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Predictive control based on stochastic disturbance trajectories for congestion management in sub-transmission grids ⋆

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Abstract: The energy transition of power grids is accompanied by a slew of new challenges arising at the design, deployment and operation levels. From the control viewpoint, the integration of renewable-energy-based power generation sources into the power grid translates into emerging uncertainties which compromise the system's stability and performance. In this paper, the main goal is to propose a model-based predictive controller that incorporates the stochastic nature of these sources into its decision-making, in order to balance upholding operational constraints with smart power generation curtailment and energy storage strategies.

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Keywords: Smart energy grids, congestion management, power systems, model-based predictive control, data-based control, relaxation, convex optimisation, robustness.

1. INTRODUCTION

To reconcile ever-growing energy demand with the urgent and paramount need of reducing fossil-fuel-based power generation, power grids require fundamental changes on both physical and cyber fronts. As a matter of fact, the deployment of renewable-energy-based power generation sources is a key step towards increasing their efficiency, flexibility and, most importantly, sustainability.

In accordance with the multiplication of renewable-energy-based power plants connected directly to transmission grids, transmission system operators (TSO) are pursuing new tools for congestion management. For obvious practical reason, strategies that require minimal infrastructure changes are preferred. As such, flexible asset management is an increasingly popular area of interest in the literature (**?**Prodan and Zio (2014); Ioakimidis et al. (2018)). It resorts to using local levers connected to the sub-transmission grid to minimize violations of the powers lines' operational power limits.

In the case study presented in this paper, several wind power generation plants are connected to the sub-transmission grid. A model-based predictive controller (MPC) determines optimal setpoints for partial curtailment of the plants' generation and for battery usage. Furthermore, it must take into account the stochastic nature of the distributed generation in its decision-making.

A time-delay model describing partial power curtailment possibilities is introduced in Iovine et al. (2021). It is based on Power Transfer Distribution Factor (PTDF) (see Wood et al. (2013); Xu Cheng and Overbye (2005)) and extends previous modeling that only allowed on/off decisions on power curtailment (see Straub et al. (2018a), Straub et al. (2018b)). In Hoang et al. (2021), the authors provide a controllability analysis with respect to the saturation effects of the control inputs with respect to the considered time-delayed model. Moreover, *ad hoc* strategies to ensure problem feasibility and to correctly prioritize the available control action are implemented.

The next step in this research focuses on the challenges posed by uncertainties due to limited local information and the stochastic nature of wind power generation. There are several ways to deal with this uncertainty: the safest approach is to use the worst disturbance trajectory in terms of constraint violation (Lee and Yu (1997)). This approach guarantees robustness but is extremely conservative and significantly restricts the controller's room for maneuver. Also on the conservative side is a trend-based approach where the controller assumes that the disturbance trend observed over the last time step persists over the entire prediction horizon. This approach is explored in Hoang et al. (2021): results prove that the controller is able to successfully maintain power levels within prescribed margins. But, this robustness comes at the cost of early

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triggering of power generation curtailment, which reduces the strategy's economic attractiveness.

There exists a plethora of control applications where the system's behaviour is influenced by one or several disturbances of stochastic nature. The well-established theory of stochastic control tackles these problems (Åström (2012)). Stochastic methods offer a richer description of disturbance behaviour to the controller, at the cost of increasing computational and memory requirements. In a model-based predictive control (MPC) framework, dealing with stochastic disturbances in convex optimization problems is quite often done through scenario-based approaches (Campi and Garatti (2011)): they provide probabilistic guarantees that the solution to the sample problem satisfies the original chance constrained problem (Alamo et al. (2009)). The literature is rife with examples of sampling-based methods (Korda et al. (2014); Lorenzen et al. (2017); Fioriti and Poli (2019)), popular for being computationally tractable.

