

Delft University of Technology

Framework to Evaluate Power Portfolio Dispatch Considering Balancing Market Participation

Vas-Corrales, Alejandro; Nguyen, Phuong; Vergara, Pedro P.; Schoot, Wouter; Soder, Lennart

DOI 10.1109/PowerTech46648.2021.9494917

Publication date 2021 Document Version Accepted author manuscript

Published in 2021 IEEE Madrid PowerTech, PowerTech 2021 - Conference Proceedings

Citation (APA)

Vas-Corrales, A., Nguyen, P., Vergara, P. P., Schoot, W., & Soder, L. (2021). Framework to Evaluate Power Portfolio Dispatch Considering Balancing Market Participation. In *2021 IEEE Madrid PowerTech*, *PowerTech 2021 - Conference Proceedings* Article 9494917 (2021 IEEE Madrid PowerTech, PowerTech 2021 - Conference Proceedings). IEEE. https://doi.org/10.1109/PowerTech46648.2021.9494917

Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

Framework to Evaluate Power Portfolio Dispatch Considering Balancing Market Participation

Alejandro Vas-Corrales¹, Phuong Nguyen¹, Pedro P. Vergara², Wouter Schoot³, Lennart Söder⁴

¹Electrical Energy Systems Group, Eindhoven University of Technology (TU/e), Netherlands

²Intelligent Electrical Power Grids, Delft University of Technology, Netherlands

³DNV-GL, Arnhem, Netherlands

⁴KTH Royal Institute of Technology, Stockholm, Sweden Emails: a.vas.corrales@student.tue.nl, p.nguyen.hong@tue.nl, p.p.vergarabarrios@tudelft.nl, Wouter.Schoot@dnvgl.com, lsod@kth.se

Abstract—The power grid is rapidly experiencing a transformation driven by renewable and climate targets which pose a huge challenge to maintain the system stability and reliability, thus balancing services become more crucial now than ever. To provide balancing services in a cost-efficient way, it is necessary to develop predictive models which can optimize power portfolio in an online manner. This paper presents the development of an Online Predictive Dispatch Optimizer and its connection with a grid model that simulates power and frequency control within interconnected power systems. The performance of the dispatch optimizer and its connection with the grid model is tested by simulating several cases where the adequacy of the model is confirmed, especially regarding its ability to manage energy imbalance in real-time. The outcomes and flexibility of this framework can be used to quantitatively evaluate the operation of power portfolio owners in the power grid.

Index Terms—Power portfolio management, predictive dispatch optimization, power balance, balancing markets, receding horizon control.

I. INTRODUCTION

The power system has been evolving recently towards a more sustainable system by increasing penetration levels of Variable Renewable Energy Sources (VRES) [1]. Although their benefits are well known, this so-called energy transition also poses a great challenge to System Operators (SOs) [2], who are the responsible entities to safeguard grid stability and reliability. The variability of VRES and an increased level of electrification throughout the grid will require the provision of additional power flexibility as balancing supply and demand is becoming more complex and uncertain.

Currently, the balancing market known well within the European context considers different balancing products with specific requirements to offer primary, secondary and tertiary frequency control, i.e. Frequency Containment Reserves (FCR), automatic Frequency Restoration Reserves (aFRR) and manual Frequency Restoration Reserves (mFRR), respectively. The former used to stabilize a frequency deviation whereas aFRR and mFRR are used to restore its nominal value. To provide balancing services in a cost-efficient way while optimizing power generation in different power markets, power portfolio control optimization is key. To maximize their profits through optimal dispatch and control, including the provision of ancillary services to the SO, the service providers need more advanced simulation tools and quantifiable models for their generation portfolios.

Previously, many authors have focused on the development of tools and models addressing that need. In [3], a mixedinteger linear programming model for dynamic ramping of generation units is used, improving the allocation of operating reserves. Gu et. al. in [4] formulated an online optimal dispatch scheduler for microgrids by means of rolling optimization, which is beneficial for managing portfolio requirements in real-time. The authors in [5] propose a flexible ramping capacity model to embed in the unit commitment (UC) and economic dispatch (ED) processes, showing that it satisfies system reliability economically. Apart from academic research, there are commercial tools such as PLEXOS to provide optimal power schedules and balance market reservation while PSS/E or PowerFactory can be used to check the generation adequacy. However, there is a lack of having an integrated tool that can anticipate changes in generation portfolios while solving real-time deviations.

