Energy Reports 13 (2025) 1029–1040

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research paper

Deterministic grid frequency deviations and the provision of frequency containment reserve with battery storage systems

Mauricio Celi Cortés [a,b,c,d,*], Lucas Koltermann [a,b,c,d], Thanh Daniel Dang [a,b,c,d], Jan Figgener [a,b,c,d], Sebastian Zurmühlen [a,b,c,d], Dirk Uwe Sauer [a,b,c,d,e]

[a] Chair for Electrochemical Energy Conversion and Storage Systems, Institute for Power Electronics and Electrical Drives (ISEA), RWTH Aachen University, Aachen, Germany
[b] Institute for Power Generation and Storage Systems (PGS), E.ON ERC, RWTH Aachen University, Aachen, Germany
[c] Center for Ageing, Reliability and Lifetime Prediction for Electrochemical and Power Electronic Systems (CARL), RWTH Aachen University, Aachen, Germany
[d] Jülich Aachen Research Alliance, JARA-Energy, Aachen, Germany
[e] Forschungszentrum Jülich GmbH, Institute of Energy and Climate Research Helmholtz-Institute Münster: Ionics in Energy Storage (IMD-4), Jülich, Germany

ARTICLE INFO

Keywords:
Deterministic frequency deviation (DFD)
European continental synchronous area
Frequency containment reserve
MILP
Grid frequency time series
Large-scale battery storage system
Time series decomposition

ABSTRACT

The synchronous grid of Continental Europe presents deterministic frequency deviations (DFD) that pose a challenge for grid stability and the provision of frequency containment reserve (FCR). There is a knowledge gap concerning the latest development of their occurrence and magnitude as well as their implications for the operation of large-scale battery energy storage systems (BESS) in the German FCR market. We analyzed the historic development of the occurrence and magnitude of DFDs from 2014 to 2023 as well as their seasonal patterns and daily profiles. For this analysis, we employed methods of time series decomposition such as classical and multiple seasonal-trend decomposition. Furthermore, we leveraged insights from our analysis to propose a rule-based approach for the storage management of BESS based on DFD-informed operation. Our results show an increase in the occurrence of high-magnitude DFDs of 37% from 2014 to 2023, with a 10 mHz rise in DFD magnitude explained by the historic trend. We found that the median occurrence of high-magnitude DFDs varies by up to 100% within a year. Our findings highlight the potential of integrating frequency behavior into FCR provision with BESS, prompted by the recent increase in DFD occurrence and magnitude.

1. Introduction

The aggregated share of wind and photovoltaic power in the total power generation of the European Union (EU) has increased by 16% from 2014 to 2023, with an overall share of renewable electricity generation in the EU of over 43% in 2023 (Eurostat, 2024; Fraunhofer ISE, 2024a). While the development of renewable generation capacities can present challenges for grid stability (Lew et al., 2020), the effect on balancing reserves is limited in the case of the German grid (Hirth and Ziegenhagen, 2015; Koch and Hirth, 2019). Conversely, energy trading is the main cause for substantial deterministic frequency deviations (DFD) that put a strain on frequency containment capabilities (Schäfer et al., 2018b). The European interconnected grid shows DFDs at full hours caused by ramping of power plants at the start and end of delivery periods of common trading products that are not aligned with load dynamics (Eurelectric, ENTSO-E, 2011; Weissbach and Welfonder, 2009; Gobmaier, 2017; Schäfer et al., 2018a). Publications from 2017 (Gobmaier, 2017) and 2018 (Schäfer et al., 2018b) reported that the introduction of short-time trading products in Europe had resulted in the reduction of DFDs. However, they still pose a challenge for grid frequency quality. A 2020 report by the European network of transmission system operators for electricity (ENTSO-E) states that DFDs had increased in magnitude in the years previous to publication, with an increased number of DFDs over 75 mHz (ENTSO-E, 2020).

DFDs cause higher loading of transport lines due to unscheduled activations of frequency containment reserve (FCR) and misuse of FCR and frequency restoration reserves (FRR) that debilitate the system against faults, the reduction of damping capabilities of inter-area oscillations, as well as increased wear and tear of generators (ENTSO-E, 2020; Elia, 2020). ENTSO-E reported the overlap of a large DFD and a technical failure resulting in a 192 mHz frequency deviation in January of 2019, the worst recorded since 2006 (ENTSO-E, 2020). This event highlights the challenge to the stability of the system and the

* Correspondence to: Campus-Boulevard 89, 52074 Aachen, Germany.
E-mail address: batteries@isea.rwth-aachen.de (M. Celi Cortés).

https://doi.org/10.1016/j.egyr.2024.12.057
Received 5 September 2024; Received in revised form 11 December 2024; Accepted 19 December 2024
Available online 31 December 2024

provision of FCR posed by DFDs. Due to the magnitude of frequency deviations, DFDs have a significant impact on the control energy provided by units active in the FCR market, such as large-scale battery energy storage systems (BESS). BESS are increasingly used for FCR in Germany (Regelleistung Online, 2020, 2021). As of 2024, there are 810 MW of BESS power pre-qualified for the provision of FCR in Germany (50Hertz, Amprion, TenneT TSO, TransnetBW, 2024b), where the total control power demand was 564 MW (50Hertz, Amprion, TenneT TSO, TransnetBW, 2024a). This represents a 29% increase in pre-qualified BESS power compared to 2023 (50Hertz, Amprion, TenneT TSO, TransnetBW, 2023). The current installed BESS capacity in Germany amounts to 1.5 GWh, of which 750 MWh were providing ancillary services as of the end of 2022 (Figgener et al., 2023, 2024).

The integration of BESS for the provision of FCR contributes to the efficiency of grid operations by providing an enhanced frequency control response that is significantly faster than traditional power plants. BESS can respond to frequency deviations within milliseconds (Koltermann et al., 2023). Furthermore, they can be controlled with high accuracy and present a high energetic efficiency, leading to precise control responses and energy savings. The provision of FCR with BESS has a positive impact on the economic viability of grid operations by reducing the FCR price due to their ability to provide the service at a lower cost (Fleer et al., 2018; Engels et al., 2019; Badeda et al., 2017). Additionally, the use of BESS for FCR can increase infrastructure longevity by managing peaks in frequency without causing additional wear and tear, in contrast to conventional power plants. The dominant mechanism of BESS aging in FCR operation has been shown to be calendar aging rather than cyclic aging, meaning that the aging of the system is only marginally affected by the micro-cycles caused by frequency deviations (Jacqué et al., 2022a,c).

In Germany, BESS fall under the definition of the transmission system operators (TSO) as units with limited energy storage, which are subject to special requirements for the provision of FCR (50Hertz, Amprion, TenneT TSO, TransnetBW, 2022). These units have various storage management options to provide the required balancing power at all times. The systemic nature of DFDs may provide opportunities for the provision of FCR by BESS units. By identifying the times and amounts of control energy caused by DFDs, it is possible to develop more economically and energy efficient storage management strategies. One possibility for storage management, hereafter referred to as setpoint adjustment (SPA), is the implementation of charging and discharging processes via scheduled transactions (50Hertz, Amprion, TenneT TSO, TransnetBW, 2022). Scheduled transactions in the context of SPA for FCR can be realized within the intraday market in 15-minute slots, as exemplified by the research-oriented BESS named M5BAT (Koltermann et al., 2022b; Jacqué et al., 2022b).

2. Literature review

2.1. Deterministic frequency deviations

Existing scientific literature concerning DFDs in continental Europe (CE) ranges from the early identification of DFDs and their causes, as well as possible countermeasures, to their use in the development of prediction algorithms for grid frequency properties. Weissbach and Welfonder (2009) analyzed the origins of DFDs in CE and formulated countermeasures to reduce their occurrence, which rely on the implementation of ramping requirements for schedule-based dispatch. Schäfer et al. (2018a) identified the substantial contribution of trading to frequency fluctuations by analyzing frequency of different synchronous grids. Schäfer et al. (2018b) evaluated the role of trading on DFDs in CE and suggested that the introduction of shorter trading intervals in previous years had improved frequency quality. Kruse et al. (2021a) provided an analysis of DFDs using explainable artificial intelligence methods, investigating the influence of load, solar power ramps, and scheduled generation ramps on DFDs. Kruse et al. (2020) proposed a weighted-nearest-neighbor predictor to forecast power grid frequency trajectories, introducing daily patterns shaped by DFDs as a benchmark for frequency predictors. Kruse et al. (2021b) introduced an explainable machine learning model to predict frequency stability indicators for different European synchronous areas (including CE) that significantly outperforms daily profiles characterized by DFDs. Rousseau et al. (2023) analyzed DFDs in CE, focusing on the Swiss contribution, and proposed countermeasures relying on the prediction of power imbalances. Weißbach et al. (2018) evaluated the mitigating effects of the introduction of quarter-hour products in European markets on DFDs.

2.2. Setpoint adjustment in the provision of FCR with BESS

Several publications have investigated the operation of BESS in the German FCR market, including strategies for SPA based on wholesale energy trading in order to ensure the needed FCR operating point. Schweer et al. (2016) optimized the operation of M5BAT in the FCR market including SPA. Thien et al. (2017) presented an FCR operating strategy for M5BAT, triggering the SPA when the battery state of energy (SOE) falls under a certain threshold. Münderlein et al. (2019) evaluated FCR operation strategies of the BESS M5BAT, including the SPA strategy based solely on SOE levels. Thien et al. (2022) analyzed different energy management algorithms, considering a state of charge (SOC) dependent SPA. Koltermann et al. (2022a) presented and validated the control algorithm of the BESS M5BAT, including an SOC based SPA in the context of FCR operation. Schlachter et al. (2020) simulated the FCR operation of batteries and power-to-heat, including an SPA strategy on the intraday market based on buying at low SOCs and selling at high SOCs. Engels et al. (2019) presented a framework to optimize the investment, size, and operation of BESS for the provision of FCR, considering degrees of freedom and intraday transactions for its SPA. In addition, Engelhardt et al. (2022) investigated different SPA strategies for FCR provision with BESS in the Nordic market, including energy recovery through the intraday market.