In a similar vein, the strategy proposed herein is a sampling-based predictive control method. First, uncertain disturbance trajectories are generated over a finite horizon. Then, their weighted combination is incorporated into the optimization problem. As opposed to the common custom of random sampling from the set of possible trajectories, herein we select trajectories based on a statistical analysis of the the disturbance's behaviour.

The paper is organised as follows: section 2 details the control-oriented system model. Next, section 3 introduces the control strategy proposed in this paper. Section 4 describes the case study treated in this paper. Analysis of the simulation results is conducted in section 5. The paper ends with a discussion of future research steps in 6.

2. MODELLING

2.1 Notations

Let us consider the following notations throughout the paper:

- $\mathcal{Z}^N$ is the set of nodes in the considered zone; n^N is its cardinality. P_n^T is the power generated in the transmission network flowing from the external network to the node $n \in \mathcal{Z}^N$ of the zone of interest.
- $\mathcal{Z}^C \subset \mathcal{Z}^N$ is the set of nodes where the curtailment of the generated power is allowed; n^C is its cardinality. P_n^G is the generated power, while P_n^C is the curtailed one at node $n \in \mathcal{Z}^C$. P_n^A is the available renewable power that can be generated each sampling time.
- $\mathcal{Z}^B \subset \mathcal{Z}^N$ is the set of nodes with a battery; n^B is its cardinality. P_n^B is the power injected from the battery on node $n \in \mathcal{Z}^C$, while E_n^B describes the battery energy at the same node.
- $\mathcal{Z}^L \subset \{(i,j) \in \{1,...,n^N\} \times \{1,...,n^N\}\}$ is the set of power lines in the zone; n^L is its cardinality. F_{ij} represents the power flow on the line ij.

The operator *diag* describes a diagonal matrix composed by the considered elements. The operator *col* produces a single column vector composed by the aggregation of other vectors. That is, given m vectors $s_i \in \mathbb{R}^n$, $i = 1,...,m$, the resulting vector $s = col[s_i], i = 1,2,\dots,m$, will be:

$$s = col[s_i] = [\ s_1^T\ s_2^T\ \dots\ s_m^T\ ]^T \in \mathbb{R}^{nm}. \tag{1}$$

2.2 State representation

The state variables of the energy transmission are: the power flows on the lines F_{ij}, the curtailed power P_n^C, the battery power output P_n^B, the battery energy E_n^B, and the generated power P_n^G. The delayed control inputs are the power variations ΔP_n^B and ΔP_n^C. The disturbance ΔP_n^T is unknown, as it represents the power variations in the nodes outside the operated zone. Finally, the variation ΔP_n^G of the generated power P_n^G is known at time instant k based on the state, control inputs and context information within the zone (namely the available power P_n^A).

The available power P_n^A at time instant k is communicated to the TSO, but its variation along the prediction horizon is stochastic, as a result of the intermittent nature of wind power generation. Consequently, the values of ΔP_n^G along the prediction horizon are implicitly defined with respect to forecasts of P_n^A and ΔP_n^A, and to the stored values of P_n^G with respect to computed ones of P_n^C.

The dynamical model is formulated as:

$$\begin{cases} F_{ij}(k+1) = & F_{ij}(k) + \sum_{n\in\mathcal{Z}^B} b_{ij}^n \Delta P_n^B(k-d) \\ & + \sum_{n\in\mathcal{Z}^C} b_{ij}^n \left[\Delta P_n^G(k) - \Delta P_n^C(k-\tau)\right] \\ & + \sum_{n\in\mathcal{Z}^N} b_{ij}^n \Delta P_n^T(k),\ \forall\ (ij) \in \mathcal{Z}^L \\ P_n^C(k+1) = & P_n^C(k) + \Delta P_n^C(k-\tau),\ \forall\ n \in \mathcal{Z}^C \\ P_n^B(k+1) = & P_n^B(k) + \Delta P_n^B(k-d),\ \forall\ n \in \mathcal{Z}^B \\ E_n^B(k+1) = & E_n^B(k) - Tc_n^B[P_n^B(k) + \Delta P_n^B(k-d)], \\ & \forall\ n \in \mathcal{Z}^B \\ P_n^G(k+1) = & P_n^G(k) + \Delta P_n^G(k) - \Delta P_n^C(k-\tau), \\ & \forall\ n \in \mathcal{Z}^C \end{cases} \tag{2}$$

