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Predictive Control for congestion management in sub-transmission areas. A parameter-varying model-based approach

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Abstract: Recent decentralised control approaches allowing to reduce congestion on transmission lines consider small sub-transmission areas where to act locally on curtailing renewables. In the present paper, we underscore the critical need for reliable models to facilitate effective control implementations and propose to consider a receding horizon approach that exploits data-based estimation of the underlying model parameters. Simulation results show the effectiveness of the proposed approach, that is capable to act when needed on minimising renewable power curtailment while adapting to the possible changes in the topology of the grid.

Keywords: Model estimation, power congestion management, model predictive control, transmission lines

1. INTRODUCTION

The evolution of power grids amid the ongoing energy transition is characterized by a notable integration of renewable energy sources, giving rise to various congestion challenges (see Meyer et al. (2020); Monforti-Ferrario and Blanco (2021)). Successful management of power congestion is pivotal in attaining the overarching objective (see Coletta et al. (2020); Liere-Netheler et al. (2020); Orrù et al. (2022)). Recent advancements in control methodologies have introduced local decentralized approaches, as in Henka et al. (2022); Dkhili et al. (2023). These approaches specifically target the control of predefined sub-transmission areas associated with particular geographical regions, which are known to encounter congestion issues due to high renewable energy generation. The novelty of such approaches lies in the local scale of the power management action; each sub-transmission area, called zone, consider a local controller who possesses only local information, i.e., of the nodes (buses) and edges inside the zone, and no communication with external agents or zones is foreseen. The localized control strategies, involving measures such as curtailment, storage, and topological adjustments, have demonstrated their efficacy in mitigating congestion challenges (see Dkhili et al. (2023); Ganet-Lepage et al. (2023)).

The control methodologies under consideration are inherently model-based, emphasizing the crucial requirement for dependable models to enable the implementation of effective control strategies. The primary objective of this paper is to expand upon the approaches explored in Dkhili et al. (2023); Ganet-Lepage et al. (2023); Pham et al. (2022) by considering scenarios where the model is not completely known or time-varying. In the existing literature, discrete-time prediction models for a sub-transmission area rely on the linearization of power flow equations, utilizing Power Transfer Distribution Factors (PTDFs) (refer to Cheng and Overbye (2005)). It is crucial to emphasize that the PTDF parameters, traditionally treated as constant in previous studies, pose challenges in precise computation. This is primarily due to the need for computations across the entire transmission grid, and these parameters are subject to influence from alterations in the network's topology. Changes in topology may occur locally or in the surrounding areas. Therefore, control methodologies need to address these uncertainties and variations through dynamic adjustments in real-time.

In the current work, we propose employing a Model Predictive Control (MPC) approach (see Camacho and Bordons (2007)) for congestion management, coupled with data-based parameter identification to accommodate potential changes and possible (partial) uncertainties in the model. This integration allows for the incorporation of real-time models into the prediction-based control design. As the model takes on a parameter-varying nature, the ensuing optimization problem involves time-varying matrices for the dynamical evolution. Based on the preliminary work in Ganet-Lepage et al. (2024), where control is not considered, various estimation methods, primarily relying on past observations, are explored, ranging from considering infinite time windows where data is collected to placing particular emphasis on finite time windows within a receding-horizon-like framework. Discussions on the impact of the observation window will enrich the paper, as well as practical considerations due to possible unexpected behaviours or high mismatches with respect to the initial values when they are considered known. For our reference baseline, we utilize the MATPOWER tool in Zimmerman et al. (2011), which supplies the static parameters for the PTDF coefficients. Based on the here new suggested

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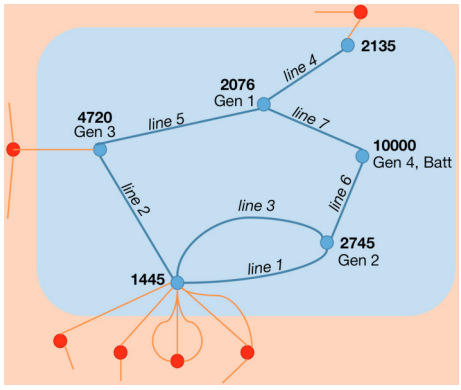

Fig. 1. Topology of the studied zone: the zone subject to the congestion management is represented in blue, the 1st-order neighbors of the zone in red. Buses id are presented in bold along with the information on the lines, generators and the battery.

possibility to couple estimation and control, recommendations for enhancing parameter estimation capabilities by establishing a persistently excitation situation created by control inputs are presented. Simulations show the effectiveness of the proposed methodology incorporating both the estimation part and the control one.

The rest of the paper is organised as follows. Section 2 introduces the considered model as well as the used estimation approaches. Section 3 describes the optimisation problem to be considered for the receding horizon approach and numerical results for the case study of interest. Section 4 outlines conclusions.

2. CONGESTION MANAGEMENT AS A MODEL-BASED CONTROL PROBLEM

2.1 Basic modelling features

The basic principle of congestion management is to avoid the violation of the safety bounds with respect to the power flows on the grid lines. This overall objective is seldom treated in a centralized framework due to the complexity of the power grid's topology, and the decisions are usually taken locally with respect to restricted information within a zone composed of buses and lines. To provide a generic illustration, let us consider a zone as depicted in blue in Fig. 1. The red region represents the complement of the network, only the first-order neighbours being visible in the graphical representation. The nodes in the zone are identified with a number in bold and can be associated to a generator "Gen", a battery "Batt", both of them or none of them, depending on the configuration. The lines are also identified with a specific id. As it can be noted here, the considered zone is composed of six nodes, seven lines, four generators and one battery.