In this research, we develop a framework that simulates the real-time dispatch of a power portfolio within an interconnected power grid focusing on the development of an Online¹ Predictive Dispatch Optimizer which calculates the optimal power and reserve minute setpoints for every power plant within the specific portfolio. A basic model of a predictive real-time dispatch can be found in [6]. The optimization considers future energy requirements, operational constraints, and real-time information by its connection with a grid model, such as KERMIT [7]. Figure 1 shows a high-level diagram of the framework, illustrating its relevant modules and the connection with the dispatch optimizer. The connection allows the optimization of a controllable generation portfolio by simultaneously accounting for the dynamics of the power plants, the power system, and the balancing services activation using the information from the system. Therefore, the main contributions of the dispatch optimizer proposed in this work are:

· Using a receding horizon control which can predict future

¹Online reflects that the optimization problem has incomplete knowledge of the future and it updates its optimal solution considering real-time information.



Figure 1. High-level diagram of the framework.

energy requirements and recalculate power trajectories while considering the real-time information thanks to the grid model connection;

• Taking into account dynamic ramp rate limits and the requirements of balancing products, specifically for aFFR² in terms of power and ramp rates reservation.

II. GENERALIZED GRID MODEL

A simplified model is used in this paper that simulates realtime system operations, frequency control, and the dynamics of power generation in the time domain of 1 second to 1 day for interconnected areas focusing only on active power, i.e. using DC power flow approximations [8]. The relevant modules are described in the following sections.

A. Inter-area Power Balance

The power balance measures the power deviation, ΔP_i^{dev} [MW], in each cluster *i* by considering production, consumption, and transmission, as shown in (1). A cluster is defined as a grouping of each individual generator and/or load within an interconnected area, and therefore, it considers the total net power (generation/consumption) and the average frequency and load angle within the area.

$$\Delta P_i^{\text{dev}} = P_i^{\text{gen}} - P_i^{\text{load}^*} + \sum_{j \in \mathcal{J}} P_{ij}^{\text{ACLines}} + \sum_{j \in \mathcal{J}} P_{ij}^{\text{HVDCLines}},$$
(1)

where P_i^{gen} is the actual produced power in cluster *i*, which is the end product of the simulation (7); $P_i^{\text{load}^*}$ is the load considering frequency dependency (3) and P_{ij}^{ACLines} and $P_{ij}^{\text{HVDCLines}}$ are the (fixed) power exchange between cluster *i* and every connected cluster *j* for AC and HVDC lines respectively. Notice in (1) that the transmission power losses are neglected. The frequency deviation, Δf_i [Hz], can also be derived as:

$$\Delta f_i = \int \Delta P_i^{\text{dev}} \cdot G_i \, \mathrm{d}t,\tag{2}$$

where G_i is the system gain [Hz/MW].

The frequency deviation is used outside the power balance module to compute FCR and aFRR signals but it is also used within the power balance module to obtain $P_i^{\text{load}^*}$ as:

$$P_i^{\text{load}^*} = P_i^{\text{load}} + \Delta P_i^{\text{load}} = P^{\text{load}}(1 + \Delta f \cdot D), \qquad (3)$$

where ΔP_i^{load} is the load variation in response to a frequency deviation and D is the percentage of self-regulated load per frequency deviation [%/Hz]; and $P_{ij}^{ACLines}$ following the DC load flow approximation [9]:

$$P_{ij}^{\text{ACLines}} = \frac{1}{X_{ij}} \sin\left(\delta_i - \delta_j\right),\tag{4}$$

$$\delta_i = \int 2\pi \Delta f_i dt, \tag{5}$$

where X_{ij} is the reactance of the AC transmission line between cluster *i* and *j* and δ_i is the load angle [rad].

 P_i^{load} , $P_{ij}^{\text{HVDCLines}}$, G_i , D and X_{ij} must be obtained from the real data or tuned in order to mimic realistic behaviours.

