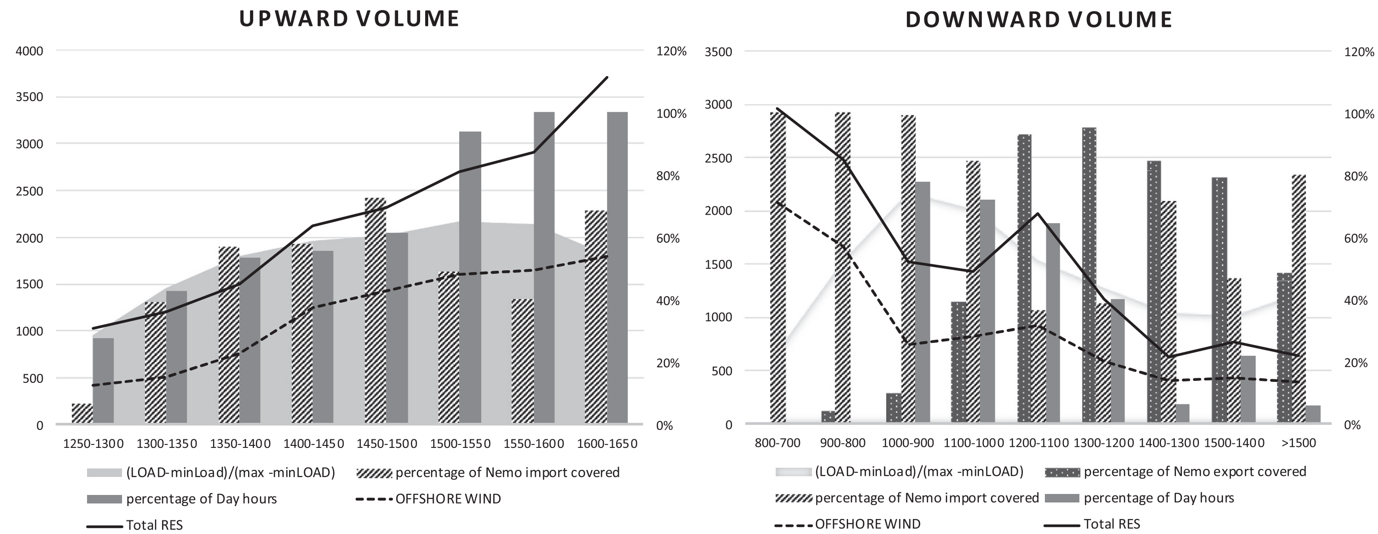

Fig. 8. Graphical representation of the FRR needs (kmeans). The x-axis represents the different levels of sizing, split in ranges of 50 MW for upward and 100 MW for downward, in increasing order. The y-axis represents the average system condition in each group of sizing. The status of the NEMO link, the percentage of day hours as well the normalized demand are expressed in %, rated on the right y-axis. The renewable generation, as well as the offshore generation, is rated in MW on the left y-axis.

Table 6
Average, minimum, maximum reserve needs, dynamic potential (Δ) and dynamic spread (expressed in MW) for the *high* and *low* 2020 scenarios.

		Upward					Downward				
		Avg	Max	Min	Δ	Spread	Avg	Max	Min	Δ	Spread
High scenario	STAT	1364			–	–	1180			–	–
	KMEANS	1325	1473	1243	39	230	1141	1390	715	38	675
	KNN	1318	1491	1190	46	301	1145	1527	628	35	899
	OO	1339	1364	1320	25	45	1160	1181	1027	20	154
Low scenario	STAT	1564			–	–	1426			–	–
	KMEANS	1471	1971	1325	93	647	1356	1710	960	70	750
	KNN	1436	1977	1245	128	731	1362	2031	844	64	1187
	OO	1546	1565	1532	18	33	1420	1427	1377	6	50

4.4. Robustness

4.4.1. 2020 study cases

In order to account for the uncertainty surrounding the precise conditions of the Belgian system in 2020, three study cases were developed which represent the *low*, *high* or *average capability of market players to deal with* the additional imbalances with respect to the increasing share of renewables. Table 6 demonstrates that the potential for dynamic sizing methods to reduce the volume of reserve requirements persists, regardless of the plausible evolution of the system towards 2020. Of course, in the *high* scenario where the impact of renewable uncertainty is mitigated, the potential for dynamic sizing to reduce FRR requirements is slightly reduced. Correspondingly, in the *low* scenario, the potential increases.

It is therefore shown that, although the ability of the market to cover imbalances has large impact on the reserve needs, the dynamic methods maintain their potential. This potential is increased in case of higher balancing needs which would result from a reduced ability of BRPs to ensure balanced portfolios in real time.