In this section, we recall in a concise manner all the elements needed in order to construct a mathematical model for the evolution of the power flows within a selected zone described as above by a subset of buses, generators, and batteries along with the power lines in view of control of the power flows. For more details on the principles and related modelling approaches, the interested reader is referred to Iovine et al. (2021); Ganet-Lepage et al. (2023).

Topological information: Let $\mathcal{Z}$ be the set of buses in the zone, $\mathcal{Z}^G \subset \mathcal{Z}$ the subset of buses with a generator, $\mathcal{Z}^B \subset \mathcal{Z}$ the subset of buses with a battery and $\mathcal{L}$ the set of power lines in the zone.
Set-up parameters related to the topological information: Let n^N, n^G, n^B, n^L be the cardinality indices of $\mathcal{Z}, \mathcal{Z}^G$, $\mathcal{Z}^B$ and $\mathcal{L}$, respectively. Then, let T be the sampling time (time step for the simulation), and the delays of the control action be τ_C (the delay of power curtailment, which is equal for all generators) and τ_B (the delay of battery power variation, equal for all batteries); $1 \leq \tau_B < \tau_C$. Let c_b be the battery coefficient of power injection, and $\overline{P_g^G}$ the maximum installed capacity of the generator g.

Time-varying parameters: Let us consider:

- $\psi_{b,l}^B(t)$; PTDF between line l and battery b at time t;
- $\psi_{g,l}^G(t)$; PTDF between line l and generator g;
- $\psi_{n,l}^N(t)$; PTDF between line l and bus n.

Let us define the variables of the state space as:
State: $F_l(t)$: power flow on line l; $P_g^C(t)$: curtailed power for generator g, i.e., the limitation of its maximum generation capacity; $P_b^B(t)$: power of battery b; $E_b^B(t)$: energy of battery b; $P_g^G(t)$: generation power for the generator g at time t; $z_g^G(t)$: generation power for the generator g at time $t+1$, equivalent to $P_g^G(t+1)$, but represented as a separated variable to avoid anti-causality: $P_g^A(t)$: available power for generator g at time t.
Disturbance: $\delta P_n^T(t)$: transit power describing the power variation at bus n due to power flows transiting between the zone and the rest of the network; $\delta P_g^A(t)$: uncertainty on the available power at time t for generator g.
Control: $\delta P_g^C(t)$: the update of the power curtailment at time t for generator g; $\delta P_b^B(t)$: the update of the battery power output decided at time t.

The system dynamics of the zone is defined, $\forall l \in \mathcal{Z}^L$, $\forall g \in \mathcal{Z}^C$, $\forall b \in \mathcal{Z}^B$, $\forall n \in \mathcal{Z}^N$, as:

$$\begin{aligned}
F_l(t+1) &= F_l(t) + \sum_{b\in\mathcal{Z}^B} \psi_{l,b}^B(t)\cdot\delta P_b^B(t-\tau_B) + \\
&\sum_{g\in\mathcal{Z}^G} \psi_{l,g}^G(t)\ \left[z_g^G(t) - P_g^G(t)\right] + \sum_{n\in\mathcal{Z}^N} \psi_{l,n}^N(t)\delta P_n^T(t) \\
P_g^C(t+1) &= P_g^C(t) + \delta P_g^C(t-\tau_C) \\
P_b^B(t+1) &= P_b^B(t) + \delta P_b^B(t-\tau_B) \\
E_b^B(t+1) &= E_b^B(t) - T\cdot c_b^B\cdot[P_b^B(t) + \delta P_b^B(t-\tau_B)] \\
P_g^G(t+1) &= z_g^G(t) \\
P_g^A(t+1) &= P_g^A(t) + \delta P_g^A(t)
\end{aligned} \tag{1}$$

$$\begin{aligned}
z_g^G(t) = \min\big(\ & P_g^A(t) + \delta P_g^A(t), \\
& \overline{P_g^G} - P_g^C(t) - \delta P_g^C(t-\tau_C)\big)
\end{aligned} \tag{2}$$

2.2 Open-loop online identification of parameters

Previous works (e.g., Pham et al. (2022), Ganet-Lepage et al. (2023)) build on the working hypothesis that the power flow dynamical equation in (1) is linear time-invariant with constant PTDFs coefficients that are computed offline, i.e.,

$$\psi_{l,g}^G(t) = \psi_{l,g}^{G,mat},\ \psi_{l,b}^B(t) = \psi_{l,b}^{B,mat},\ \psi_{l,n}^N(t) = \psi_{l,n}^{N,mat} \tag{3}$$

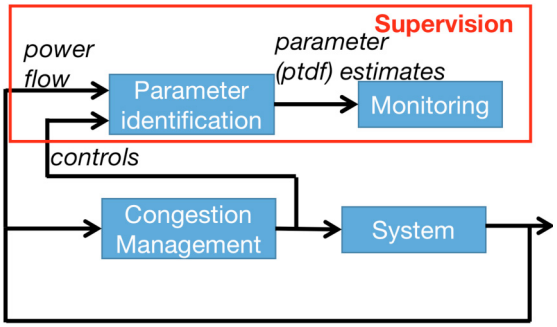

Fig. 2. Open-loop monitoring of the model parameters.