B. Automatic Generation Control

In order for the SO to automatically provide an aFRR control signal to the power plants, an ACG controller is used, which minimizes the Area Control Error (ACE), defined as [10] as:

$$ACE = \left(\sum_{j \in \mathcal{J}} P_{ij}^{ACLines} - P_S^{ACLines}\right) - B\Delta f - E_{ME}, \quad (6)$$

where P_{ij}^{ACLines} and P_S^{ACLines} are, respectively, the actual and scheduled AC power exchange [MW] within the control area, B is the frequency bias [MW/Hz], an approximation of the frequency response regarding the power used to stabilize frequency, Δf is the frequency deviation [Hz] which needs to be offset for time error corrections and E_{ME} is a correction factor [MW] for meter measurement errors.

The ACE raw signal needs to be filtered and processed to be finally distributed amongst every generator providing aFRR.

C. Power Plant Dynamic

The actual response for every power plant is simulated, considering the individual response to every signal as follows:

$$P_i^{\text{gen}} = \sum_{g \in \mathcal{G}_i} \left(P_g^{\text{disp}} + P_g^{\text{FCR}} + P_g^{\text{aFRR}} \right) \tag{7}$$

where P_g^{disp} , P_g^{FCR} , and P_g^{aFRR} are, respectively, the actual power respone to the dispatch setpoints, FCR signal and aFRR signal for every generator g within the cluster \mathcal{G}_i .

 $^{^{2}}$ FCR and mFRR are not considered in the optimization as they are activated at the unit level (Dutch case), therefore their allocation cannot be optimized within the dispatch.

1) Dispatch setpoint response: The dispatch setpoint is the actual power that needs to be followed to avoid energy imbalances. Its response is modelled by applying a first-order model where the time constant, θ_g , is based on the type of generator:

$$\frac{\Delta P_g^{\text{disp}}(s)}{\Delta P_g^{\text{set}}(s)} = \frac{1}{\theta_g s + 1} \tag{8}$$

A noise, also filtered by a first-order model is then added to the signal, modeling the disturbances of the system. The noise mimics the real behavior of a power plant governor. Finally, the actual production is limited by the production and ramp rate limits, the latter defined as a function of the output power (see section III-A).

2) FCR response: The power plant response to the FCR signal is simulated based on grid code requirements as a first order model multiplied by the droop (x) [%] and deadband settings associated to each type of power plant and its capacity:

$$\frac{\Delta P_g^{\text{FCR}}}{P_q^{\text{nom}}} = \frac{100}{x} \frac{\Delta f}{f_{\text{nom}}} \tag{9}$$

3) aFRR response: The power plant response to the aFRR activation signal, i.e. a frequency change, is simulated by providing the maximum reserved ramp rate for aFRR including a time delay, following minimum aFRR requirements in the Netherlands.

III. ONLINE PREDICTIVE DISPATCH OPTIMIZER

The dispatch optimizer is built to simulate the power dispatch and aFRR reserves allocation of a power portfolio within a required period of time, calculating the optimal setpoints for every generator on a configurable time step (e.g. minute basis). The required input parameters of the model are:

- Energy program [MWh]: Committed energy to be delivered by every unit in every Imbalance Settlement Period (ISP), which is the time unit for which the imbalance of every Balance Responsible Party (BRP) is calculated³.
- aFRR power reserves [MW]⁴: Committed power reserves to be delivered in case aFRR activation is required.
- Imbalance Cost [€/MWh]: Cost of imbalances to be used in the objective function.
- Dispatch Horizon (*DH*): Number of ISPs to be considered in the dispatch optimization.
- Power Plant Characteristics: The definition includes operational power limits [MW], marginal cost [€/MWh] and ramp rate limits [MW/min] the latter two defined as step power blocks to linearize the problem.
- The specific optimization parameters are introduced within the mathematical formulation in Section III-C.

³ISP is considered to be 15 minutes in this research as it is the case in the Netherlands and defined by European Regulation to be harmonized across all European energy markets [11].

⁴Only allocation of aFRR reserves is considered as it is the only product that can be optimized on portfolio level. This research assumes that FCR and mFRR reservation is already included in the definition of the operational power limits, ensuring provision of FCR or mFRR power if required.