where b_{ij}^n are constant parameters given by PTDF computations, c_n^B are constant power reduction factors for the batteries, and $d \geq 1$ and $\tau \geq 1$ are operational time delays due to the delayed control actions on the battery power output and power curtailment for the generators, respectively. We consider the batteries to act faster with respect to the possibility to curtail renewable power, and consequently $\tau \geq d$.
In particular, the term $\Delta P_n^G(k)$, is defined as

$$\Delta P_n^G(k) = \min\left(f_n^G(k), g_n^G(k)\right), \tag{3}$$

with

$$f_n^G(k) = P_n^A(k) + \Delta P_n^A(k) - P_n^G(k) + \Delta \hat{P}_n^C(k-\tau), \tag{4}$$

$$g_n^G(k) = \overline{P}_n^G - P_n^C(k) - P_n^G(k). \tag{5}$$

where $\overline{P}_n^G > 0$ is the maximum installed generating capacity of the renewable power plants in the sub-transmission grid, with $\forall n \in \mathcal{Z}^C$, and the value of $\Delta \hat{P}_n^C(k)$ is defined in the following. Accordingly, the proposed modeling allows for the possibility to pre-compute the term $\Delta P_n^G(k)$ based on values of $P_n^A(k)$, $P_n^G(k)$, $P_n^C(k)$, $\Delta P_n^A(k)$, and $\Delta P_n^C(k)$, while maintaining the system's linearity with respect to the control signal $\Delta P^C(k)$ via the offline computation of the min(.). A more detailed discussion of this approach is provided in Hoang et al. (2021).

Consequently, the computational burden of dedicated model-based predictive control laws remains minimal since the convex optimisation structure of the problem is preserved. This is a key factor for real-time implementation, the preferred setting in light of the reaction times required by TSOs for congestion management.

To describe the model in a compact form, we define:

$$F = col[F_{ij}],\ \forall\ (i,j) \in \mathcal{Z}^L; \tag{6a}$$
$$P^C = col[P_n^C],\ \Delta P^C = col[\Delta P_n^C],\ \forall\ n \in \mathcal{Z}^C; \tag{6b}$$
$$P^B = col[P_n^B],\ \forall\ n \in \mathcal{Z}^B; \tag{6c}$$
$$E^B = col[E_n^B],\ \Delta P^B = col[\Delta P_n^B],\ \forall\ n \in \mathcal{Z}^B; \tag{6d}$$
$$\Delta P^T = col[\Delta P_n^T],\ \forall\ n \in \mathcal{Z}^N; \tag{6e}$$
$$P^G = col[P_n^G],\ \Delta P^G = col[\overline{P}_n^G],\ \forall\ n \in \mathcal{Z}^C. \tag{6f}$$

Now, let us define

$$x(k) = [F(k)\ \ P^C(k)\ \ P^B(k)\ \ E^B(k)\ P^G(k)]^T, \tag{7}$$
$$u_C(k) = \Delta P^C(k), \quad u_B(k) = \Delta P^B(k), \tag{8}$$
$$w(k) = \Delta P^G(k), \quad \zeta(k) = \Delta P^T(k). \tag{9}$$

In order to deal with the known actuator delays $\tau \geq 1$ and $d \geq 1$, we define an extended state $\tilde{x}$ as

$$\tilde{x}(k) = [x(k)\ u_C(k-\tau)\ ...\ u_C(k-1)\ u_B(k-d)\ ...\ u_B(k-1)]^T. \tag{10}$$