Therefore, the classical congestion management process is considered decoupled with respect to parameter identification algorithms, which are used only for monitoring purposes (see Fig. 2). Recently, real-time monitoring of the PTDF parameters has been investigated, showing that Least Squares-based methodologies can be adapted to receding horizon configurations and topology constraints (see Ganet-Lepage et al. (2024)). Several practical considerations are made, e.g., the importance of having an initial reference value to consider in case of missing data or unexpected behaviours (named regularisation) and the impact of the excitation on the quality of parameter identification. In the present paper, we briefly recall the main elements of the open-loop PTDF identification based on real-time data collection as a motivation for its further integration in the feedback decision-making.

Two strategies are considered for collecting data for estimation purposes:

a) a variable horizon, ranging from the initial time when data collection is available to the current one;
b) a fixed horizon, where a receding time windows is considered for collecting data for the estimation. In practice, a fixed number of previous sampling times is here considered (10 or 30 steps).

The optimisation problem used to estimate these time-varying PTDFs relies on power flow variations δF_l and generation power variations δP_g^G:

$$\delta F_l(t) = F_l(t+1) - F_l(t), \quad \delta P_g^G(t) = z_g^G(t) - P_g^G(t) \quad (4)$$

The power flow equation for a given line $l \in \mathcal{L}$ becomes:

$$\begin{aligned}\delta F_l(t) = &\sum_{b\in\mathcal{Z}^B} \delta P_b^B(t-\tau_B)\cdot\psi_{l,b}^B(t) \\ &+ \sum_{g\in\mathcal{Z}^G} \delta P_g^G(t)\cdot\psi_{l,g}^G(t) + \sum_{n\in\mathcal{Z}^N} \delta P_n^T(t)\cdot\psi_{l,n}^N(t)\end{aligned} \quad (5)$$

The following notations are introduced for data collections:

$$\delta F(t) = \begin{bmatrix}\delta F_1(t)\\ \vdots\ l\\ \delta F_{n^L}(t)\end{bmatrix} \in \mathbb{R}^{n^L},\ \delta P^B(t) = \begin{bmatrix}\delta P_1^B(t)\\ \vdots\ b\\ \delta P_{n^B}^B(t)\end{bmatrix} \in \mathbb{R}^{n^B},$$

$$\delta P^G(t) = \begin{bmatrix}\delta P_1^G(t)\\ \vdots\ g\\ \delta P_{n^G}^G(t)\end{bmatrix} \in \mathbb{R}^{n^G},\ \delta P^T(t) = \begin{bmatrix}\delta P_1^T(t)\\ \vdots\ n\\ \delta P_{n^N}^T(t)\end{bmatrix} \in \mathbb{R}^{n^N}$$

Let $\Psi^B(t) = \left[\psi_{l,b}^B(t)\right] \in \mathbb{R}^{n^L\times n^B}$, $\Psi^G(t) = \left[\psi_{l,g}^G(t)\right] \in \mathbb{R}^{n^L\times n^G}$, $\Psi^N(t) = \left[\psi_{l,n}^N(t)\right] \in \mathbb{R}^{n^L\times n^N}$, and the block matrix $\Psi(t) = \left[\Psi^B(t)\ \Psi^G(t)\ \Psi^N(t)\right] \in \mathbb{R}^{n^L\times(n^B+n^G+n^N)}$.

Consequently, by considering all lines l the power flow equation (5) is rewritten as,:

$$\delta F(t) = \Psi(t)\cdot\begin{bmatrix}\delta P^B(t-\tau_B)\\ \delta P^G(t)\\ \delta P^T(t)\end{bmatrix} \quad (6)$$

By considering the past H_p-step horizon, i.e., from $t-H_p$ to $t-1$, we define the matrices:

$$\Delta F(t) = \left[\delta F(t-H_p)\cdot\overset{t}{\cdot}\cdot\delta F(t-1)\right] \in \mathbb{R}^{n^L\times H_p},$$

$$\Delta P^B(t-\tau_B) = \left[\delta P^B(t-H_p-\tau_B)\cdot\overset{t}{\cdot}\cdot\delta P^B(t-1-\tau_B)\right] \in \mathbb{R}^{n^B\times H_p},$$

$$\Delta P^G(t) = \left[\delta P^G(t-H_p)\cdot\overset{t}{\cdot}\cdot\delta P^G(t-1)\right] \in \mathbb{R}^{n^G\times H_p},$$

$$\Delta P^T(t) = \left[\delta P^T(t-H_p)\cdot\overset{t}{\cdot}\cdot\delta P^T(t-1)\right] \in \mathbb{R}^{n^N\times H_p},$$

and the block matrix $\Delta P(t) = \begin{bmatrix}\Delta P^B(t-\tau_B)\\ \Delta P^G(t)\\ \Delta P^T(t)\end{bmatrix}$. As already discussed, each matrix is the collection of past observations from $t-H_p$ up to $t-1$.

2.2.1. Basic Least square problem Under the assumption of constant PTDFs over the observation horizon, a linear regression can be defined to reconstruct these PTDFs $\Psi(t)$:

$$\Delta F(t) = \Psi(t)\cdot\Delta P(t) + \mathcal{S}(t) \quad (7)$$

where $\mathcal{S}(t) \in \mathbb{R}^{H\times n^L}$ corresponds to the slack matrix of the difference between the left-hand side and the rest of the right-hand side.