A. Receding Horizon Control

A set of optimization time steps \mathcal{N}_k is considered in every optimization k, starting at time step n_k and reduce its size in a cyclic way until the optimization reaches a new ISP. It is defined as:

$$\mathcal{N}_k = \{n_k, n_k + 1, \dots, ((n_k - 1) \setminus \lambda + DH)\lambda\}, \quad (10)$$

where λ is the number of time steps within every ISP; *DH* is the number of ISPs considered in the optimization, and $(n_k - 1) \setminus \lambda = \text{floor}(\frac{n_k - 1}{\lambda})$ denotes the integer division operation, which ensures that the final time step in \mathcal{N}_k always lies at the border between two ISPs. The starting time of proceeding optimizations is given by $n_{k+1} = n_k + \tau_{\text{opt}}$, where τ_{opt} is the number of time steps to proceed after each optimization. The simulation is terminated as soon as the end time of the simulation study is reached.

B. Dynamic Ramp Rate Definition

Ramp rate limits are introduced as a step function dependent on the output power Therefore, they can be dynamically set throughout the simulation according to the actual power plants power output. Using the receding horizon control, the result of the last optimization execution is already known and it is used as a look-up table to set the limit in the next execution.

C. Mathematical Formulation

The optimization problem is formulated as a linear program with the following objective function and constraints.

1) Objective Function: The aim of the Online Predictive Dispatch Optimizer is to minimize the total operating costs, represented in (11), where term (i) refers to the production cost, (ii) to reserves cost, (iii) to ramping costs and (iv) to imbalance costs.

$$\min \sum_{n_k \in \mathcal{N}_k} \sum_{g \in \mathcal{G}_i} \left[\sum_{s \in \mathcal{S}} \underbrace{C_{g,s}^{\text{prod}} \cdot \gamma \cdot P_{n_k,g,s}^{\text{set}}}_{i} + \underbrace{C_g^{\text{res}} \cdot R_{n_k,g}^{\text{set}}}_{ii} + \sum_{d \in \mathcal{D}} \underbrace{C_{g,d}^{\text{rr}} \cdot V_{n_k,g,d}}_{iii} \right] + \sum_{t_k \in \mathcal{T}_k} \sum_{c \in \mathcal{C}} \underbrace{C_c^{\text{imb}} \cdot I_{t_k,c}}_{iv} \quad (11)$$

2) Model Constraints: The constraints deal with operational limits and market requirements.

• Energy Balance

$$\sum_{n_k \in \mathcal{N}_k} \sum_{g \in \mathcal{G}_i} \sum_{s \in \mathcal{S}} \gamma \cdot P_{n_k, g, s}^{\text{set}} + (I_{t_k, 1} - I_{t_k, 2}) = E_{t_k}^*, \quad \forall t_k \in \mathcal{T}_k \quad (12)$$

· Maximum and minimum power limits

$$\sum_{s \in \mathcal{S}} P_{n_k,g,s}^{\text{set}} + R_{n_k,g}^{\text{set}} \le \overline{P}_g, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (13)$$

$$\sum_{s \in \mathcal{S}} P_{n_k, g, s}^{\text{set}} - R_{n_k, g}^{\text{set}} \ge \underline{P}_g, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (14)$$

• Reserves requirement

$$\sum_{g \in \mathcal{G}} R_{n_k,g}^{\text{set}} = R_{n_k}^{aFRR}, \quad \forall n_k \in \mathcal{N}_k$$
(15)

• Ramp Up & Down Reservation

$$\sum_{s \in \mathcal{S}} (P_{n_k,g,s}^{\text{set}} - P_{n_k-1,g,s}^{\text{set}}) + \alpha \cdot R_{n_k,g}^{\text{set}}$$
$$\leq \overline{\Delta P}_{g,1}, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (16)$$

$$\sum_{s \in \mathcal{S}} (P_{n_k,g,s}^{\text{set}} - P_{n_k-1,g,s}^{\text{set}}) - \alpha \cdot R_{n_k,g}^{\text{set}}$$
$$\geq \overline{\Delta P}_{g,2}, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (17)$$

• Ramp Up & Down Limits

$$\sum_{s \in \mathcal{S}} (P_{n_k,g,s}^{\text{set}} - P_{n_k-1,g,s}^{\text{set}}) + (R_{n_k,g}^{\text{set}} - R_{n_k-1,g}^{\text{set}})$$
$$\leq \overline{\Delta P}_{g,1}, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (18)$$

$$\sum_{s \in \mathcal{S}} (P_{n_k,g,s}^{\text{set}} - P_{n_k-1,g,s}^{\text{set}}) - (R_{n_k,g}^{\text{set}} - R_{n_k-1,g}^{\text{set}})$$
$$\geq \overline{\Delta P}_{g,2}, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (19)$$