The resulting dynamical system is as follows:

$$\tilde{x}(k+1) = \tilde{A}\tilde{x}(k) + \\ + \underbrace{\begin{bmatrix} \tilde{B}_C\ \tilde{B}_B \end{bmatrix}}_{\tilde{B}} \underbrace{\begin{bmatrix} u_C(k) \\ u_B(k) \end{bmatrix}}_{u(k)} + \underbrace{\begin{bmatrix} \tilde{D}_w\ \tilde{D}_\zeta \end{bmatrix}}_{\tilde{D}} \underbrace{\begin{bmatrix} w(k) \\ \zeta(k) \end{bmatrix}}_{\eta(k)} \tag{11}$$

The interested reader is referred to Hoang et al. (2021) for explicit definition of $\tilde{A}$, $\tilde{B}_C$, $\tilde{B}_B$, $\tilde{D}_w$, and $\tilde{D}_\zeta$.

We remark that reactive voltage aspects are not considered in this work. This modeling is adapted to identify in real-time the need for acting on curtailment or storage charge/discharge. Alternate Current (AC) feasibility is a consequence of online updates of $cos(\phi)$ from active power and current real-time measurements, where $cos(\phi)$ is the usual power/current ratio at each bus.

3. MODEL-BASED PREDICTIVE CONTROL BASED ON UNCERTAIN TRAJECTORIES

The objective of this work is to maintain power flow on the power lines within the regulatory bounds by managing the flexible assets within the zone at a minimal economic cost. In practical terms, this is done by using a storage unit (battery) and partial curtailment of wind power generation. The latter lever incurs economic costs in the form of under-exploitation of the renewable energy infrastructure when the wind parks do not generate the maximum available power due to curtailment setpoints.

Furthermore, a working assumption is that the controller can only increase curtailment due to the fact that a decrease in curtailment requires the validation of a supervisory level beyond the scope of this paper. Therefore, the controller must walk the line between ensuring operational security and minimizing curtailment of wind power generation.

Moreover, it must take into account the intermittence of renewable-energy-based power generation which encompasses an uncertainty characterisation problem. To address this issue, at each time step, the controller generates possible trajectories for distributed generation over the prediction horizon N. Then, it infuses the optimisation problem with a combination of said trajectories, in order to select the best control strategy over a finite horizon.

Ideally, the controller should be able to span all potential trajectories, but this is infeasible in practice due to the completeness of the set $\mathcal{W}$ of disturbance values. Indeed, if $w(k) \in \mathcal{W}$ then the trajectory $[w(k) \ldots w(k+N)] \in \mathcal{W}^N$. For this reason, the set $\mathcal{W}$ is sampled so as to have a finite number of possible disturbance values. The disturbance trajectories and their probabilities are considered as input data from the controller's viewpoint. The process driving their selection falls outside the scope of this paper.

The proposed control strategy incorporates $N_s > 1$ disturbance trajectories $w(k)$ into the optimisation problem and relaxes the power lines' constraints accordingly. The working assumption is that the N_s scenarios $w^j = [w^j(0)w^j(1)\ldots w^j(N-1)], \forall j \in 1,\ldots,N_s$ have associated probabilities p^j such that $\sum_1^{N_s} p^j = 1$. The particular case where $N_s = 1$ is presented in Hoang et al. (2021): simulation results have shown that using an extreme disturbance trajectory guarantees robustness but produces very conservative control actions, namely manifesting as preventive curtailment of wind power generation. The objective herein is to better exploit the controller's degrees of freedom while robustness requirements are relaxed.