$\Delta F(t)$ and $\Delta P(t)$ are data, namely past observations. We want to select the PTDFs in $\Psi(t)$, such that the Frobenius-norm of the slack matrix $\mathcal{S}(t)$ is the smallest, noted $\|.\|_F$.

Thus, the targeted optimization problem is defined as:

$$\Psi_1^*(t) = \arg\min_{\Psi(t)} \|\Delta F(t) - \Psi(t)\cdot\Delta P(t)\|_F \quad (8)$$

We stress that the PTDFs represent a percentage of generation power which is distributed over a line: the flow is directed, thus to move in both directions. Then, the percentage can also be negative. Therefore, we consider the following constraint:

$$-\mathbf{1} \le \Psi \le \mathbf{1} \quad (9)$$

where $\mathbf{1} \in \mathcal{R}^{(n^B+n^G+n^N)\times n^L}$ is a vector composed by ones.

For any given bus, the power generated is entirely spread on the lines connected with this bus. Topological constraints on the PTDFs resume the property: the sum of the PTDFs of all lines connected to this bus is equal to 100% (it si true for any type of PTDF; ψ^B,ψ^G or ψ^N):

$$\sum_{l\in\mathcal{L}\text{ s.t. }n=\text{fromBus of }l} \psi_{l,n} - \sum_{l\in\mathcal{L}\text{ s.t. }n=\text{toBus of }l} \psi_{l,n} = 100\% \quad (10)$$

As lines are directed edges, the direction is dealt with a positive or negative coefficient.

2.2.2. Least Squares optimisation with regularisation To tackle high variability of the estimation in case of missing data or unexpected values, we introduce a regularized version of the Least Squares method with topology constraint.

The PTDF estimation variables are decomposed into two parts: the default time-invariant PTDF Ψ^{mat} defined in Eq.(3), plus a new variable $\Delta\Psi(t)$ that represents the variation of the PTDF with respect to the time-invariant variable.

$$\Psi(t) = \Psi^{mat} + \Delta\Psi(t) \tag{11}$$

where Ψ^{mat} is the matrix similar to $\Psi(t)$ but with the entries replaced by the elements in (3). Since the time-invariant PTDFs Ψ^{mat} respect the topology constraint in (10), the variation variables $\Delta\Psi(t)$ should not change this property:

$$\sum_{l\in\mathcal{L} \text{ s.t. } n=\text{fromBus of } l} \delta\psi_{l,n}(t) - \sum_{l\in\mathcal{L} \text{ s.t. } n=\text{toBus of } l} \delta\psi_{l,n}(t) = 0 \tag{12}$$

where $\delta\psi_{l,n}(t)$ are the entries of $\Delta\Psi(t)$. Thus, the optimisation problem of the regularized Least-Squares method with constraints is:

$$\begin{aligned}\Psi_2^*(t) = &\arg\min_{\Delta\Psi(t)} \|\Delta F(t) - \Psi(t)\cdot\Delta P(t)\|_F + c\|\Delta\Psi(t)\|_F \\ &\text{s.t. } (9),(10),(11),(12)\end{aligned} \tag{13}$$

The first term aims to find PTDFs such that the linear regression is accurate. The second term aims at allowing variations in the PTDF but by avoiding unrealistic PTDF values. Arbitrarily, we choose $c = 1$ in the next simulation but this can be further used as tuning parameter.

2.3 Identification results and comparisons: an overview

We consider here the process illustrated in Fig. 2, involving a closed-loop congestion-management that is decoupled from the PTDF identification mechanism. At each time step, the system receives input signals from the controller. Simulation data, including power flow and controller outputs, are then used for parameter identification. The red block in Fig.2 indicates the supervision objective of the PTDF identification, which will be subject to updates in the subsequent section.

Four methods were considered, encompassing both grid-based properties and data-driven observation approaches: MATPOWER's computation of the PTDF, relying on the topology and power network properties; Utilizing Matlab's built-in pseudoinverse function; Solving a Least Squares optimization problem formulated with Yalmip (see Lofberg (2004)) and solved using Gurobi; Extending the last approach with additional topological constraints, i.e., ensuring that for a given bus, the sum of the PTDF between the bus and all adjacent edges equals 100%. Detailed information on the performance of the various approaches is available in Ganet-Lepage et al. (2024). Here, we provide a brief overview. Since the results from the pseudoinverse and least squares approaches are similar when considering all past data, we focus here on a past fixed-window data collection.

Comparison of 10-step and a 30-step horizon estimations without the topology constraint exhibit similar performances. In the tested scenario (see Fig. 3), introducing topological constraints yields identification results close to the reference values provided by MATPOWER. The topology constraint increases the sensitivity with a short fixed-size horizon estimation. This is motivated by the

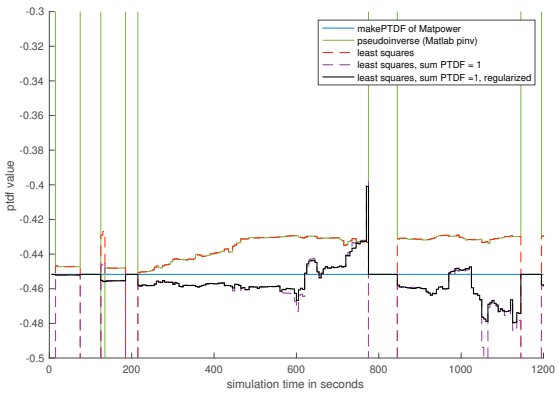

Fig. 3. Estimation of the PTDF parameters using a receding horizon window of 10-step. "sum PTDF=1" refers to the topological constraint. The use of different constraints, implementation schemes and regularisation is illustrated on line 7 with generator 4.