2.3. Research gap

Existing literature regarding DFDs mainly focuses on identifying their causes and recommending measures to counteract them at the system level but they do not present detailed daily profiles or analyze the FCR energy demand focused on the operation of assets in the provision of FCR. Furthermore, there is a lack of information on the seasonality of profiles across the year. There is no analysis of the development of occurrence and magnitude of DFDs in the recent years, with the last official report from ENTSO-E on the topic dating back to 2020, with an analysis of the development of DFDs until January of 2019 (ENTSO-E, 2020). Although complex methods such as those mentioned in the literature review provide detailed insights into DFD causes, they are computationally intensive and unnecessary for obtaining operationally relevant insights. Simpler statistical approaches, like those employed by ENTSO-E, fail to capture key nuances in frequency trends that are relevant for BESS operation. The multiple seasonal-trend decomposition using locally estimated scatterplot smoothing (LOESS) (MSTL) method, which is highly cited for its balance of computational efficiency and accuracy, has not yet been applied to analyze DFDs in the scientific literature. This gap suggests the use of methods that leverage computational efficiency to gain insights that can be applied to the provision of FCR with BESS.

In the context of the provision of FCR, the storage management of SPA of BESS is commonly done in the intraday market. Our literature research shows that no previous studies have proposed a price-aware SPA strategy that leverages insights from DFDs and historic intraday prices instead of a purely SOC driven activation. The literature review shows that the operation of BESS in the FCR market is well studied, but SPA strategies remain the same. SPA costs have become an important component of the business model for FCR provision with BESS, following the increase in intraday prices during the energy crisis. The investigation of more sophisticated SPA strategies based on intraday market trades is key to achieving a more robust business case for the provision of FCR with BESS.

3. Contribution

3.1. Regarding the analysis of DFDs

In our study, we utilized methods of time series decomposition in order to determine daily frequency profiles based on ten years of European grid frequency data. Here we analyze the differences in DFDs between summer and winter months, as well as between weekdays and weekends. Furthermore, we analyze historic frequency data and discuss the influence of increased variable renewable energy production on the FCR control energy demand in the ENTSO-E area. Following, we identify trends in the magnitude and occurrence of full-hour DFDs over the years with the help of MSTL. We contribute to the body of knowledge with a detailed analysis of the latest data in order to assess development of DFDs over recent years, using high quality frequency data from 2014 to 2023 to present the latest development of DFDs. In contrast to the reviewed literature, we present representative daily profiles of DFDs and FCR energy demands while analyzing seasonalities and trends in the data. In addition, the use of MSTL for the analysis of DFDs is a novel approach that has not been proposed in the literature before. The use of classical decomposition methods, as well as MSTL, provides advantages in terms of a higher computational efficiency with sufficient accuracy, allowing for the analysis of ten years of frequency data. This work not only contributes to the understanding of frequency dynamics in the context of rising intraday prices but also establishes a foundation for designing SPA strategies that enhance the economic and operational efficiency of BESS providing FCR.

3.2. Regarding the provision of FCR with BESS

SPA in the intraday market is very well studied and applied as seen in the literature review. However, insights into the deterministic behavior of the grid frequency and its relationship with energy prices in the intraday market have not been implemented in SPA strategies within the development of energy management algorithms. We address this gap by discussing the implications of DFDs for the controller design of BESS in the German FCR market and by proposing a price-aware rule-based approach for SPA that leverages insights from DFD-dominated daily profiles and intraday market data for the first time. This approach aims to improve storage efficiency and reduce costs for BESS providing FCR, compared to traditional SPA strategies. Furthermore, the proposed rule-based approach includes a typically grid supporting SPA activation strategy. This is contrast to the traditional SPA strategies for BESS, where activation is solely based on current SOE levels and not on the price nor on the typical FCR energy demand.

4. Methodology

In this section, we present the methods used to extract daily frequency profiles using a ten-year dataset of grid frequency data from the CE region. In addition, we outline our approach to identifying and quantifying DFDs occurring at full hours, along with the criteria used to define them. Furthermore, we detail the methodology used to calculate the provision of FCR by BESS according to the requirements of the German TSOs.

4.1. Extraction of daily grid frequency profiles

To extract daily frequency profiles from the frequency data obtained from the CE grid, we utilized the "seasonal_decompose" function available in the Python library "statsmodels" (Seabold and Perktold, 2010). This function employs classical decomposition methods to extract trend, seasonality, and residual components from the data. Specifically, we applied additive decomposition. Our procedure involves filtering the data and subsequently applying "seasonal_decompose" over a one-day period. This approach aligns with the main recurrence period of grid frequency patterns in the CE region (Kruse et al., 2020), enabling the extraction of meaningful daily grid frequency profiles. Since non-recurring frequency deviations are explained by the residual of the decomposition, we assume the seasonality component of the frequency deviations, i.e. the extracted daily profile, is attributable to deterministic deviations in the system. For this reason, we focus the analysis on the seasonal component of the time series decomposition.

Eq. (1) shows the utilized additive decomposition method of time series data into trend, seasonal, and residual components. In order to determine the daily frequency profile, we decomposed the ten-year frequency time series $f(t)$ into the daily trend $T_d(t)$, the daily seasonal component $S_d(t)$, and the daily residual $e_d(t)$. Eqs. (2) and (3) show the decomposition of frequency data for the summer months of June and July and the winter months of December and January, respectively. These months show the most pronounced seasonal differences in the frequency behavior within the year. Furthermore, the difference in frequency behavior between weekdays and weekends is captured by splitting the data as shown in Eqs. (4) and (5).

$$Y(t) = T(t) + S(t) + e(t) \tag{1}$$

$$f_{summer}(t) = T_d(t) + S_d(t) + e_d(t) \tag{2}$$

$$f_{winter}(t) = T'_d(t) + S'_d(t) + e'_d(t) \tag{3}$$

$$f_{weekday}(t) = T''_d(t) + S''_d(t) + e''_d(t) \tag{4}$$

$$f_{weekend}(t) = T'''_d(t) + S'''_d(t) + e'''_d(t) \tag{5}$$

The seasonal terms $S_d(t)$, $S'_d(t)$, $S''_d(t)$, and $S'''_d(t)$ of these equations represent the four daily grid frequency profiles extracted in this work. They containing the recurrent behavior of the data for the ten years analyzed, corresponding to deterministic frequency deviations. The separation of the time series into summer and winter months, as well as weekdays and weekends, allows us to subtract the influence of known seasonalities on the daily frequency profiles. This enables the use of a single seasonality method, which is more computationally efficient than MSTL. MSTL would be able to identify multiple seasonalities within one dataset but is too computationally intensive to process ten years of frequency data.

4.2. Extraction of DFDs

We apply the ENTSO-E criterion to identify and quantify DFDs as absolute "peak-to-peak" frequency deviation values (ENTSO-E, 2020). Furthermore, we identify DFDs based on peak frequency deviations that occur within 5-minute windows before and after the full hour. Fig. 1 presents our approach to DFD extraction and data preparation.

After extracting these peak-to-peak values, we use an MSTL decomposition (Bandara et al., 2021) from the Python library "statsmodels" (Seabold and Perktold, 2010) on the absolute peak-to-peak values in order to discern trends across years. Our MSTL analysis accounts for daily, weekly, and yearly seasonal patterns, as well as a trend component that explains the growth in DFD magnitude over the years and a non-assignable residual component. Our analysis focuses on

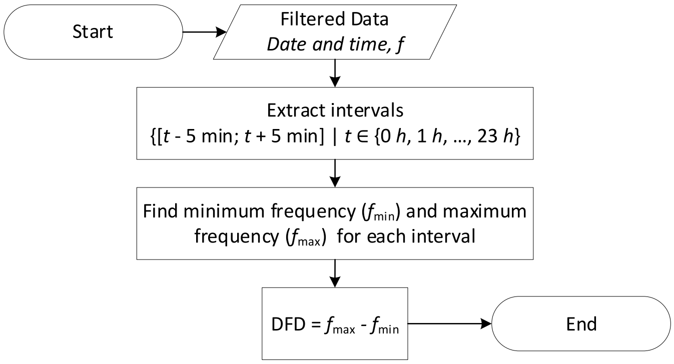

Fig. 1. Flowchart for the extraction of peak-to-peak values of DFDs at full hours from frequency data.

the trend component of the MSTL decomposition, which explains the evolution of DFD magnitudes over the years.

Eq. (6) shows the decomposition of the DFD data $f_{DFD}(t)$ extracted from the frequency time series into trend $T(t)$, seasonal $S(t)$, and error $e(t)$ components. We applied MSTL decomposition to the time series data, resulting in a seasonal term that considers yearly $S_y(t)$, weekly $S_w(t)$, and daily $S_d(t)$ seasonalities, as shown in Eq. (7). In Eq. (8), the trend component results from the subtraction of the seasonal components and the error term from the DFD time series. This trend component of the MSTL decomposition is the focus of the analysis, showing the evolution of DFD magnitudes over a period of 10 years for the first time.

$$f_{DFD}(t) = T(t) + S(t) + e(t) \tag{6}$$

$$S(t) = S_y(t) + S_w(t) + S_d(t) \tag{7}$$

$$T(t) = f_{DFD}(t) - S_y(t) - S_w(t) - S_d(t) - e(t) \tag{8}$$

In contrast to classical seasonal decomposition methods, MSTL is able to identify multiple seasonal components within a dataset, which is particularly useful for the analysis of long-term frequency data. The subtraction of accurately calculated multiple seasonal components from the time series allows for a more precise trend estimation across the ten-year dataset. Furthermore, MSTL is able to capture changes in seasonal components over time, preventing these changes to be misinterpreted as part of the trend. These characteristics speak for the suitability of MSTL for the analysis of magnitude increases in hourly DFD values over a decade. MSTL was not used for the calculation of daily frequency profiles since it is too computationally intensive to process the amount of data considered, which has a resolution of one second.