This is reflected in the introduction of a relaxation variable $\varepsilon^j \in \mathbb{R}^N$ such that $j \in \{1,\ldots,N_s\}$, which serves to relax the power lines' boundary constraints as follows, $\forall\ i \in [1,N],\ \ \forall\ j \in [1,N_s]$:

$$-\overline{L}^j(k+i) \leq F(k+i) \leq \overline{L}^j(k+i) \tag{12}$$

with

$$\overline{L}^j(k+i) = \overline{L}(1+\varepsilon^j(k+i)). \tag{13}$$

The controller's cost function is defined as:

$$J(k) = \sum_{i=1}^{N} ||\tilde{x}(k+i) - \tilde{x}_r||^2_{\tilde{Q}} \\ + \sum_{i=0}^{N} \lambda(i)||u_C(k+i)||^2_{R_C} + \sum_{i=0}^{N} \theta(i)||u_B(k+i)||^2_{R_B} \\ + \sum_{j=1}^{N_s}\sum_{i=0}^{N} \psi(i,j)p^j \left\|\varepsilon^j(k+i)\right\|^2_{Q_\varepsilon} \tag{14}$$

where $\tilde{Q}$, R_C, R_B, and Q_ε are square semi-definite positive matrices with respect to the sizes of $\tilde{x}, u_C$, u_B, and ε^j, respectively. We consider weight functions $\lambda(i)$, $\theta(i)$, and $\psi(i,j)$. The probability p^j is associated to disturbance trajectory j.

Now, let us formulate the following set of constraints, $\forall\ i \in [0,N-1]$, $\forall\ j \in [1,N_s]$:

- system dynamics, $\forall\ j \in [1,N_s]$

$$\tilde{x}^j(k+1) = \tilde{A}\tilde{x}^j(k) + \\ + \underbrace{\begin{bmatrix} \tilde{B}_C\ \tilde{B}_B \end{bmatrix}}_{\tilde{B}} \underbrace{\begin{bmatrix} u_C(k) \\ u_B(k) \end{bmatrix}}_{u(k)} + \underbrace{\begin{bmatrix} \tilde{D}_w^j\ \tilde{D}_\zeta \end{bmatrix}}_{\tilde{D}} \underbrace{\begin{bmatrix} w^j(k) \\ \zeta(k) \end{bmatrix}}_{\eta(k)} \tag{15}$$

These constraints are generated using a pre-determined set of N_s disturbance trajectories. Disturbances originating outside the sub-transmission grid, represented by $\zeta(k)$, are assumed null throughout this paper.

- control input bounds

$$0_{\mathbf{n}^{\mathbf{C}}\times\mathbf{1}} \leq u_C(k+i) \leq \overline{P}^G; \quad (16a)$$

$$\underline{P}^B - \overline{P}^B \leq u_B(k+i) \leq \overline{P}^B - \underline{P}^B. \quad (16b)$$

- extended state bounds

$$\tilde{x}_{\min}(k+i) \leq \tilde{x}(k+i) \leq \tilde{x}_{\max}(k+i), \quad (17)$$

with

$$\tilde{x}_{\min}(k+i) = [-\overline{L}_i^j \; 0_{\mathbf{n}^{\mathbf{C}}\times\mathbf{1}} \; \underline{P}^B \; \underline{E}^B \; 0_{\mathbf{n}^{\mathbf{C}}\times\mathbf{1}} \; u_{\min}^T]^T \quad (18a)$$

$$\tilde{x}_{\max}(k+i) = [\overline{L}_i^j \; \overline{P}^G \; \overline{P}^B \; \overline{E}^B \; \overline{P}^G \; u_{\max}^T]^T \quad (18b)$$

where $\overline{L}_i^j$ groups power lines' capacities, $\overline{P}^G > 0$ is the maximum installed generation capacity, $\underline{P}^B < 0$ and $\overline{P}^B > 0$ are bounds of battery power, $\underline{E}^B < 0$ and $\overline{E}^B > 0$ are bounds of battery energy, and $u_{\min}$ and $u_{\max}$ are lower and upper bounds of the contron inputs, respectively.

- relaxation parameters' bounds

$$0 \leqslant \varepsilon^j(k+i) \leqslant \varepsilon_{max1} \quad (19)$$

$$\frac{1}{NN_s}\sum_{j=1}^{N_s}\sum_{i=1}^{N} \varepsilon^j(k+i) \leqslant \varepsilon_{max2} \quad (20)$$

where ε_{max1} is the upper bound of allowed power overshooting on each power line, during each time step, for each trajectory, and ε_{max2} is the upper bound of averaged allowed power overshooting on the power lines, for all considered trajectories.