Ramp Up & Down variable definition

$$\sum_{s \in \mathcal{S}} (P_{n_k,g,s}^{\text{set}} - P_{n_k-1,g,s}^{\text{set}}) + (R_{n_k,g}^{\text{set}} - R_{n_k-1,g}^{\text{set}})$$
$$\leq V_{g,1}, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (20)$$

$$\sum_{s \in \mathcal{S}} (P_{n_k,g,s}^{\text{set}} - P_{n_k-1,g,s}^{\text{set}}) - (R_{n_k,g}^{\text{set}} - R_{n_k-1,g}^{\text{set}})$$
$$\geq -V_{g,2}, \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \quad (21)$$

· Lower variables bounds

$$R_{n_k,q}^{\text{set}} \ge 0 \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i \tag{22}$$

$$I_{t_k,c} \ge 0 \quad \forall t_k \in \mathcal{T}_k, c \in \mathcal{C} \tag{23}$$

$$V_{n_k,q,d} \ge 0 \quad \forall n_k \in \mathcal{N}_k, g \in \mathcal{G}_i, d \in \mathcal{D}$$
(24)

In the objective function, the decision variables are $P_{n_k,g,s}^{\text{set}}$, the power setpoint in every optimization step time n_i for every generator g and power segment⁵ s within the portfolio; $R_{n_k,g}^{\text{set}}$, the reserve setpoint; $V_{n_k,g,d}$, the ramp rate for direction $d \in \mathcal{D} = \{1,2\}$, where 1 is for ramping up and 2 for ramping down; and $I_{t,c}$, the energy imbalance in period (ISP) $t_k \in \mathcal{T}_k = ((\mathcal{N}_k - 1) \setminus \lambda + 1)$ (following same methodology as for \mathcal{N}_k in (10)) and case $c \in \mathcal{C} = \{1,2\}$, where 1 is for energy surplus and 2 for shortage. On the other hand, $C_{g,s}^{\text{prod}}$, $C_{g,s}^{\text{res}}$, $C_{g,s}^{\text{rrs}}$ and $C_{g,s}^{\text{imb}}$ are the production, reserves, ramp rate and imbalance costs, respectively, and γ is a conversion factor from min to h.



Figure 2. Portfolio energy program in every ISP used for all the study cases.

Within the model constraints, (12) introduces $E_{t_k}^*$, the scheduled energy per period, where the already generated energy (using the connection with the grid model) is subtracted if not at the beginning of the ISP. (13)(14) set the limits with \overline{P}_g and \underline{P}_g , the maximum and minimum power, respectively, of every generator g, note that reserves are considered within the constraint. (15) makes sure that $R_{n_k}^{\text{aFRR}}$, the aFRR reserves requirement, is met in every time step. In (16) and (17) an α percentage of the reserves is used as a ramp rate reservation, where $\overline{\Delta P}_{g,1}$ and $\overline{\Delta P}_{g,2}$ are the ramp rate limits for ramping up and down, respectively. Equation (18) and (19) set the ramp up & down limits considering also the reservation. Finally, (22) to (24) set the lower bound limits for the variables.

IV. STUDY CASES & PERFORMANCE METRICS

The cases consider the same six power plants portfolio and energy program. Figure 2 shows the portfolio energy program for every ISP. Also for all the cases the aFRR reserved capacity is defined as 60 MW throughout the whole simulation and the parameter α , percentage of reserves to reserve as a ramp rate, defined as 7% according to TenneT requirements [12].

The dispatch optimizer parameters are set as:

- C_g^{res} , reserves cost, set to 0. Allocation of reserves will depend only on operational constraints and production costs. Defining different reserves costs it is not important in the interpretation of results.
- C^{rr}_{g,d}, ramping cost, modeled as a small penalty 0.01€/(MW/min) to avoid power plants ramping against each other if they have similar marginal costs. This is important since it leads to a reduction in ramping capabilities and increases the wear and tear of the units.
- C_c^{imb} , imbalance cost, set as a big penalty to assess the capabilities of the dispatch optimizer to reduce as much as possible the energy imbalance.
- *DH*, dispatch horizon and τ_{opt} , optimization sample time, are the variable parameters defining the study cases.