subsequent coupling constraints, which amplify the effect of a single PTDF variation over the neighbours, such that the sum of PTDFs is balanced according to 10. With the considered 10-step horizon (Fig. 3), the parameter estimation is impacted by the lack of input signal excitation, which leads to singularities in the regression matrix and ultimately results in PTDF values on the boundaries of the admissible interval. Regularisation plays an essential role in the mitigation of such episodes. Consequently, despite the topology constraint the estimations is evolving closer to MATPOWER's values.

In summary, various tuning parameters and configurations can be used for the reconstruction in real time of the PTDFs. These PTDF parameters can be further made available to the controller through parameter adaptation of the dynamical model. Note, however, that the effectiveness of the controllers' decisions will be impacted by the quality of data. In particular, the associated data may not provide meaningful PTDF parameters if the system lacks excitation.

For a variable horizon that accumulates data from the beginning of a simulation, past observations of the system remain useful for PTDF estimation, but a forgetting mechanism needs to be adopted in order to discharge the memory of the identification block. Alternatively, the use of a constant receding horizon estimation exhibits good convergence but remains fragile when the persistence of excitation is not guaranteed. In such cases, the regularisation around a default value diminishes the impact on the PTDF estimation.

2.4 Congestion management as a control problem

Given the model description above, the operational problem related to congestion management can be resumed by the following objectives:

- Maintain power flows within the capacity of the lines by means of curtailment and battery storage
- Minimize the generation curtailments whenever possible
- Prioritize the use of battery storage for congestion management

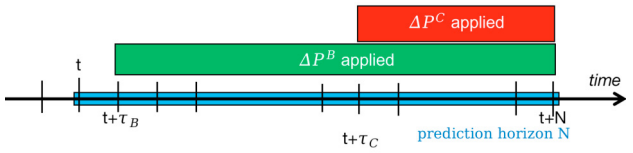

Fig. 4. A visual representation of the prediction horizon and the possibility to tuse the control inputs over it.

- After the overflow mitigation, bring the battery power output close to zero in order to prepare for the next congestion episode.

As it can be seem from these main objectives, the curtailment and storage signals are used in a feedback control framework using the available measurements in terms of power flows, production and energy at the level of the battery. In order to fine-tune the model parameters, the next section will detail an optimization-based design that exploits the dynamical constraints and the available data in real time.

3. TIME-VARYING MPC

This Section combines the previously introduced estimation methodologies in real-time together with the possibility to control the system using a predictive strategy.

3.1 Model-based Predictive Control principles for congestion management

The systems having actuation delays for both the battery and the curtailment (see Hoang et al. (2021)), a receding horizon control approach as the MPC is considered to compensate them. The prediction horizon is illustrated in Fig. 4. Given a current time t, the prediction spans over N steps, accounting for control delays. Three phases emerge: 1) until the activation of the first delayed battery control action, the systems evolve uncontrolled; 2) subsequently, until the first curtailment is activated, only battery controls are applied (shown in green on Fig. 4), and overflows cannot be avoided; 3) finally, with the combined effect of curtailment and battery control actions (in green and red on Fig. 4), no overflow is tolerated up to the end of the horizon. Over the horizon, transit power disturbances $\Delta P_n^T(t)$, plus states and disturbances of available power are estimated.

The MPC targets the following goals, which will be described in a cost function J to be minimized:

- I Forbid power flows to be over the capacity lines after the activation of the first curtailment control;
- II Limit power flows to be over the capacity lines until the activation of the first curtailment control;
- III Minimize the curtailment controls over the horizon;
- IV Contain the power overflows during the horizon by using the battery;
- V Concentrate the battery utilisation over the whole horizon instead of in a single instant;
- VI Bring back the battery power output to $\check{P}_b^B$ in case of no overflow nor curtailment signal.

The considered constraints over the prediction horizon are, $\forall t' \in [t, t+N]$:

$$\underline{P_b^B} \leq P_b^B(t') \leq \overline{P_b^B}, \quad 0 \leq P_g^C(t') \leq \overline{P_g^G} \tag{14a}$$

$$\underline{E_b^B} \leq E_b^B(t') \leq \overline{E_b^B}, \quad -\overline{P_g^G} \leq \delta P_g^C(t') \leq \overline{P_g^G}, \tag{14b}$$

$$\underline{P_b^B} - \overline{P_b^B} \leq \delta P_b^B(t') \leq \overline{P_b^B} - \underline{P_b^B}, \tag{14c}$$

When both control actions are delayed and cannot occur, there are no constraints on the overflow. However, when the battery comes into play, i.e., $\forall t' \in [t+1+\tau_B, t+\tau_C]$, soft constraints are applied. They are implemented via slack variables $\mathcal{E}_l(t')$, and result to describe the power line overflow on line j at time t' with respect to its limit $\overline{L}_l$ as, $\forall t' \in [t+1+\tau_B, t+\tau_C]$:

$$-\overline{L}_l - \mathcal{E}_l(t') \leq F_l(t') \leq \overline{L}_l + \mathcal{E}_l(t'), \quad \mathcal{E}_l(t') \geq 0 \tag{15}$$

Then, no overflow is tolerated when both curtailment and battery controls are applied $\forall t' \in [t+1+\tau_C, t+N]$, therefore hard constraints are defined as:

$$-\overline{L}_l \leq F_l(t') \leq \overline{L}_l \tag{16}$$

These constraints satisfy objective I.