In addition to the development of DFD magnitude over time, we analyze daily patterns of DFD peak-to-peak values, the count of DFDs over 75 mHz and 100 mHz, and their monthly distribution within the year. For the evaluation of the daily DFD pattern, as well as for the monthly distribution of DFD occurrences, we used box plots. Especially in the case of the daily pattern, this is useful in order to observe the distribution of high magnitude DFDs and outliers. High magnitude outliers are critical since their overlap with actual non-deterministic errors, such as the outage of a large power plant, can compromise the stability of the grid.

4.3. Frequency containment reserve with BESS

In Germany FCR reserves are automatically activated based on the currently measured grid frequency. No FCR needs to be provided within the dead band of ±10 mHz around the target frequency of 50 Hz. The target balancing power $P(\Delta f)$ to be supplied at the grid connection point is calculated as follows (50Hertz, Amprion, TenneT TSO, TransnetBW, 2022):

$$P(\Delta f) = \begin{cases} 0, & |\Delta f| < 10 \text{ mHz} \\ P_{\text{FCR}} \cdot \frac{\Delta f}{200 \text{ mHz}}, & 10 \text{ mHz} \leq |\Delta f| < 200 \text{ mHz} \\ \operatorname{sgn}(\Delta f) \cdot P_{\text{FCR}}, & |\Delta f| \geq 200 \text{ mHz}, \end{cases} \tag{9}$$

where Δf is the frequency deviation from 50 Hz and P_{FCR} is the marketed FCR power of the BESS. Degrees of freedom in the form of overfulfillment of up to 120% of the target FCR power are allowed by regulation. However, we do not use this overfulfillment to calculate the target power of an BESS in the equation. This is an assumption based on the operation of M5BAT, where the overfulfillment is deactivated. In order to determine the influence of DFDs on the energy delivery of the BESS, we calculate the control energy to be provided 10 min before and after the full hour h. The control energy is given by the integral of the function $P(\Delta f)$ from:

$$\int_{h/h-10 \text{ min}}^{h+10 \text{ min}/h} P(\Delta f)\, dt \approx \sum_{n=1}^{600} P(\Delta f_n) \cdot \Delta t_n, \tag{10}$$

where Δf_n represents the frequency deviation at each one-second time step and Δt is the time step duration (in this case, 1 s). We assume that the BESS has an instantaneous response based on response speed measurements performed on the BESS M5BAT (Koltermann et al., 2023). Furthermore, the BESS must be able to provide FCR for at least 15 min at all times, with an additional 5 min reserved for reserve operation in both directions, defining the allowable operating range of the system. In order to stay within this operating range, an SPA is necessary. In the investigated application, the SPA is performed via scheduled transactions in the intraday market.

5. Data foundation

The grid frequency data used in this study were collected at one-second resolution from 2014 to 2023. Measurements were recorded at three locations in the Munich region, employing four monitoring devices to mitigate local disturbances and ensure the validity of the data (Dr. Gobmaier GmbH, 2023). Furthermore, data concerning renewable power generation in the ENTSO-E area from 2015 to 2023 were obtained from the ENTSO-E Transparency Platform (ENTSO-E, 2024).

6. Results and discussion

6.1. Ten years of frequency data

Fig. 2 shows a heatmap with the grid frequency in CE from 2014 to 2023. Here we observe significant and consistent frequency deviations corresponding to DFDs at full hours throughout the years, with less significant deviations observed at quarter hours. The direction of the frequency deviations varies throughout the day due to different factors responsible for systematic mismatches between load and generation at different times of day. In addition, a clear seasonality in the occurrence of DFDs between summer and winter is particularly pronounced during the evening hours. This seasonality is most pronounced around the winter and summer solstices, pointing to the role of lighting related load at the evening twilight (Gobmaier, 2017). Furthermore, a constant overfrequency can be observed in March of 2018. On March 3rd, 2018, a grid time deviation of −359 s, caused by systematic schedule deviations in the area of Serbia and Kosovo, was recorded (Dr. Gobmaier GmbH, 2024). In order to correct the deviation, the Continental European TSOs maintained the average grid frequency at 50.01 Hz throughout March, explaining the overfrequency observed in the heatmap (ENTSO-E, 2018).

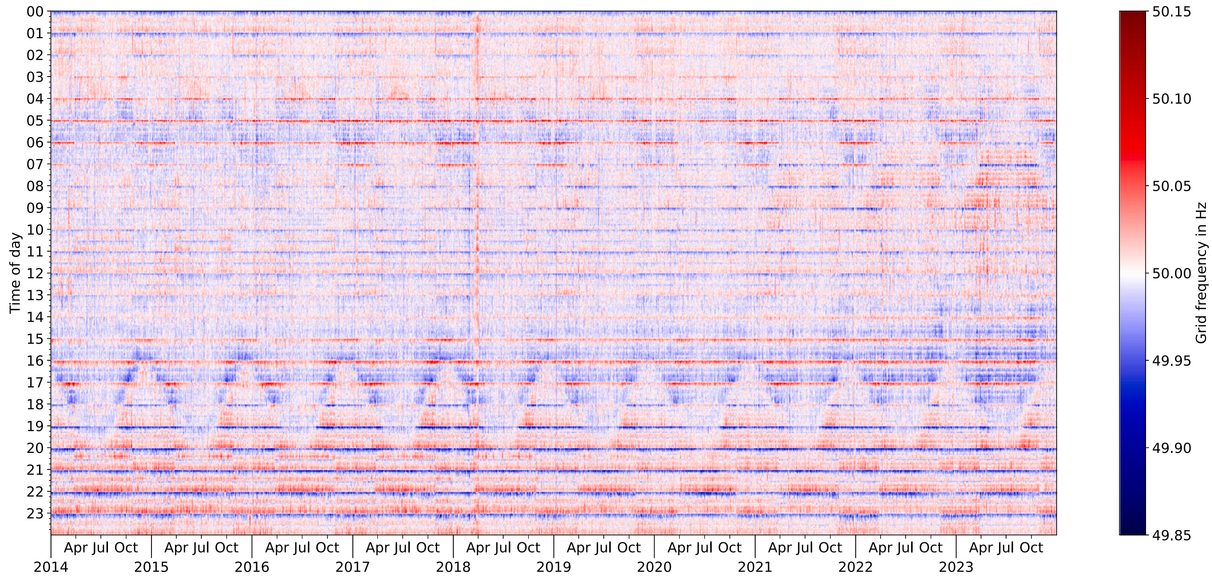

Fig. 2. CE grid frequency from 2014 to 2023 in 1-second resolution, sorted by UTC time and date.

Based on these seasonal patterns and the known differences in load profiles between weekdays and weekends, we derive daily profiles for summer and winter as well as for weekdays and weekends to analyze the direction, onset, and magnitude of DFDs. Furthermore, we analyze the historic development of DFDs to identify any trends in magnitude and occurrence over time.

6.2. Seasonalities in DFDs

Fig. 3 shows daily grid frequency profiles for summer and winter as well as the difference in frequency between both profiles. To enable a valid comparison of frequency deviation magnitudes between summer and winter, one hour is adjusted in the UTC time for the summer profile. This adjustment accounts for daylight saving time, which is common practice in CE. The summer profile is calculated with the data from June and July and the winter profile with the data from December and January, corresponding to the representative summer and winter months in Europe. The data used in both cases corresponds to the 10-year dataset (2014–2023).

The analysis of both summer and winter frequency profiles shows significant hourly peak-to-peak DFD values. Morning DFDs (5:00 to 7:00 a.m.) show positive peak-to-peak deviations ranging from 33 to 57 mHz in the summer and from 49 to 76 mHz in the winter. Thus, morning DFDs are, on average, 22 mHz higher in magnitude in the winter. From 9:00 a.m. to 1:00 p.m., DFDs in a distinctly negative direction can be observed with peak-to-peak values ranging from 25 to 40 mHz in winter, with winter DFDs averaging 10 mHz higher magnitudes. DFDs experience a clear direction change in the positive direction in the afternoon hours, which include 4:00 to 6:00 p.m. in the summer and 3:00 to 4:00 p.m. in the winter. Afternoon DFDs range from 27 to 62 mHz and are on average 16 mHz higher in winter. Evening and night DFDs see the largest shift in negative direction, with peak-to-peak values ranging from 35 to 93 mHz and with summer DFDs averaging 4 mHz higher in magnitude. However, winter DFDs start at 6:00 p.m., compared to summer DFDs starting at 9:00 p.m., and are thus more significant for the daily profile. These DFDs reach their peak magnitude in the evening and decrease consistently until 2:00 a.m. During the full hours that mark the four major directional shifts of DFDs throughout the day, mild DFDs with a magnitude under 25 mHz are observed. These hours include 3:00 a.m., 4:00 a.m., 8:00 a.m., and 2:00 p.m. across both summer and winter. Additional times such as 3:00 p.m., 7:00 p.m., and 8:00 p.m. during summer, and 5:00 p.m. in winter also exhibit minor DFDs.