4.4.2. 2027 post-nuclear case study

Removing the larger 1-GW nuclear units from the system results in reduced outage risk, which in turn results in lower average upward reserve requirements for all methods. Thus, upward reserve requirements decrease, despite the additional forecast risk of newly added renewable capacity in 2027. In the case of the static sizing method, this reduction leads to a need of 1284 MW (which implies a reduction of 133 MW in upward requirements relative to the 2020 reference case).

For the fully dynamic methods, the reduction of upward FRR requirements is even greater, and results in FRR needs of 1186 MW for kmeans and 1160 MW for knn (Table 7). Thus, the potential of dynamic methods to reduce upward FRR requirements increases from 52 to 64 MW to 98–124 MW for kmeans and knn respectively. This is explained as the outage risk of the nuclear units will no longer be the main driver for upward FRR requirements. Since nuclear unit scheduled as base load are largely static, they prevent dynamic sizing from reaching its full potential. In particular, the upward FRR requirements in 2027 dimensioned with the fully dynamic methods decrease below 1000 MW during periods when NEMO-link is predicted to be exporting. Table 7 shows the increase in the spread of the dynamic methods, from 346 to 407 MW to 629–739 MW. Downward FRR requirements are not affected by the nuclear outage risk, therefore there is no compensation for the increase in prediction risk resulting from additional renewable generation. Thus, the downward FRR requirements increase to 1340 MW in the static sizing method, and to 1286 MW in the fully dynamic methods. Table 7 shows that although the dynamic potential and spread increases, this effect is fairly limited.

Table 7
Average, minimum, maximum reserve needs, dynamic potential (Δ) and dynamic spread (expressed in MW) for the *post-nuclear 2027*scenario.

[MW]	Upward					Downward				
	Avg	Max	Min	Δ	Spread	Avg	Max	Min	Δ	Spread
STAT	1284			–	–	1340			–	–
KMEANS	1186	1534	905	98	629	1286	1700	866	54	834
KNN	1160	1532	793	124	739	1286	1778	841	54	937
OO	1253	1284	1205	31	78	1327	1340	1272	13	67

In conclusion, the dynamic sizing method remains functional in a post-nuclear context. The potential for reductions in upward FRR requirements is significantly increased. In contrast, results show that the outage-only potential is further reduced.

4.5. Financial impact of reductions in FRR needs

In this section, the reductions in hourly FRR needs are used in order to estimate the impact of dynamic reserve sizing on procurement costs. For this purpose, the potential hourly price variations of reserving FRR capacity are estimated, which are expressed in €/MW-h (Fig. 9). A piece-wise linear model is developed based on estimated up- and downward FRR reservation prices when facing low, moderate or high FRR needs resulting from the kmeans method. Since there are no historical hourly price observations available, the following assumptions are adopted:

- The prices for upward FRR needs relate to historical monthly price observations for mFRR in Belgium during the last years. These historical observations are published by Elia on its website, with prices varying between 2.5 and 5.5 €/MW-hour.
- Belgium does not currently support a downward FRR market. In the absence of data for Belgium, we estimate prices for downward FRR based on historical data of German mFRR prices.

Nevertheless, as this approach may underestimate price increases when facing high FRR needs, a second more conservative approach assumes an inelastic price which increases to 11.5 and 12.0 €/MW-h for up- and downward FRR needs respectively.

Table 8 demonstrates the financial gains in the reference scenario for 2020 (defined in Section 3). Results in Table 8 show that the financial gains are positive, even when facing high price spikes. According to these results, yearly savings can be obtained that range between M€2.51 and M€2.97 for machine learning methods. For the outage only method, these savings are limited between M€1.48 and M €1.71. The implementation cost of a dynamic sizing tool is estimated by Elia to range between €850,000 and €1,100,000 per year. This estimated cost includes the project development and yearly recurrent cost of operating a dynamic sizing method. Dynamic sizing therefore results in a positive business case.

5. Conclusions and policy implications

This article compares a range of methods for the dynamic sizing of operating reserves. The investigated methods are compliant with the European legislative and regulatory framework. These methods are presented as an alternative to the current static sizing method generally applied by system operators, whereby the required reserve capacity is fixed for a longer period, generally an entire year. With increasing renewable generation, for which the risk of system imbalances depend on the generation forecasts, such a static sizing approach is expected to result in an oversizing of operating reserves contracted by system operators, at least during some periods. This oversizing results in an unnecessary cost for the system and its users.