Therefore, the selected objective function is:

$$\begin{aligned} J(t) = \gamma_1 \underbrace{\sum_{t'=t+\tau_B+1}^{t+\tau_C} \sum_{l \in \mathcal{L}} \mathcal{E}_l(t')}_{\text{overflows}} + \gamma_2 \underbrace{\sum_{t'=t}^{t+N} \sum_{g \in \mathcal{N}^C} \delta P_g^C(t')}_{\text{curtailment control}} \\ + \gamma_3 \underbrace{\sum_{t'=t}^{t+N} \sum_{b \in \mathcal{N}^B} (\delta P_b^B(t') - \delta \check{P}_b^B)^2}_{\text{battery control}} \\ + \gamma_4 \underbrace{\sum_{t'=t+1}^{t+N} \sum_{b \in \mathcal{N}^B} (P_b^B(t') - \check{P}_b^B)^2}_{\text{batteries' power output}} \end{aligned} \tag{17}$$

where $\delta \check{P}_b^B, \check{P}_b^B$ are used to represent a reference value of the corresponding variables. The positive parameters γ_1, γ_2, γ_3 and γ_4 are to be selected properly with respect to the design's priorities. The adherence to the constraint defined in (15), coupled with the consideration of associated costs in (17), fulfills objective II. Objective III is addressed through the imposition of costs on curtailment controls. Additionally, objective V is met by incorporating costs on battery controls, subsequently satisfying objective IV through a judicious selection of coefficients γ. Objective VI is achieved by introducing costs associated with the battery state.

3.2 On-line parameter identification coupled with model-based predictive control

We consider now the PTDFs coefficients becoming time-varying, i.e., the constraints in (3) are removed. Consequently, the power flow equation in (1) exhibits time dependency due to the time-varying PTDFs. This presents a notable departure from earlier works as Iovine et al. (2021); Hoang et al. (2021); Pham et al. (2022); Ganet-Lepage et al. (2023). The optimization problem consists then of two key components. Firstly, employing a historical horizon there is parameter identification of PTDFs at the current time t: $\psi_{l,b}^B(t), \psi_{l,g}^G(t), \psi_{l,n}^N(t)$. Secondly, after the parameter identification at time t, the predictive control

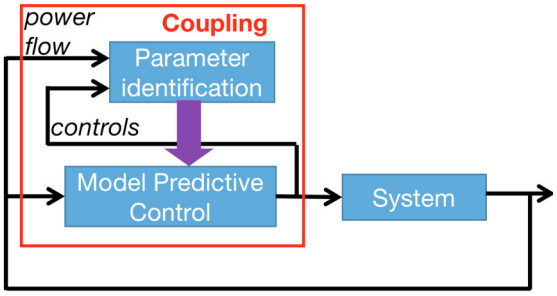

Fig. 5. On-line identification coupled with MPC

phase unfolds with a prediction horizon in the future. We assume that the PTDFs remain constant over this prediction horizon and fix them to the just-identified values. An optimization problem is then solved. This methodology establishes a coupling (see Fig. 5) between parameter identification and model predictive control that is missing in previous work as Ganet-Lepage et al. (2024).

The optimisation problem representing this coupling two-phase approach is:

$$\begin{aligned} \mathcal{O} = \min_{\delta P_g^C(t'),\delta P_g^B(t')} \; & J(t) \;\; in \;\; (17) \\ s.t. \quad & (1),(2),(14) \quad \forall t' \in [t, t+N] \\ & (15) \quad \forall t' \in [t+\tau_B+1, t+\tau_C] \\ & (16) \quad \forall t' \in [t+\tau_C+1, t+N] \\ & (13) \quad \forall t' \in [t-H_p, t-1] \end{aligned} \tag{18}$$

We remark that (13) corresponds to the parameter identification using the past horizon, while the other equations are based on the prediction horizon.

3.3 Case study

We demonstrate the methodology through a case study involving controllers based on various parameter identification methods. The objective is to evaluate the performance of a controller that integrates online parameter identification with MPC in a simulated zone. The zone shown in Fig. 1 is considered for tests. Since line 1 emerges as the most susceptible to overflow hazards and considering the topology, Generator 2, Generator 4, and the battery are identified as the most influential elements for power flow on line 1, as outlined in Table 1.

Impact	PTDF of gen on line 1
Gen 2	40%
Gen 4	30%
Batt	30%
Gen 1	13%
Gen 3	4%

Table 1. PTDFs of line 1

Five scenarios are selected, each employing a different parameter identification method based on the information from the preceding section and Ganet-Lepage et al. (2024), as illustrated in Table 2.