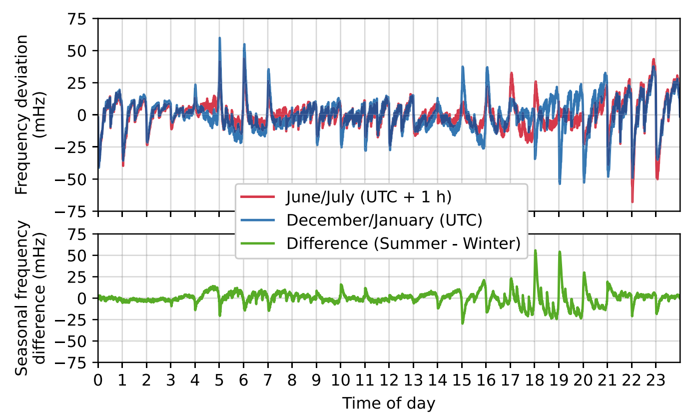

Fig. 3. Frequency deviations in the months of June and July, representing the summer, versus frequency deviations the months of December and January, representing the winter.

Fig. 4 presents daily frequency profiles for both weekdays and weekends, as well as the frequency difference between both profiles. The difference in DFD magnitude between the profiles is mainly observed during morning hours. Significant morning DFDs occur from 4:00 to 7:00 a.m. during weekdays and at 6:00 and 7:00 a.m. during weekends and range from 28 to 74 mHz in magnitude, with 19 mHz higher average peak-to-peak values during weekdays. The significant difference in DFD magnitude between weekdays and weekends is consistent with the known differences in load profiles between these days. The observed variations in DFDs are likely attributable to known differences in load ramps between weekdays and weekends.

The daily pattern of frequency deviations in the power grid is driven by the mismatch between constant power generation and fluctuating electric loads, shifting directions depending on the time of day. These deviations are most pronounced at full hours (DFDs) due to schedule-induced imbalances, with the direction and magnitude dependent on the load gradient. Positive gradients cause overfrequency, while negative gradients result in under-frequency (Weissbach and Welfonder, 2009). Evenings and nights experience increased magnitude DFDs due to fewer active generators and thus fewer rotating masses to compensate for deviations (Gobmaier, 2017). However, solar power ramps can smooth out fluctuations at different times of the day, and rapid

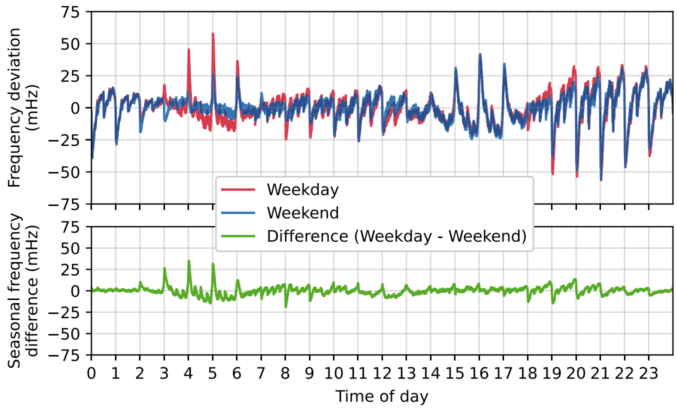

Fig. 4. Frequency deviations on weekdays versus weekends.

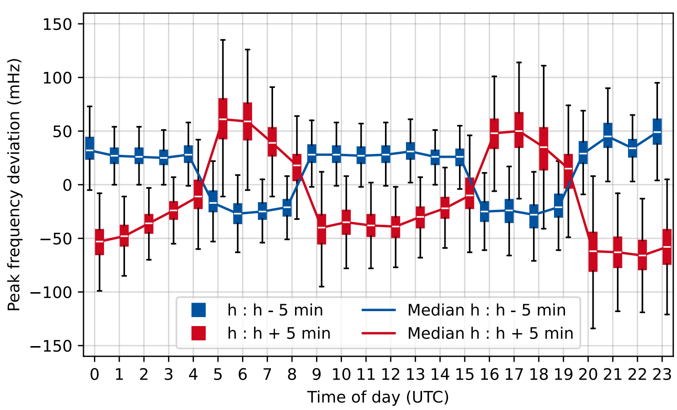

Fig. 5. Peak frequency deviations found 5 min before and after full hours from 2014 to 2023.

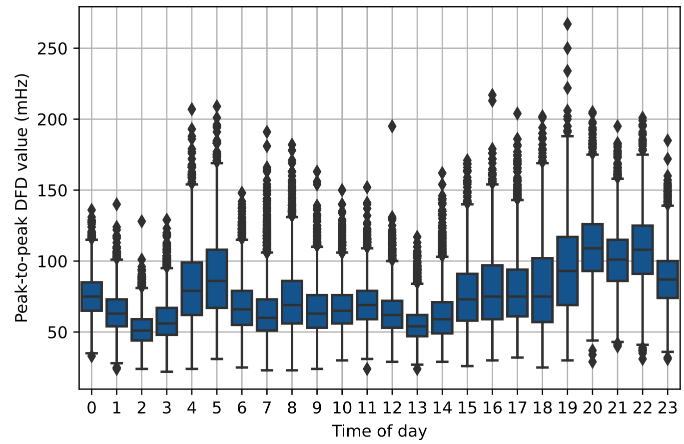

Fig. 6. Peak-to-peak DFD values from 2014 to 2023 sorted by time of day in UTC and UTC + 1 h in daylight savings time.

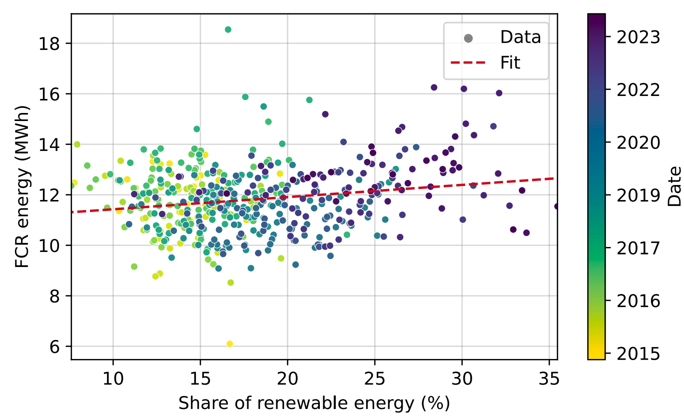

Fig. 7. Correlation between weekly absolute FCR control energy and share of renewable energy production in the ENTSO-E area (2015–2023).

adjustments from sources like hydro power can cause deviations to move opposite to the load curve, highlighting the intricate balance between generation schedules, renewable energy contributions, and grid stability (Kruse et al., 2021a).

Daily frequency profiles are already a good predictor of frequency deviations (Kruse et al., 2021b,a). However, they do not consistently explain the magnitude of DFDs, which is influenced by variable predictors such as load and generation ramps (Kruse et al., 2021a). Fig. 5 shows the distribution of peak frequency deviations occurring withing 5-minute windows before and after full hours based on data from 2014 to 2023. While we can observe that the range of the median values is consistent with the daily frequency profiles obtained by time series decomposition, peak deviations can differ significantly. Systematic high magnitude variations from the median values represent a risk for grid stability, since the overlap of these systematic deviations with non-deterministic faults can lead to a critical situation. This is especially relevant for the negative peak deviations, which are consistently higher than the positive peak deviations and for which control power needs to be fed in. In contrast to positive deviations, extreme negative deviations can cause load curtailment measures.

Fig. 6 shows the distribution of absolute peak-to-peak DFD values. We observe that the DFDs consistently exceed the magnitudes predicted by the daily profiles. Higher DFDs than predicted by the daily profiles are especially concerning, as they consistently exceed the 75 mHz and 100 mHz criteria (ENTSO-E, 2020) causing a misuse of FCR reserves and debilitating the system against faults.

6.3. Historic development of FCR control energy and renewable energy production in continental Europe

In Fig. 7, a scatter plot shows the weekly share of renewable energy production in the ENTSO-E area and the weekly FCR energy calculated for 1 MW of marketed FCR according to the German FCR conditions. Renewable energy production increased in the past years but remains in the region of 10% to 30%. A weak correlation with a coefficient of 0.193 indicates that there is no significant connection between the increased renewable energy production and the use of FCR.

This weak correlation leads to the assumption that a further increase in renewable energy production has no critical impact on the grid stability and energy supply in the ENTSO-E area. This is consistent with the findings from Kruse et al. (2021b), where hourly frequency stability indicators in CE were mainly explained by day-ahead load ramps, reflecting the significant influence of DFDs in contrast to Great Britain (GB), where frequency deviations were largely affected by renewable energy generation. Due to the importance of DFDs for grid frequency stability in CE, it is key to analyze the development of their magnitude and occurrence over recent years.

Rather than the proportion of renewable energy production, the demand of FCR control energy is mainly driven by deterministic deviations. The ramping behavior of generators and the capability to coordinate the ramping, as well as the volume of trades in the day-ahead market and even the volume of new wholesale products could act as predictors for the FCR control energy demands of the future. In the immediate future, historical DFD values and profiles, such as the ones presented in this work, are a good predictor of FCR energy activation.