- weighted relaxation bounds

$$\frac{1}{\tau}\sum_{j=1}^{N_s}\sum_{i=0}^{\tau-1} p^j\varepsilon^j(k+i) \leqslant \varepsilon_{max3} \quad (21)$$

$$\frac{1}{N-\tau}\sum_{j=1}^{N_s}\sum_{i=\tau}^{N} p^j\varepsilon^j(k+i) = 0 \quad (22)$$

where τ is the curtailment setpoint delay and ε_{max3} is the upper bound of accumulated allowed power overshooting on the power lines, weighted by the trajectories' respective probabilities.
The relaxation is only allowed in the interval $[k+1, k+\tau]$, to cope with the limitations imposed by the delay on the curtailment action. Once curtailment becomes possible ($[k+\tau+1, N]$), the relaxation is no longer allowed.

The predictive control problem under uncertainties is:

$$\mathcal{O} = \arg \min_{u_C(k),u_B(k),\ldots,u_C(k+N-1),u_B(k+N-1)} J(k) \; in \; (14)$$
$$subject \; to \; constraints \; ((15)-(22)) \quad (23)$$

The number of possible discrete trajectories of wind power generation increases exponentially with the prediction horizon. That being said, the proposed approach selects a fixed number of those trajectories to be included in the optimisation problem. As a result, the trajectory generation process becomes computationally heavier as the prediction horizon gets longer but the control problem does not. In fact, the optimisation problem's complexity is linear as a function of the number of trajectories N_s.

4. CASE STUDY

The case study used in this paper, previously used in Hoang et al. (2021), is a sub-transmission zone located near Dijon, France. Four wind power farms are connected to nodes 2076, 2745, 4720, and 10000 of maximum power generations 66 MW, 54 MW, 10 MW, and 78 MW, respectively. A battery of capacity 10 MW is connected to node 10000.

The following working hypotheses are considered:

(1) generators produce the maximum available renewable-energy-based power or the maximum allowed one;
(2) only a higher-level controller can decrease the power curtailment setpoints. For this reason, the proposed controller deals only with curtailment increase;
(3) the state of charge (SOC) of the battery is updated each second by a SCADA system. Together with the considered high voltage, these short time intervals with respect to longer ones taken here into account for control purposes, both sampling and prediction horizon, allow to neglect losses due to the battery system (conversion, cooling and transformers). A different control level is supposed to manage the SOC with respect to longer time horizons (see Straub et al. (2019));
(4) the loads are constant.

For the purposes of this study, disturbances due to absorbed/generated power outside the studied sub-transmission zone are considered null. The wind power generation data used in this study is displayed in Figure 1.

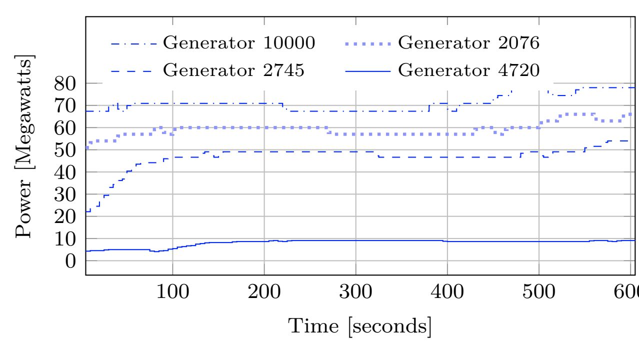

Fig. 1. Wind power generation data used in the case study.

5. RESULTS AND ANALYSIS

In this section, the performance of the proposed controller is analysed with respect to a conservative reference strategy in terms of inner-zone disturbances. Simulations are run in Matlab2021, for a period of 10 minutes, and using the case study described in section 4. To emulate a real power transmission network, the function *runpf* of MATPOWER is used to simulate the AC power flow on the whole transmission network of the French electricity grid Zimmerman et al. (2011), Josz et al. (2016).