In terms of figures, the PTDF estimates between Line 1 and Gen 2, Gen 4, or the battery are depicted in Fig. 6, Fig. 7, and Fig. 8, respectively. Line 1's power flow is presented in Fig. 9. For generators, Gen 2 is shown in Fig. 10, and

Case	Parameter identification method
a	MATPOWER's PTDF
b	all past horizon Least Squares with topology
c	all past horizon Regularized Least Squares with topology
d	30-step horizon Regularized Least Squares with topology
e	10-step horizon Regularized Least Squares with topology

Table 2. Simulation cases shown in the figures

Gen 4 in Fig. 11. The battery is illustrated in Fig. 12. As for the omitted elements, during this simulation, line 1's potential overflows govern the controls, and Generators 1 and 3 have minimal influence on line 1, as indicated in Table 1. We stress that the focus is not on the battery energy during this simulation.

Overall, examining line 1's power flow in Fig. 9, the controllers effectively handle the overflows. The PTDF estimates closely align with the reference values from MATPOWER's PTDF. Battery controls are implemented when power flows approach their limits, and curtailment controls on generators are also activated when the battery capacity is insufficient.

Cases (a), (b), and (c) of the simulations are considered together due to their similarities. In Fig. 9, starting from 400 seconds, line 1's power flow approaches the limit, necessitating controls to prevent overflows. During this period, the MPC predicts that the generations of Gen 2 and Gen 4 will sharply increase, reaching the maximum capacity of the generators. This scenario would result in an overflow on line 1. To address this issue, the MPC decides to fully utilize the battery over the horizon, as shown in Fig. 12, and to curtail Gen 2, as illustrated in Fig. 10, which is the generator with the most significant influence on line 1, as indicated in table 1. Regarding Generator 4 in Fig. 11, two small curtailment controls are applied at 300 and 400 seconds. These occur when the prediction expects Gen 4's generation to reach its remaining capacity while Gen 2 would not reach it. Consequently, curtailing Gen 4 becomes necessary to reduce its generation, while this is not the case for Gen 2.

Case (b) is the only scenario without a PTDF reference, making accurate PTDF estimation between the battery and the line possible only by applying battery controls and observing their consequences on the lines with data measures. The controller refrains from acting until 400 seconds, causing an absurd PTDF estimate between the battery and line 1 at that time, as shown in Fig. 7. Due to this incorrect PTDF estimate related to the battery, the controller makes erroneous battery controls, justifying subsequent curtailment controls on Gen 4, which is on the same bus as the battery, instead of applying curtailment controls on Gen 2, as in the other cases. After battery controls are implemented after 430 seconds, the PTDF estimate between the battery and line 1 gradually evolves towards a value close to those of other PTDF estimation methods, as depicted in Fig. 8. It is worth noting that in the cases of generators, variations in generation power, due to external available powers, create a persistence of excitation allowing accurate PTDF estimation between a line and a generator.

In conclusion, the PTDF estimate of the battery in case (b) is initially wrong, leading to different battery and curtailment controls. However, each controller effectively man-

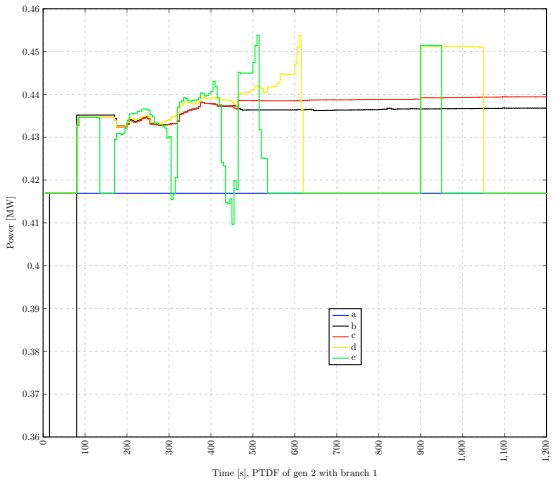

Fig. 6. PTDF estimate between generator 2 and line 1, the 5 cases of table 2 are considered.

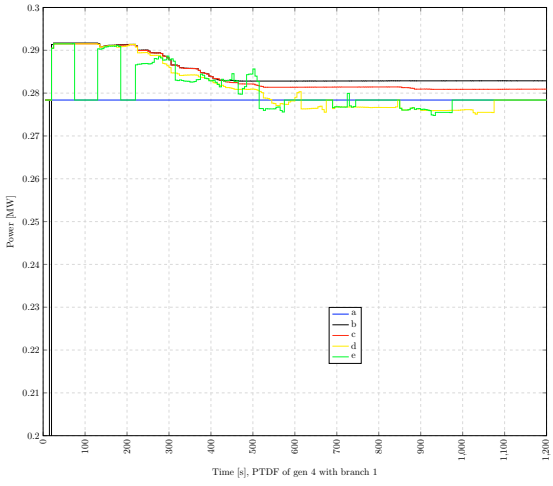

Fig. 7. PTDF estimate between generator 4 and line 1, the 5 cases of table 2 are considered.

ages overflows. Case (a) represents the standard method used in previous works. Case (b) corresponds to a scenario where no PTDF reference is provided, and the estimator relies solely on cumulative data measures. Case (c) involves a PTDF reference, aiming to slightly enhance the PTDF values using cumulative data measures. Cases (d) and (e) are similar to case (c) but with a storage constraint on the data measures. Therefore, simulations show the effectiveness of the proposed method regardless of the choice of a kind of coupled estimator-controller.