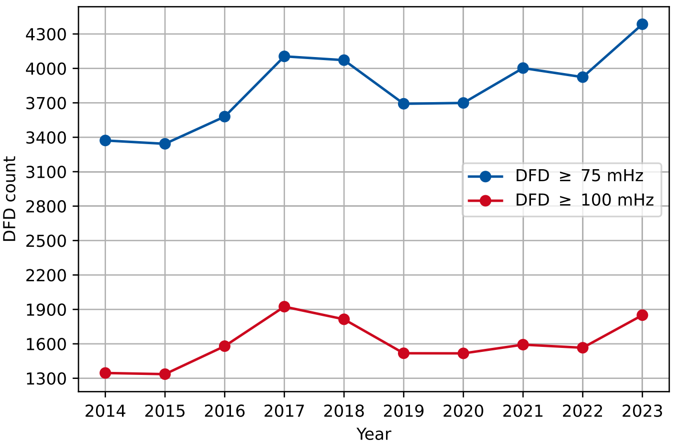

Fig. 8. Yearly occurrence of DFDs with values greater or equal to 75 mHz and 100 mHz from 2014 to 2023.

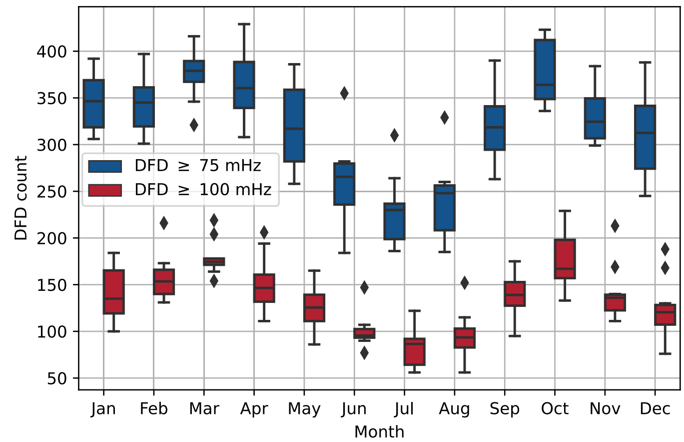

Fig. 9. Monthly occurrences of DFDs with values greater than or equal to 75 mHz and 100 mHz from 2014 to 2023.

6.4. Historic development of DFDs

In the following, we investigate the historical development of DFDs from 2014 to 2023, focusing on those with peak-to-peak values greater than or equal to 75 mHz and 100 mHz due to their significance in the provision of FCR. Fig. 8 shows the development of the occurrence of these DFDs. Notably, 2017 and 2018 saw significant rises in DFDs above both thresholds. In 2017, occurrences of DFDs greater than or equal to 75 mHz and 100 mHz increased by 23% and 44%, respectively, compared to 2015. Although 2018 maintained a high frequency of DFDs at or above both thresholds, there was a slight decrease compared to the previous year. This trend aligns with the findings of the 2020 ENTSO-E report (ENTSO-E, 2020), which described a rise in DFD occurrences. By 2020, the occurrence of DFDs ≥ 75 mHz decreased by 10% relative to 2017, and the occurrence of DFDs ≥ 100 mHz decreased by 21%. Yet, a resurgence was observed by 2023, with DFDs ≥ 75 mHz occurring 19% more frequently than in 2020, surpassing the 2017 peak occurrence by 7%. The number of DFDs ≥ 100 mHz increased by 22% from 2020 but remained 4% below the 2017 peak.

The occurrence of DFDs in CE is mainly explained by day-ahead market transactions at full hours with power ramping at different rates which cause temporary discrepancies between the scheduled and the actual power delivery, thus resulting in frequency deviations. Here, the relatively faster ramping generation units represent an important contributor to frequency deviation (Kruse et al., 2021b,a). The trend of increasing incidence of high magnitude DFDs could be explained by a possible increase in fast-ramping generation units in CE. This trend can result in an intensified impact of DFDs on grid stability and operational efficiency. In addition to the already mentioned misuse of FCR reserves, DFDs cause additional unscheduled power flows resulting in higher loading of transport lines at hour changes throughout the day, using reliability margins designed for system outages (ENTSO-E, 2020). Finally, DFDs cause increased wear and tear of synchronous generators and can be increase the cost of FCR due to additional deterioration of infrastructure (ENTSO-E, 2020).

Fig. 9 displays the monthly occurrences of DFDs greater than or equal to 75 mHz and 100 mHz, based on data from 2014 to 2023. The analysis reveals a significant variation between March and July, with median occurrences of DFDs ≥ 75 mHz of 379 and 230, respectively, indicating a 65% higher occurrence in March. This variation is even more significant for DFDs ≥ 100 mHz, with March presenting a median count of 175 and July a median count of 87, a difference of little over 100%. This pattern highlights seasonal differences, with lower DFD counts (≥ 75 mHz, ≥ 100 mHz) observed during summer months and higher counts in winter months. This trend aligns with the earlier onset of high-magnitude evening DFDs in winter, resulting in their more frequent occurrence during this season. This behavior is consistent across both thresholds of DFDs, with a greater variability observed for DFDs ≥ 75 mHz and more uniform occurrences for DFDs ≥ 100 mHz.

This seasonal variability can be taken into consideration when designing SPA strategies for BESS providing FCR. However, they do not directly affect their strategic planning or operational reliability. BESS are particularly fast at responding to frequency deviations and have high ramping capabilities, thus we do not see any clear effects in terms of system responsiveness. Furthermore, during the process of prequalification, BESS are required to ramp up and down to full power in order to test their responsiveness. These power gradients are necessarily higher than the gradients caused by DFDs, since they correspond to the power delivery corresponding to a 200 mHz deviation. In terms of reserve allocation strategies, DFDs are indeed more significant in the winter than in the summer, however this does not represent any significant degradation for the BESS so that it would be economically advantageous to market it differently at these times. Here, the deciding criterion when marketing a BESS is the current FCR market price, rather than the DFDs.

Our analysis shows that recent years have seen a remarkable increase in high-magnitude DFD occurrences, highlighting the growing challenges in power system stability and the critical role of effective FCR. The surge in DFDs greater than or equal to 75 mHz and 100 mHz has contributed to an overall rise in DFD magnitude. Fig. 10 shows the trend of DFD magnitude development in the last ten years. This trend is the result of the MSTL decomposition of the DFD peak-to-peak values. Our MSTL analysis incorporates daily, weekly, and yearly seasonality components, as well as a trend component that explains DFD magnitude growth throughout the years independent of periodic fluctuations and residual noise.

The analysis reveals an evolution of DFD magnitudes that are explained by the trend component, with an initial increase of 7.2 mHz by 2018 since the beginning of 2014, followed by a reduction of 5.2 mHz by October 2019 compared to 2018. A subsequent increase of 3.7 mHz by the end of 2021 was followed by a minor decrease of 2.2 mHz towards the end of 2022. Furthermore, we observe a consistent rise throughout the year 2023. By the end of 2023, the trend accounted for a 82.6 mHz contribution to DFD magnitude, marking a 10 mHz rise compared to 2014 and a 2.8 mHz increment from 2018. This trend highlights the importance of integrating grid frequency behavior into FCR unit operations, prompted by the recent increase in DFD occurrence and magnitudes. Therefore, we propose exploring DFD-informed BESS operation strategies in the context of SPA algorithms.

BESS will need to be designed and dimensioned to withstand regular surges in power caused by DFDs, luckily this is not such a problem

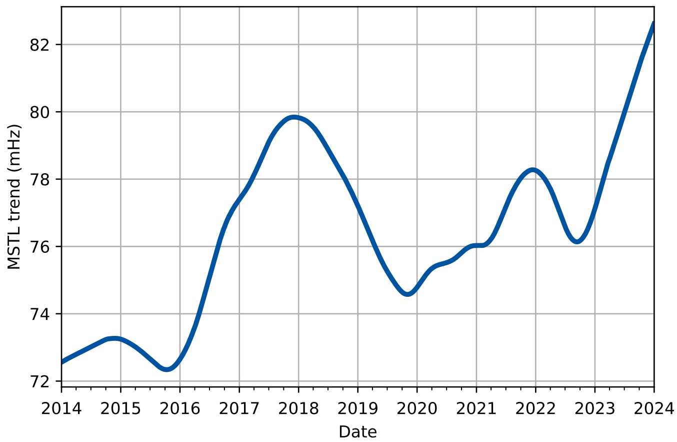

Fig. 10. DFD magnitude development explained by the trend component of an MSTL decomposition from 2014 to 2023.

for BESS but rather for more traditional power plants which are not designed for regular high-magnitude ramping, which leads to increased wear and tear (ENTSO-E, 2020). This fact consolidates the adequacy of BESS for the provision of FCR rather than traditional power plants. Nevertheless this should be considered when deciding which battery chemistry should be used, as some technologies may experience more stress in this operation. In the case of lithium ion technologies, current BESS designs are able to handle DFDs, although in the long term higher power deliveries could cause marginally higher degradation. Capacity and power requirements for BESS providing FCR are specified in the pre-qualification requirements of the TSOs and are by definition adequate to deal with DFDs, since the BESS reserves the FCR power to respond to a 200 mHz frequency deviation at all times while active in the FCR market. It is possible to slightly over-dimension BESS capacity in order to reduce the depth of discharge of DFD related battery cycles. In practice, however, aging of BESS in FCR operation is dominated by calendar aging rather than cyclic aging (Jacqué et al., 2022a,c).

6.5. Comparison with literature results

In the following, we present a brief overview of results from relevant DFD literature as well as a comparison with the results presented in this work. Table 1 shows this overview of five literature sources that contain results that can be compared to our analysis. These focus on the daily frequency profiles that are mainly calculated by average values of the whole year, while others consider only winter months. Other metrics analyzed in our paper such as FCR energy demand profiles, seasonality of DFDs, and general trends in DFD magnitude are not found in the reviewed literature. Kruse et al. (2021b) and Kruse et al. (2021a) do not present any results that can be compared with the ones presented in this work as they focus on the origins of DFDs.