A. Study Cases

Different study cases are summarized in Table I. Notice that Case 0 do not connect the optimizer module, while Case 1 and 2 connects the optimizer but do not include feedback of real-time information. Additionally, Case 5 includes a test on

 $^{^{5}}$ In this formulation, power plants marginal costs and ramp rate limits are linearized. Therefore, every generator have a different marginal cost and ramp rate for every power segment *s*.

Cases	Optimizer Connection	Real-time Information	$ au_{ m opt}$ [min]	DH
Case 0	X	n/a	n/a	n/a
Case 1	1	×	5	2
Case 2	1	×	1	2
Case 3a	1	1	5	2
Case 3b	✓	✓	5	3
Case 4a	✓	✓	1	2
Case 4b	1	1	1	3
Case 5	1	1	1	2
Case 6a	×	n/a	n/a	n/a
Case 6b	1	1	1	2

Table I STUDY CASES SETUP



Figure 3. Imbalance Delta Price per ISP. Data retrieved from [13]

passive imbalance strategies by simulating a perfect imbalance price forecast included into the model, while Case 6a and 6b compare Case 0 and 4a, respectively, but including the variable generation of renewable energy and how the system will behave in both scenarios.

B. Performance Metrics

To verify the performance of the studied cases, the following parameters are considered.

1) Production Cost Difference $[\in]$: Obtained by calculating the difference between the total production cost for every studied case and Case 0.

2) Energy Imbalance Volume [MWh]: Difference between the energy program for every ISP and the actual produced power (without considering FCR and aFRR).

3) Energy Imbalance Cost $[\in]$: To assess the imbalance cost throughout the simulation, the imbalance price delta is used, which is the difference between the day ahead and imbalance price for every ISP. Real-available price is retrieved from TenneT's settlement website [13], Figure 3.

V. RESULTS

This section presents the results obtained after running the simulations for all the cases. Table II provides a concise view of the results.

Table II RESULTS. METRICS COMPARISON

Cases	Prod. Cost Diff [€]	Energy Imb. [MWh]	Imb. Cost [€]
Case 0	-	86.3	892
Case 1	-29,320	42.4	216
Case 2	-29,414	36.8	250
Case 3a	-29,610	32.5	393
Case 3b	-29,596	31.9	375
Case 4a	-29,494	10.7	123
Case 4b	-29,603	11.1	114
Case 5	n/a	146.4	-20,435
Case 6a	n/a	374.1	783
Case 6b	n/a	12	109



Figure 4. Energy imbalance volume and cost comparison in Cases 0 to 4b.

A. Cases 0 to 4

This subsection analyses specifically Cases 0 to 4 as they do not include any extra source of imbalance to be specifically addressed. As it can be seen directly from the Table II and Figure 4, Case 0 provides the worst results both in terms of production cost and energy imbalance. This was expected since it is not considering dispatch optimization.

Analysing production cost, as far as the dispatch optimizer is used, there is an existing saving around $30k \in$ in all the cases. Therefore, it can be concluded that the optimization is indeed reducing costs, although considering real-time information or modifying the configuration setup ($\tau_{opt} \& DH$) does not provide further production cost reduction.

Regarding energy imbalance, the connection of the dispatcher and configuration of τ_{opt} is key to reach an important reduction. *DH* configuration, however, cannot be determined to be decisive as its contribution is too small. Figure 4 shows graphically the comparison of the results where it can be seen that just connecting the dispatch optimizer (Cases 1&2) reduces imbalance by half. Cases 3a & 3b achieve a reduction of the imbalance by introducing real-time information but since τ_{opt} is big (5 min) it is not able to reduce it further. Cases 4a & 4b, however, achieve the best results as the optimization redispatches the imbalance in every minute of the simulation.

As for the imbalance cost, since it follows the imbalance price delta, it is not directly proportional to the energy imbalance. It is worth noticing that if the imbalance direction



Figure 5. Energy imbalance comparison between Case 4a and 5.

coincides with the system needs, imbalance will be remunerated instead of charged. For this reason, even if cases 1 and 2 have a higher imbalance compared to cases 3a and 3b, their final cost is higher.