The control scheme operates over a prediction horizon of 50 s, with a time step of 5 s. The power lines' maximum capacities are fixed at ±45 MW. Chosen values for the relaxation parameters introduced in section 3 are the following: $\varepsilon_{max1} = 0.05$, $\varepsilon_{max2} = 0.2$, $\varepsilon_{max3} = 0.2$.

Per the conservative reference strategy, the wind power generation gradient is assumed constant all along the prediction horizon:

$$\Delta P^A(k+i) = \Delta P^A(k), \forall\ i \in [1, N] \tag{24}$$

which leads to

$$P^A(k+N) = P^A(k) + N * \Delta P^A(k). \tag{25}$$

This assumption leads to a conservative generation curve over the prediction horizon, which is more likely to trigger the power lines' boundary constraints more often. Although such a trajectory is a low-probability one, it is in line with the TSO's strategy of prioritizing safety and operational security. The most obvious drawback from the TSO's viewpoint is that the overestimation of the constraint violation will lead to more aggressive curtailment strategy. This is a double sentence since it undermines the promotion of renewable energy and incurs an economic cost.

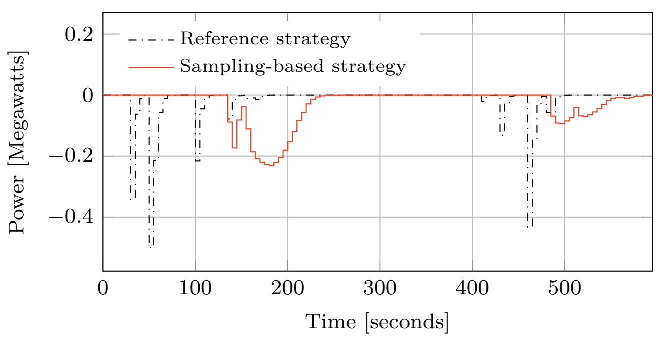

Fig. 2. Battery power input P_b.

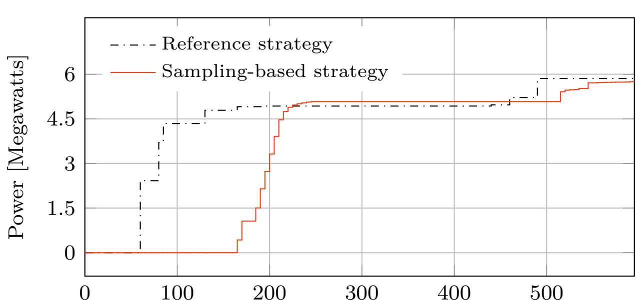

Fig. 3. Curtailed power generation P_c for one of the generation parks within the sub-transmission grid.

The proposed sampling-based MPC described in section 3 aims to mitigate the economic cost of the conservative strategy by allowing for contained overshooting on the power lines and considering less drastic disturbance trajectories.

In Figure 2, setpoints of the battery power input are displayed for both strategies. Figure 3 depicts the power generation curtailment profile for one of the wind park generators connected to the sub-transmission grid. Figure 4 displays the extrema of power flows on the power lines of the sub-transmission grid with respect to their capacities.

As expected, the reference strategy is more conservative: it acts quicker and more aggressively, and on both levers despite the prioritisation of the curtailment in the objective