Fig. 11 shows the daily profile calculated as the average of all values from 2014 to 2023, without any seasonal consideration, as well as the difference between this profile and the seasonal summer and winter profiles proposed in this work. For this comparison, we subtracted the seasonal profiles from the average profile. This analysis is done in order to address the method of whole year average used in the literature. We can observe that the average profile is not representative of the whole year, with clear differences when compared to the seasonal profiles calculated with time series decomposition. This discrepancy is most marked when considering the summer daily profile. Here, the evening hours present the highest deviations from the average profile, with the most pronounced negative difference of −49 mHz at around 7:00 p.m. This behavior in the evening hours is characteristic of the winter months and it dominates the average profile, making it unsuitable to

Table 1
Calculation of frequency daily profiles in literature.

Source	Method employed	Main focus of the work
Weissbach and Welfonder (2009)	Ensemble average of winter months	Origins of DFDs and proposed countermeasures
Weißbach et al. (2018)	Ensemble average of winter months	Analysis of effects of mitigating measures to reduce DFDs
ENTSO-E (2020)	Average of January 2019	ENTSO-E report on origins of DFDs and countermeasures
Kruse et al. (2020)	Average	Focus on frequency forecast methods
Rousseau et al. (2023)	Average of 2020	Proposal of forecast-based DFD countermeasures

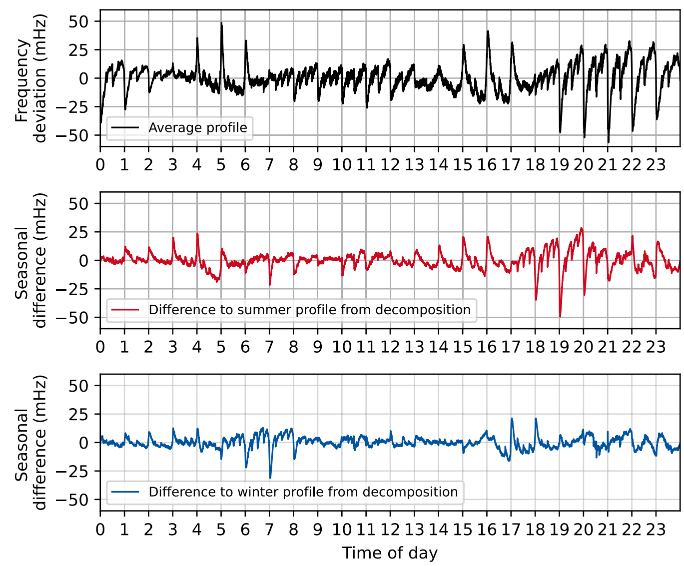

Fig. 11. Daily frequency profile calculated with the average of all values from 2014 to 2023 and the difference between this profile and the seasonal summer and winter profiles presented in this work.

represent the summer months. Positive differences can reach up to around 25 mHz and can be observed in the early morning hours at 3:00 a.m. and 4:00 a.m., in the afternoon at 3:00 p.m. and 4:00 p.m., and in the evening at 20:00 p.m. When considering the difference to the winter profile, we observe that the differences compared to the average profile are less pronounced, reaching −31 mHz at around 7:00 a.m. Positive differences reach 20 mHz at 5:00 p.m. and 6:00 p.m.

Fig. 12 shows a daily frequency winter profile calculated with the average of values of January to March and October to December from 2014 to 2023 and the difference between this profile and the winter profile proposed in this work. This ensemble average winter profile has been calculated in reference to the profile calculated in Weissbach and Welfonder (2009), where these months have been considered. In contrast, the winter profile calculated with time series decomposition uses the months of June and July as the data foundation. When comparing the ensemble average profile with the decomposition profile, we observe few differences, showing that the profile is adequately representative of DFD magnitudes in the winter months. However, a positive difference of 17 mHz can be observed at 5:00 p.m. and a negative difference of −15 mHz at 7:00 a.m. We attribute these differences both to the different selection of months as well as to the different method employed to calculate the profile.

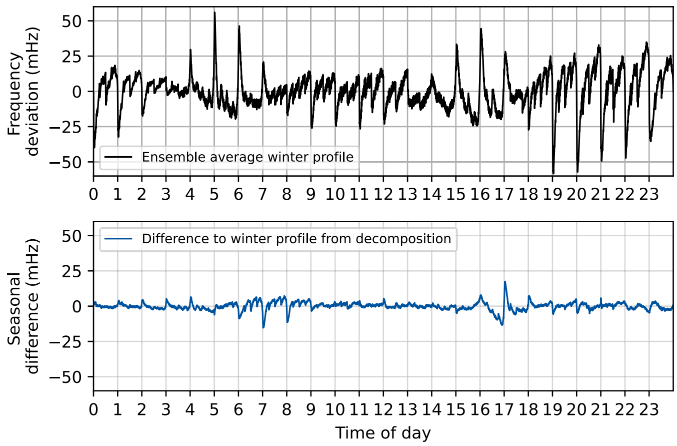

Fig. 12. Daily frequency winter profile calculated with the average of values of January to March and October to December from 2014 to 2023 and the difference between this profile and the winter profile presented in this work.

6.6. Recommendations for the controller design of battery systems providing FCR

In this section, we utilize the insights gained from our analysis of frequency and intraday price data in order to propose a DFD-informed rule for triggering SPA in the context of BESS operation in the FCR market. For this, we calculate the control energy corresponding to 1 MW of FCR reserved power for ten minutes before and after full hours using frequency data from 2014 to 2023, as shown in Fig. 13. Here, the blue boxes represent the control energy ten minutes before the full hour and the red boxes represent the control energy ten minutes after the full hour. We observe that the change in direction of the control energy around the full hour is consistent with the direction of DFDs identified in the frequency daily profile. Furthermore, we identify the evening hours as period of the day with the most pronounced control energy demand before and after the full hour. This behavior is consistent with the known increase in DFD magnitude during the evening hours, as shown in the daily frequency profiles. The periods of the day ranging from 8:00 a.m. to 1:15 p.m., and from 7:00 p.m. to 2:15 a.m. are marked by positive control energy demands, indicating the injection of power into the grid. These periods are especially relevant for the SPA strategy of the BESS, since these are the periods that will be mostly responsible for discharging the system.

Most SPA actions are triggered in order to charge the BESS and maintain the SOE range needed for FCR operation. That means energy is bought in the 15-minute intraday market. Discharging operations are occasionally necessary but less frequent than charging operations. For this reason, we identify the periods of the day where the intraday price is lower based on the weighted average intraday prices from 2014 to 2023 (EPEX SPOT, 2024; Fraunhofer ISE, 2024b). Fig. 14 shows the median of the weighted average intraday price throughout the day. The red area represents 50% of the data and the blue area represents 75% of the data. We can observe peaks in the daily price profile around 8:00 a.m. and 7:00 p.m. as well as price lows around 3 a.m. and 2 p.m. We identify periods of the day when prices are typically low and thus are favorable for the activation of SPA to charge the BESS. These periods range from 0:45 a.m. to 6:15 a.m. and from 11:45 a.m. to 3:15 p.m. We observe that these periods overlap with the periods of positive control energy demand, however there is enough leeway for the activation of SPA at different times.

The intraday price within the hour decreases or rises opposite to the direction of DFDs. The hourly product stays constant while the load decreases, which causes an overproduction of power. This has an effect both on grid frequency, causing DFDs, and on the intraday price profile.

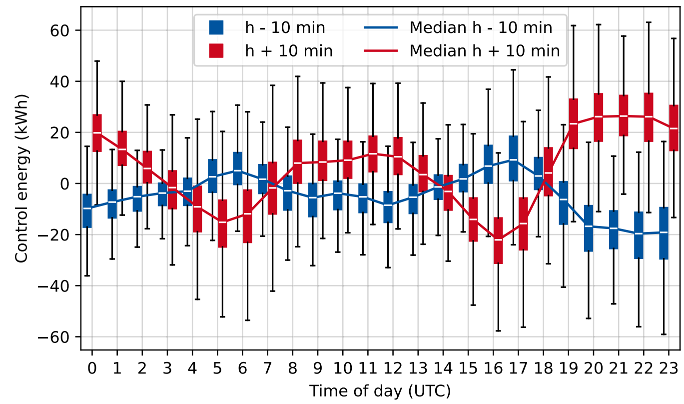

Fig. 13. FCR control energy corresponding to 1 MW of FCR reserved power for ten minutes before and after full hours from 2014 to 2023.

When there is an over-generation relative to the load profile, prices decrease and when the load is higher than the generation of the hourly products, prices increase. Similarly to DFDs, these price changes occur around full hours. For this reason, SPA should be triggered immediately before or after the full hour, depending on the time of day. Within the low price periods defined, it should be distinguished between SPA triggering before or after the full hour depending on the time of the changes of direction of DFDs, which occur at 3:00 a.m. and 2:00 p.m.

Fig. 15 shows the proposed algorithm for the activation of SPA in the intraday market. In both low-price phases between 0:45 and 6:15, and again from 11:45 to 15:15, energy for SPA charging is bought as soon as the SOE is low enough. If the SPA is triggered before 3:00 in the first phase or before 14:00 in the second, energy is purchased before the full hour, if the SPA is triggered after these times, energy is bought after the full hour. In this way, it is possible to utilize typically low intraday prices to recharge the BESS. In both cases, the control energy demand is negative, which means that triggering the SPA in charging direction is typically grid-supportive as well as cost efficient.

The proposed algorithm can be described mathematically as follows. Let:

- $SOE(t)$ represent the state of energy at time t.
- $SOE_{threshold}$ be the threshold value of SOE.
- t represent the current time.
- $t_{phase\ 1} = 03:00$ a.m..
- $t_{phase\ 2} = 14:00$ p.m..