B. Case 5

Case 5 simulates the profitability of passive balancing by assuming that imbalance price delta is perfectly predicted. Figure 5 shows the evolution of the imbalance throughout the simulation for Case 4a and 5. The energy that actually computes as energy imbalance is the value at the end of every ISP and it can be seen how the dispatch optimizer introduces imbalance as intended when imbalance price delta (Figure 3) is above or below 50/-50 \in /MWh in Case 5.

The potential profitability by intentionally deviate 50MW from the energy program is above $20,000 \in$.

C. Case 6

Case 6 introduces the variability and uncertainty of VRES. Realistic wind imbalance has been introduced in the simulation, Figure 6a). Figure 6b) shows the comparison between the energy imbalance in every ISP for Case 6a and 6b. The dispatch optimizer is completely capable to deal with the uncertainty of wind power as the imbalance is redistributed amongst the power portfolio in the most economical way.

VI. CONCLUSIONS

This paper introduces the formulation of an Online Predictive Dispatch Optimizer and its connection to a grid model which simulates the balancing market and frequency control within inter-connected areas on a second basis. The proposed method provides the optimal setpoints and aFRR reserves to a power portfolio by means of a receding horizon control and linear constrained optimization. Numerical simulations show that the dispatch optimization is able to minimize production costs while reducing energy imbalance, not only from the actual deviation between the dispatch setpoints and the actual production but also from other sources of imbalance such as VRES.

REFERENCES

 J. R. Aguero, E. Takayesu, D. Novosel, and R. Masiello, "Modernizing the Grid: Challenges and Opportunities for a Sustainable Future," *IEEE Power and Energy Magazine*, 2017.



Figure 6. a) Wind Imbalance throughout the simulation for Case 6a & 6b. b) Energy imbalance comparison per ISP.

- [2] M. I. Henderson, D. Novosel, and M. L. Crow, "Electric Power Grid Modernization Trends, Challenges, and Opportunities," *IEEE Technol*ogy Trend Paper, no. November, 2017.
- [3] C. M. Correa-Posada, G. Morales-España, P. Dueñas, and P. Sánchez-Martín, "Dynamic ramping model including intraperiod ramp-rate changes in unit commitment," *IEEE Transactions on Sustainable Energy*, 2017.
- [4] W. Gu, Z. Wang, Z. Wu, Z. Luo, Y. Tang, and J. Wang, "An Online Optimal Dispatch Schedule for CCHP Microgrids Based on Model Predictive Control," *IEEE Transactions on Smart Grid*, 2017.
- [5] H. Kwon, J. K. Park, D. Kim, J. Yi, and H. Park, "A flexible ramping capacity model for generation scheduling with high levels of wind energy penetration," *Energies*, 2016.
- [6] J. Frunt, "Analysis of Balancing Requirements in Future Sustainable and Reliable Power Systems," Ph.D. dissertation, Eindhoven University of Technology, Available: https://research.tue.nl/en/publications/ 2011. [Online]. analysis-of-balancing-requirements-in-future-sustainable-and-reli
- [7] DNV GL, "Evaluating Grid Performance With KERMIT. 2014 KERMIT Summit," DNV GL, Tech. Rep., 2014.
- [8] B. Roffel and W. W. de Boer, "Analysis of power and frequency control requirements in view of increased decentralized production and market liberalization," *Control Engineering Practice*, 2003.
- [9] A. J. Wood, B. F. Wollenberg, and G. Sheblé, "Power Generation Operation and Control. 3rd Edition," in *Power Generation Operation* and Control. John Wiley & Sons, Inc., 2013, ch. 10, p. 658.
- [10] NERC, "Balancing and Frequency Control. A Technical Document Prepared by the NERC Resources Subcommittee," NERC, Princeton, Tech. Rep., 2011.
- [11] The European Commission, "Commission Regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing," *Official Journal of the European Union*, vol. 2017, no. November, pp. 312/6 – 312/53, 2017. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ. L_.2017.312.01.0006.01.ENG&toc=OJ:L:2017:312:TOC#d1e2376-6-1
- [12] TenneT, "Product information automatic Frequency Restoration Reserve," TenneT TSO B.V., Tech. Rep., 2020. [Online]. Available: https://www.tennet.eu/fileadmin/user_upload/SO_NL/ Product_information_aFRR.pdf
- [13] "TenneT Settlement prices." [Online]. Available: https://www.tennet.org/english/operational_management/System_ data_relating_processing/settlement_prices/index.aspx