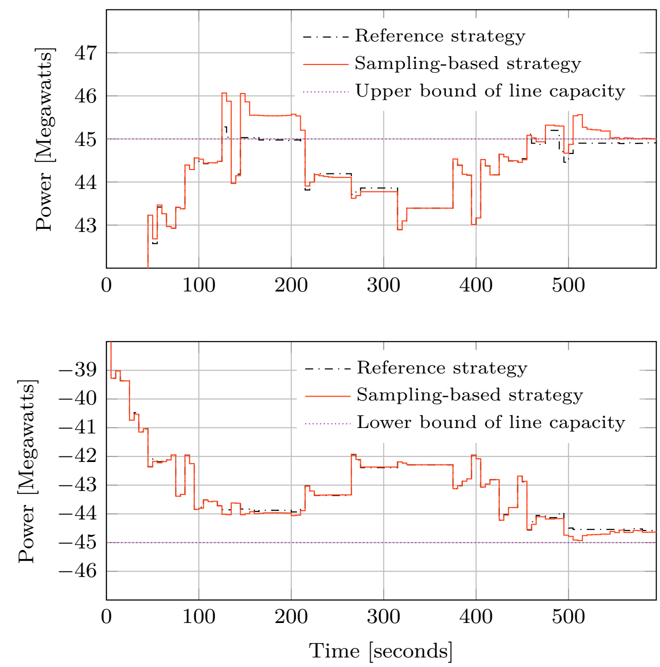

Fig. 4. Extrema of power flows with respect to powers' lines capacities.

function, in order to prevent overshooting on the power lines before it appears. Nevertheless, this aggressive course of action goes against the control strategy's interest in two main ways. First, it incurs irreversible economic costs as wind power generation is curtailed and cannot be dialled back up without supervisory level intervention. Second, it contradicts with the broader directive of fostering the deployment of renewable-energy-based power generation in power grids. The sampling-based strategy moves in to mitigate these troublesome effects. As it stands, it only intervenes once the constraints are violated, but only within the limits of what the relaxation parameter's allow. This is observed first from the beginning of the second minute and then again during the eighth minute of the simulation.

As a consequence, it draws more on the battery, with respect to the reference strategy, to reign in the imminent overshooting. The delayed intervention of the sampling-based controller is advantageous since it results in a 21.47% decrease in curtailment levels for distributed generation with respect to those given by the conservative controller at reasonable constraint violation costs, for the considered case study.

It should be noted that the overshooting on the power lines is only allowed by the sampling-based controller within the limits of the relaxation formulated through Equations (19), (20), and (22). Consequently, the sampling-based controller leans on the contained overshooting on the power lines to optimise the operation's economic cost without comprising the system's safety.

The introduction of relaxation variables as shown in Eq. (12) is justified by the fact that small and brief overshooting over the conservative bounds $(\underline{L}, \overline{L})$ can be handled by the power lines without permanent damage. As a matter of fact, the extension of these bounds to dynamic ones that determine the amplitude and duration of 'safe overshooting' is explored thoroughly in Pham et al. (2022). As a result, values of relaxation bounds ε_{max1}, ε_{max2}, and ε_{max3} are chosen to ensure that the permitted constraint violation remains safe from an operational viewpoint.

The appraisal of the control strategy's performance boils down to a trade-off between minimization of constraint violation (namely of power lines' boundaries) and minimization of wind power generation curtailment and, by extension, optimisation of the economic cost of the wind parks' operation. At the implementation stage, the complexity of the control strategy also comes into play, namely the computational cost of the trajectory generation process. In other terms, the application for which the controller is developed dictates its priorities: the conservative trend-based strategy is better-suited for applications with high security imperatives, while the sampling based method presented herein is shown to give more room for maneuver, at reasonable computational cost, provided some liberty can be taken with constraint violations.

It should be noted that the discussion of the controller actions' economic cost conducted above is focused on the lost revenue of curtailing wind power generation but disregards the losses due to equipment wear, namely effects of the battery's life span. This is especially the case in the setting where battery use is prioritised over the curtailment.

6. CONCLUSION

A sampling-based predictive controller is developed for congestion management in sub-transmission grids and its performance is evaluated with respect to a conservative trend-based strategy. Prospects of this work include analysis of the risk incurred by the selection of a reduced number of disturbance trajectories and the handling of uncertainty due to intermittent power generation outside the considered sub-transmission grid, optimal placement of the battery and study of the economic cost of battery use.

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