Algorithm 1 Setpoint adjustment algorithm

```
1:  Start
2:  if SOE(t) < SOE_threshold then
3:      if t < t_phase1 or t < t_phase2 then
4:          Buy energy before full hour
5:      else
6:          Buy energy after full hour
7:      end if
8:  else
9:      Do nothing
10: end if
11: End
```

The proposed rule-based approach for storage management (SPA) of BESS providing FCR offers a clear comparative advantage over traditional SOE-based SPA strategies discussed in this work. It does so by incorporating insights from historical intraday price profiles as well as the DFD-related FCR control energy profiles presented. By aligning energy purchasing with periods of lower prices, the approach

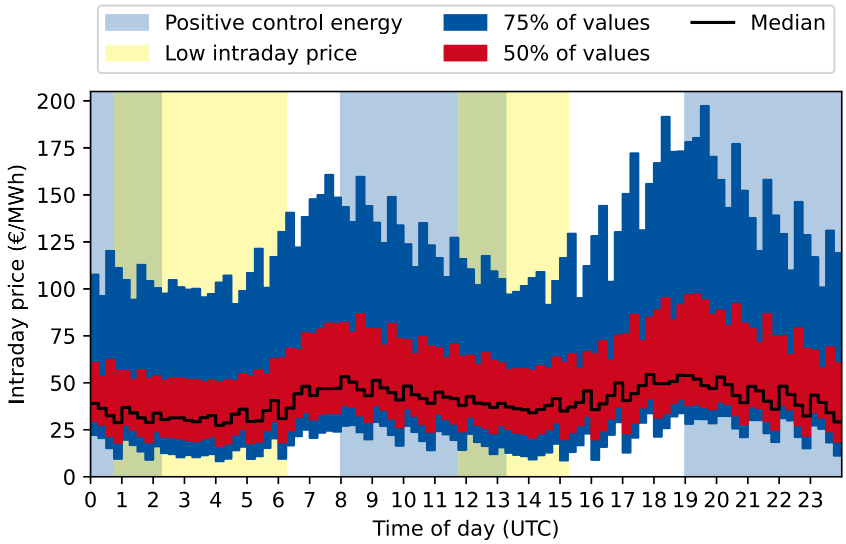

Fig. 14. Weighted average 15-minute intraday price profile from 2014 to 2023 in UTC time.

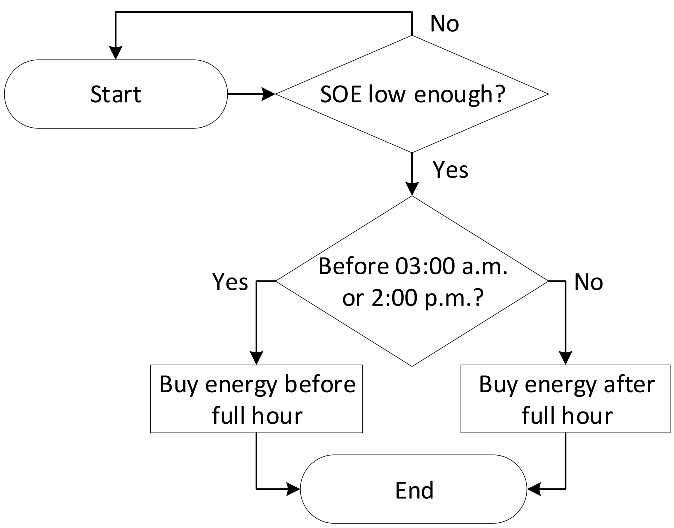

Fig. 15. Proposed algorithm for triggering SPA in the intraday market.

reduces costs while promoting grid-supportive behavior during SPA charging. This grid supporting behavior could help mitigate the effects of DFDs, at least marginally. Unlike existing FCR strategies, which react solely to SOE, this method proactively adjusts to market dynamics and DFD patterns, enabling more efficient use of the BESS under conditions of increasing price volatility. This adaptability and integration of DFD trends into decision-making enhance both the economic and operational performance of the system.

7. Conclusion and outlook

We have analyzed ten years of grid frequency data from the CE region to identify daily frequency profiles and DFDs. We observed seasonal differences in DFDs between summer and winter, as well as between weekdays and weekends. In addition, the largest deviations occur during full hours, due to power plant ramps, load curves, and trading activities. This is significant for FCR activation, which peaks around the hour change. Control energy is then activated accordingly, suggesting that recurring patterns could inform strategies for SPA in the context of storage management or for the multi-market operation of BESS. We found that the increased renewable energy production in the ENTSO-E area has no significant impact on the FCR control energy demand, showing a weak correlation coefficient of 0.193 between FCR control energy demand and the share of renewable energy production between 2015 and 2023. Although we have found that the seasonality patterns in DFDs have remained mostly unchanged, the historic development of DFDs showed a marked increase in high-magnitude DFD occurrences, with a rise in DFD magnitudes between 2014 and 2023. DFDs with magnitudes over 75 mHz increased by 30% while DFDs with magnitudes over 100 mHz increased by 37% from 2014 to 2023. Furthermore, we observed a clear seasonal pattern in the occurrence of high-magnitude DFDs, with DFDs above 75 mHz and 100 mHz occurring 65% and 100% more frequently in March than in July, respectively. Our MSTL analysis of DFD data showed an increase of 10 mHz in DFD magnitude explained by the trend component from 2014 to 2023. This trend highlights the growing challenges in power system stability as well as the potential for integrating this knowledge into the operation of FCR units, especially those with limited storage such as BESS. We found that changes in the direction of control energy around full hours align with DFD patterns, with the most significant demand for control energy occurring in the evening hours. Our analysis shows that intraday prices within the hour decrease or rise opposite to the direction of DFDs, presenting significant changes around full hours. Based on these findings, we propose the investigation of a rule-based approach for the activation of SPA in the intraday market for BESS providing FCR that leverages insights from DFD-dominated daily profiles and intraday market data to improve storage efficiency and reduce costs.

The use of time series decomposition methods improve the understanding of FCR energy demand profiles that represent an opportunity to implement more efficient and profitable operation strategies for BESS active in this market. In contrast to more conventional techniques, this method can capture the peaks of power values as well as the typical FCR energy demand more accurately and representatively compared to the calculation of mean energies. Furthermore, the consideration of weekly as well as seasonal patterns offers especially useful insights for BESS operation. To the best of our knowledge, insights into frequency behavior have not been used to develop operational strategies for BESS

The increase of high magnitude DFDs is indeed a challenge for the stability of the power system. If a high magnitude DFD overlaps with a large non-deterministic error, such as the outage of a large power plant, the necessary FCR power to mitigate the error may exceed the total marketed capacity. FCR power claimed by DFDs is not available for the mitigation of other errors, effectively making the grid vulnerable at these moments. Furthermore, the provision of FCR with BESS is challenged by the increase in intraday prices, driving up SPA costs. A more effective SPA strategy based on the proposed algorithm can offer a competitive advantage for the operation of BESS in the currently saturated FCR market.

Building on the findings presented, future work will focus on the simulative validation of the proposed SPA algorithm by means of an BESS digital twin, as well as its implementation within the real-world operation of an BESS active in the FCR market, such as the M5BAT hybrid battery system. This will lay the groundwork for the development of a robust and adaptable storage management strategy informed by DFD behaviors and intraday market data. Furthermore, parameter variations such as energy-to-power ratios of the BESS and different power requests for SPA, as well as the incorporation of weather dependencies can be investigated. Finally, the use of insights from the analysis of frequency data presents potential not only for storage management in the context of FCR but also in the context of multi-market operation strategies for BESS, where knowledge of FCR demand activation patterns can be leveraged to optimize the scheduling of energy transactions across different markets.

CRediT authorship contribution statement

Mauricio Celi Cortés: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lucas Koltermann:** Writing – review & editing, Validation, Project administration, Methodology, Data curation, Conceptualization. **Thanh Daniel Dang:** Writing – review & editing, Visualization, Validation, Software, Methodology, Data curation, Conceptualization. **Jan Figgener:** Writing – review & editing, Conceptualization. **Sebastian Zurmühlen:** Writing – review & editing, Project administration. **Dirk Uwe Sauer:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the German Federal Ministry of Economic Affairs and Climate Action (BMWK) and by the project partner Uniper SE as part of the public projects M5BAT (Funding Code: 03ESP265F) and EMMUseBat (Funding Code: 03EI4034).

Data availability

The authors do not have permission to share data.

References

50Hertz, Amprion, TenneT TSO, TransnetBW, 2022. Prequalification Process for Balancing Service Providers (FCR, aFRR, mFRR) in Germany ("PQ conditions"). [Online]. Available: https://www.regelleistung.net.

50Hertz, Amprion, TenneT TSO, TransnetBW, 2023. Präqualifizierte Leistung in Deutschland. [Online]. Available: https://www.regelleistung.net/xspproxy/api/staticfiles/regelleistung/pq-leistungindeutschland(stand01.01.2023).pdf.

50Hertz, Amprion, TenneT TSO, TransnetBW, 2024a. FCR capacity market R1. [Online]. Available: https://www.regelleistung.net/.

50Hertz, Amprion, TenneT TSO, TransnetBW, 2024b. Präqualifizierte Leistungen in Deutschland. [Online]. Available: https://www.regelleistung.net/xspproxy/api/staticfiles/regelleistung/startseite/pq-leistung-in%20deutschland.pdf.

Badeda, J., Meyer, J., Sauer, D.U., 2017. Modeling the influence of installed battery energy storage systems on the German frequency containment reserve market. In: NEIS 2017; Conference on Sustainable Energy Supply and Energy Storage Systems. pp. 1–7.