The results of a proof of concept for Belgium towards 2020 confirm that dynamic sizing methods based on machine learning result in a better management of reliability, in the sense of exposing the system to less risk during high-risk periods, and avoiding to over-protect the system during low-risk periods. The results further confirm that all three dynamic sizing methods which are presented in the study can potentially reduce average FRR requirements. However, it is also found that this potential is higher for the machine learning methods (up to 64 MW and 46 MW potential reductions in up- and downward FRR requirements respectively) compared to a simplified method based on dynamic adjustments to forced outage (up to 31 MW and 15 MW potential reductions in up- and downward requirements respectively). The outage-only method is nevertheless considered by the Belgian system operator as an option for gradual implementation in 2019, due to its appealing simplicity in terms of operational implementation. Finally, the dynamic sizing methods presented in the paper were tested against two alternative scenarios in terms of the ability of market players to balance their portfolio, as well as one scenario for 2027. The results

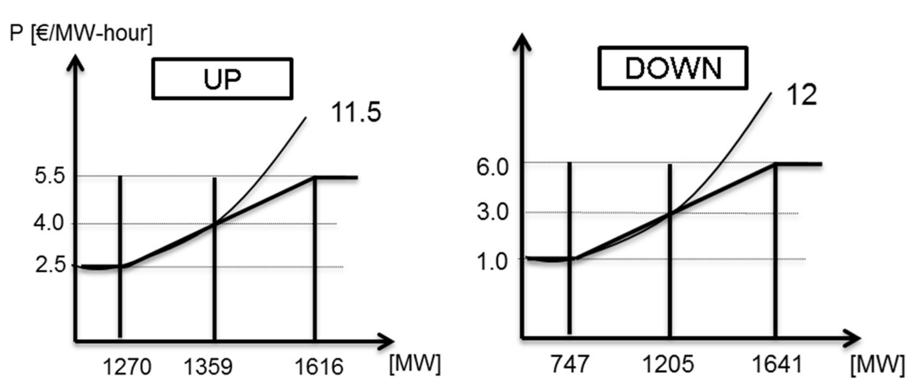

Fig. 9. Representation of the generic reserve price in function of the FRR needs [MW] for two scenarios in 2020.

Table 8
Financial gains of dynamic sizing methods compared to the static approach.

[€]	Reference scenario			Conservative scenario		
	UP	DOWN	TOTAL	UP	DOWN	TOTAL
OO	1.104.388	379.735	1.484.123	1.308.069	400.458	1.708.527
KNN	2.122.126	845.976	2.968.102	2.219.783	343.086	2.562.869
KMEANS	1.765.411	1.003.736	2.769.146	1.785.307	725.788	2.511.096

further confirm the robustness of the dynamic sizing methods in terms of reducing average reserve requirements.

The implementation of dynamic dimensioning methods has policy, regulatory and market operation consequences. Firstly, the implementation of dynamic sizing requires important modifications in the procurement of reserve capacity. Indeed, dynamic sizing requires a daily procurement of FRR, as opposed to weekly or monthly. In particular, the allocation of the overall FRR capacity requirements derived from dynamic sizing towards contracted reserves, non-contracted reserves and reserve sharing is an important design consideration moving forward. The determination of this allocation procedure will need to account for the implications of daily procurement and product design, and will need to be conducted in close collaboration with all balancing service providers. Nevertheless, these evolutions are expected to further open the market, although it is not clear which effect varying reserve needs will have on the prices.

Secondly, as the dynamic sizing computes the expected system imbalance distributions closer to real-time, it avoids the required "extrapolations" of historic system imbalances in a static framework. The latter resulted in over- or underestimations resulting in area control errors, monitored by ENTSO-e and used to assess the dimensioning methodology. A dynamic sizing approach allows to reactively adapt the calculation method and its parameters.

Finally, the introduction of dynamic sizing requires a modified regulatory framework to be embedded in the LFC block Operational Agreement. This regulatory framework will be subject to public consultation by the TSO, and further subject to approval by the regulator. However, whereas in the past the regulator approved the reserve sizing methodology and results in a yearly recurrent report, a dynamic approach requires the approval of the methodology alone, according to which the sizing results will be determined in the day-ahead time frame. This also requires a modification of the federal grid code, which delineates the authority of the regulator over the dimensioning of reserve capacity in Belgium. The regulatory framework should ensure transparency and intuitiveness of the method and the corresponding results.

The goal of Elia is to implement the dynamic dimensioning for the procurement of operating reserves in Belgian reserve capacity auctions during 2019 and 2020. This will include an extensive training period. Due to their greater complexity, the machine learning methods will require a testing period of at least one year. An important factor for Elia to approve the deployment of dynamic sizing methods is the expectation that the dynamic sizing methods will be subject to further improvements, both in terms of design (e.g. in the identification of new imbalance drivers) as well as algorithms (e.g. in the improvement of the adopted statistical methods). An important consideration in the implementation of dynamic sizing is the ability of the method to cope with extraordinary system and network conditions (for instance a solar eclipse). Indeed, the analysis of the imbalance drivers has shown that predicting imbalance risk is not straightforward, and that a significant part of the system imbalance remains unexplained by day-ahead system conditions. The question remains regarding the extent to which this predictive ability can be further improved. This effort of explaining the residual uncertainty associated to system imbalance will require continuous efforts following the conclusion of the present study, and will be the subject of future research by the authors and within Elia.

Acknowledgement

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