4. CONCLUSIONS

This paper enhances the feasibility of estimating PTDF parameters in model-based control strategies for power congestion management in sub-transmission areas. The proposed control scheme effectively estimates and controls the local area, thus to relax the need of perfect knowledge of the system based on a computation that requires knowledge of the whole transmission grid. A comparative analysis of the impact of various estimation methods on the considered receding horizon control approach is presented. Future research will concentrate on refining the

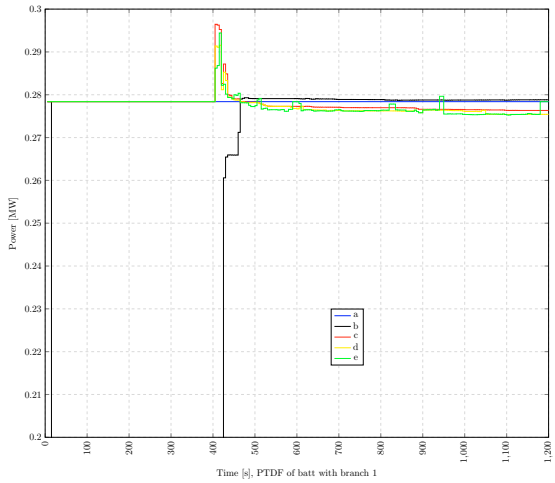

Fig. 8. PTDF estimate between battery and line 1, the 5 cases of table 2 are considered.

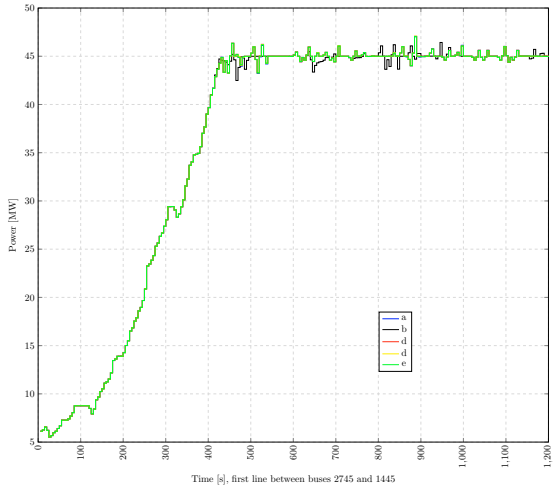

Fig. 9. Line 1's power flow, the 5 cases of table 2 are considered.

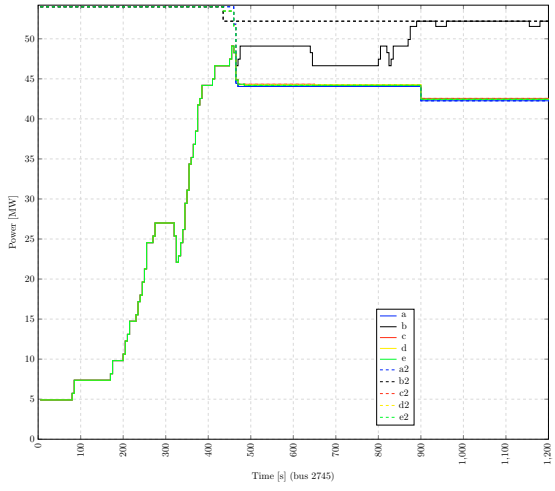

Fig. 10. Generator 2's information, the 5 cases of table 2 are considered. Continuous lines mean generation powers, dotted lines means remaining capacities.

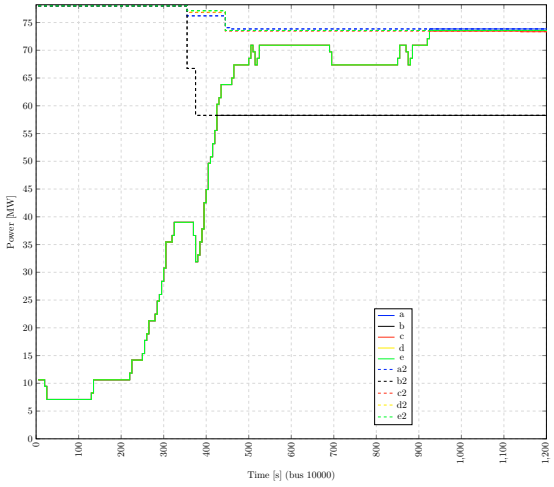

Fig. 11. Generator 4's information, the 5 cases of table 2 are considered. Continuous lines mean generation powers, dotted lines means remaining capacities.

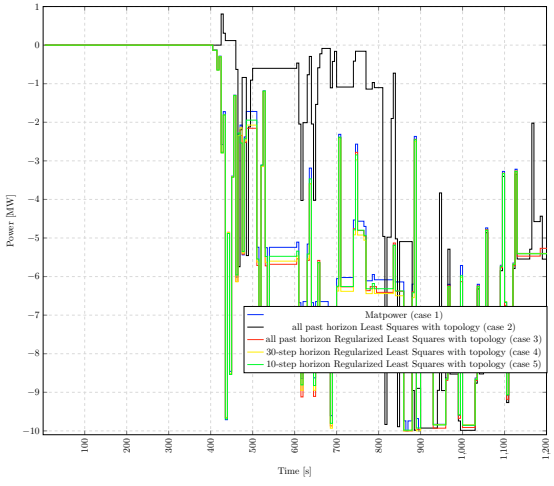

Fig. 12. Battery power output, the 5 cases of table 2 are considered.

estimation of PTDF parameters, particularly in scenarios involving changes in topology.

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