Bandara, K., Hyndman, R.J., Bergmeir, C., 2021. MSTL: A seasonal-trend decomposition algorithm for time series with multiple seasonal patterns.

Dr. Gobmaier GmbH, 2023. Aufgezeichneten und validierten Messdaten der Netzfrequenz.

Dr. Gobmaier GmbH, 2024. Aktuelle informationen. [Online]. Available: https://www.netzfrequenzmessung.de/aktuelles.htm.

Elia, 2020. Report on deterministic frequency deviations: Lowering the contribution of the Belgian control block. [Online]. Available: https://www.elia.be/.

Engelhardt, J., Thingvad, A., Zepter, J.M., Gabderakhmanova, T., Marinelli, M., 2022. Energy recovery strategies for batteries providing frequency containment reserve in the nordic power system. Sustain. Energy Grids Netw. 32, 100947, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352467722001928.

Engels, J., Claessens, B., Deconinck, G., 2019. Techno-economic analysis and optimal control of battery storage for frequency control services, applied to the German market. Appl. Energy 242, 1036–1049, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261919305379.

ENTSO-E, 2018. Frequency deviations - Continental European TSOs have restored the situation to normal. [Online]. Available: https://www.entsoe.eu/news/.

ENTSO-E, 2020. Report on deterministic frequency deviations. [Online]. Available: https://eepublicdownloads.entsoe.eu/clean-documents/Publications/SOC/Report_Deterministic_Frequency_Deviations_final_version.pdf.

ENTSO-E, 2024. Actual generation per production type. [Online]. Available: https://transparency.entsoe.eu/.

EPEX SPOT, 2024. Market data.

Eurelectric, ENTSO-E, 2011. Deterministic frequency deviations - root causes and proposals for potential solutions. [Online]. Available: https://eepublicdownloads.entsoe.eu/clean-documents/pre2015/publications/entsoe/120222_Deterministic_Frequency_Deviations_joint_ENTSOE_Eurelectric_Report_Final_.pdf.

Eurostat, 2024. Production of electricity and derived heat by type of fuel. [Online]. Available: https://ec.europa.eu/eurostat/en/.

Figgener, J., Hecht, C., Bors, J., Spreuer, K., Kairies, K.-P., Stenzel, P., Sauer, D.U., 2023. The development of battery storage systems in Germany: A market review (status 2023). [Online]. Available: https://arxiv.org/abs/2203.06762.

Figgener, J., Hecht, C., Sauer, D.U., 2024. Battery charts. [Online]. Available: https://www.battery-charts.de/.

Fleer, J., Zurmühlen, S., Meyer, J., Badeda, J., Stenzel, P., Hake, J.-F., Sauer, D.U., 2018. Techno-economic evaluation of battery energy storage systems on the primary control reserve market under consideration of price trends and bidding strategies. J. Energy Storage 17, 345–356, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X17304218.

Fraunhofer ISE, 2024a. Annual renewable share of public net electricity generation and load in the European Union. [Online]. Available: https://energy-charts.info/charts/renewable_share/chart.htm?l=en&c=EU&interval=year&legendItems=01&share=ren_share.

Fraunhofer ISE, 2024b. Electricity production and spot prices in Germany. [Online]. Available: https://energy-charts.info/.

Gobmaier, T., 2017. Netzfrequenz als Indikator für die Stabilität des Verbundnetzes. In: 10. Internationale Energiewirtschaftstagung an der TU Wien. [Online]. Available: https://www.netzfrequenzmessung.de/IEWT_Netzfrequenz_Stabilitaet_Paper.pdf.

Hirth, L., Ziegenhagen, I., 2015. Balancing power and variable renewables: Three links. Renew. Sustain. Energy Rev. 50, 1035–1051, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032115004530.

Jacqué, K., Koltermann, L., Figgener, J., Zurmühlen, S., Sauer, D.U., 2022a. The influence of frequency containment reserve on the cycles of a hybrid stationary large-scale storage system. J. Energy Storage 52, 105040, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22010428.

Jacqué, K., Koltermann, L., Figgener, J., Zurmühlen, S., Sauer, D.U., 2022b. The influence of frequency containment reserve on the efficiency of a hybrid stationary large-scale storage system. J. Energy Storage 52, 104961, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22009677.

Jacqué, K., Koltermann, L., Figgener, J., Zurmühlen, S., Sauer, D.U., 2022c. The influence of frequency containment reserve on the operational data and the state of health of the hybrid stationary large-scale storage system. Energies 15 (4), [Online]. Available: https://www.mdpi.com/1996-1073/15/4/1342.

Koch, C., Hirth, L., 2019. Short-term electricity trading for system balancing: An empirical analysis of the role of intraday trading in balancing Germany's electricity system. Renew. Sustain. Energy Rev. 113, 109275, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032119304836.

Koltermann, L., Drenker, K.K., Celi Cortés, M.E., Jacqué, K., Figgener, J., Zurmühlen, S., Sauer, D.U., 2023. Potential analysis of current battery storage systems for providing fast grid services like synthetic inertia – Case study on a 6 MW system. J. Energy Storage 57, 106190, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X2202179X.

Koltermann, L., Jacqué, K., Figgener, J., Zurmühlen, S., Sauer, D.U., 2022a. Operational validation of a power distribution algorithm for a modular megawatt battery storage system. Batter. Supercaps 6 (3), e202200414, [Online]. Available: https://chemistry-europe.onlinelibrary.wiley.com/doi/abs/10.1002/batt.202200414.

Koltermann, L., Jacqué, K., Figgener, J., Zurmühlen, S., Uwe Sauer, D., 2022b. Balancing group deviation & balancing energy costs due to the provision of frequency containment reserve with a battery storage system in Germany. Int. J. Electr. Power Energy Syst. 142, 108327, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061522003477.

Kruse, J., Schäfer, B., Witthaut, D., 2020. Predictability of power grid frequency. IEEE Access 8, 149435–149446.

Kruse, J., Schäfer, B., Witthaut, D., 2021a. Exploring deterministic frequency deviations with explainable AI. In: 2021 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids. SmartGridComm, pp. 133–139.

Kruse, J., Schäfer, B., Witthaut, D., 2021b. Revealing drivers and risks for power grid frequency stability with explainable AI. Patterns 2 (11), 100365, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666389921002270.

Lew, D., Bartlett, D., Groom, A., Jorgensen, P., O'Sullivan, J., Quint, R., Rew, B., Rockwell, B., Sharma, S., 2020. Getting to 100% renewables: operating experiences with very high penetrations of variable energy resources. IET Renew. Power Gener. 14 (19), 3899–3907, [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-rpg.2020.0573.

Münderlein, J., Steinhoff, M., Zurmühlen, S., Sauer, D.U., 2019. Analysis and evaluation of operations strategies based on a large scale 5 MW and 5 MWh battery storage system. J. Energy Storage 24, 100778, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X18307679.

Regelleistung Online, 2020. Batteriespeicher dominieren den PRL-Markt. [Online]. Available: https://www.regelleistung-online.de/batteriespeicher-dominieren-den-prl-markt/.

Regelleistung Online, 2021. Update 2020: Weiteres Wachstum der Batteriespeicher im PRL Markt. [Online]. Available: https://www.regelleistung-online.de/update-2020-weiteres-wachstum-der-batteriespeicher-im-prl-markt/.

Rousseau, J., Vorwerk, J., Avramiotis, I., Welti, C., Hug, G., 2023. Employing imbalance forecasts to proactively counteract deterministic frequency deviations. In: 2023 IEEE Belgrade PowerTech. pp. 1–6.

Schäfer, B., Beck, C., Aihara, K., Witthaut, D., Timme, M., 2018a. Non-Gaussian power grid frequency fluctuations characterized by Lévy-stable laws and superstatistics. Nat. Energy 3 (2), 119–126, [Online]. Available: http://dx.doi.org/10.1038/s41560-017-0058-z.

Schäfer, B., Timme, M., Witthaut, D., 2018b. Isolating the impact of trading on grid frequency fluctuations. In: 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe. ISGT-Europe, pp. 1–5.

Schlachter, U., Worschech, A., Diekmann, T., Hanke, B., von Maydell, K., 2020. Optimised capacity and operating strategy for providing frequency containment reserve with batteries and power-to-heat. J. Energy Storage 32, 101964, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X20317990.

Schweer, D., Maaz, A., Moser, A., 2016. Optimization of frequency containment reserve provision in M5BAT hybrid battery storage. In: 2016 13th International Conference on the European Energy Market. EEM, pp. 1–5.

Seabold, S., Perktold, J., 2010. Statsmodels: Econometric and statistical modeling with python. In: 9th Python in Science Conference. [Online]. Available: http://conference.scipy.org.s3-website-us-east-1.amazonaws.com/proceedings/scipy2010/seabold.html.

Thien, T., Axelsen, H., Merten, M., Sauer, D.U., 2022. Energy management of stationary hybrid battery energy storage systems using the example of a real-world 5 MW hybrid battery storage project in Germany. J. Energy Storage 51, 104257, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22002857.

Thien, T., Schweer, D., vom Stein, D., Moser, A., Sauer, D.U., 2017. Real-world operating strategy and sensitivity analysis of frequency containment reserve provision with battery energy storage systems in the German market. J. Energy Storage 13, 143–163, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X17300282.

Weißbach, T., Remppis, S., Lens, H., 2018. Impact of current market developments in Europe on deterministic grid frequency deviations and frequency restauration reserve demand. In: 2018 15th International Conference on the European Energy Market. EEM, pp. 1–6.

Weissbach, T., Welfonder, E., 2009. High frequency deviations within the European power system: Origins and proposals for improvement. In: 2009 IEEE/PES Power Systems Conference and Exposition. pp. 1–6.