

Smart Grid: Model Predictive Control of a Battery for the Operational Control of a Small Electrical Network

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Résumé—The massive integration of renewable energy sources, which are inherently variable, compromises the stability of low-inertia microgrids. This paper presents a Model Predictive Control (MPC) strategy to manage a battery energy storage system in order to maintain grid frequency. The linearized dynamic model is discretized and integrated into an MPC using MATLAB/Simulink. Simulations show a significant reduction in frequency overshoot compared to classical droop control, while respecting power constraints.

Index Terms—Smart grid, battery storage, Model Predictive Control, frequency regulation, microgrid.

I. INTRODUCTION

The ongoing energy transition, characterized by an increasing integration of renewable energy sources (RES) into power grids, presents new challenges in terms of stability, flexibility, and energy management. These sources, often intermittent and difficult to predict, introduce rapid imbalances between electricity production and consumption, especially in low-inertia microgrids. In this context, Battery Energy Storage Systems (BESS) have proven to be effective tools for providing fast power reserves and maintaining grid frequency within acceptable ranges.

This project addresses this challenge by developing a Model Predictive Control (MPC) strategy to dynamically control a BESS within a small electrical network. The main objective is to design a controller capable of anticipating short-term energy imbalances to ensure frequency stability while optimizing storage performance.

Particular attention is given to the integration of real operational constraints (such as the battery's maximum power, state of charge, or limits on the rate of frequency variation), which gives the developed model direct applicability in industrial scenarios. The project is based on a simulated microgrid model in MATLAB/Simulink, including a photovoltaic source, a variable load, and a battery. Following a targeted literature review, an MPC strategy is developed, implemented, and evaluated across various disturbed scenarios.

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II. SYSTEM MODELING

The studied system is an isolated microgrid composed of a variable load, a photovoltaic (PV) source, a diesel synchronous generator, and a battery energy storage system (BESS). The control objective is to stabilize the local grid frequency by dynamically adjusting the power injected or absorbed by the battery. This section presents the simplified dynamic equations of the system for their integration into a predictive controller (MPC).

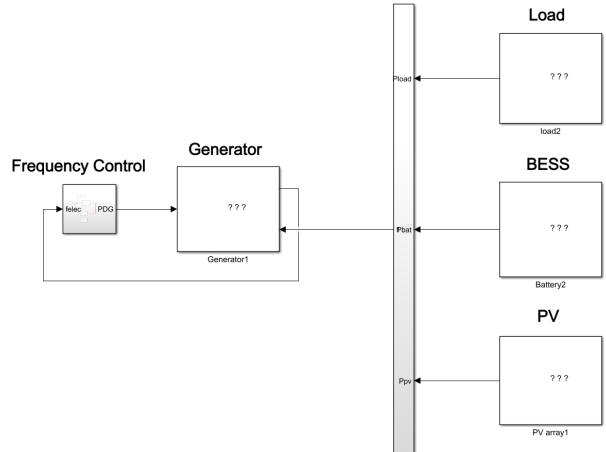


FIGURE 1 – Representation of the microgrid.

A. Frequency Dynamics

The swing equation for a synchronous machine (1), although originally designed for synchronous machines, can be used in our microgrid since the BESS acts as a source of virtual inertia. The power imbalance between the load and PV production causes frequency variations, which the battery dynamically compensates for. This inertial behavior justifies the use of a model inspired by the swing equation, as validated in several recent works on frequency control in microgrids.

$$\frac{2H}{\omega_{\text{nom}}} \frac{d\omega}{dt} = P_{\text{mech}} - P_{\text{elec}} \quad (1)$$

Using the relationship between angular velocity (2) and frequency in (1), we obtain :

$$\omega = 2\pi f \implies \frac{d\omega}{dt} = 2\pi \frac{df}{dt} \quad (2)$$

$$\frac{2H}{\omega_{\text{nom}}} 2\pi \frac{df}{dt} = P_{\text{mech}} - P_{\text{elec}}$$

By replacing $\omega_{\text{nom}} = 2\pi f_{\text{nom}}$:

$$\begin{aligned} \frac{2H}{2\pi f_{\text{nom}}} 2\pi \frac{df}{dt} &= P_{\text{mech}} - P_{\text{elec}} \\ 2\left(\frac{H}{f_{\text{nom}}}\right) \frac{df}{dt} &= P_{\text{mech}} - P_{\text{elec}} \\ 2H' \frac{df}{dt} &= P_{\text{mech}} - P_{\text{elec}} \end{aligned}$$

The frequency dynamics of an isolated electrical system can thus be expressed by the classical equation derived from the conservation of rotational kinetic energy (3) :

$$\begin{aligned} 2H' \frac{d(\Delta f)}{dt} &= P_{\text{bat}} - (P_{\text{load}} - P_{\text{PV}}) \\ \frac{d(\Delta f)}{dt} &= \frac{1}{2H'} (P_{\text{bat}} - (P_{\text{load}} - P_{\text{PV}})) \end{aligned} \quad (3)$$

where :

- H' is the equivalent inertia constant of the system ;
- $\Delta f = f - f_{\text{nom}}$ is the deviation from nominal frequency (50 Hz) ;
- P_{bat} is the power delivered by the battery ;
- $P_{\text{imbalance}} = P_{\text{load}} - P_{\text{PV}}$ is the difference between the load and PV production.

This equation expresses the fact that any imbalance between consumption and PV production must be compensated by injecting or withdrawing power via the BESS, in order to maintain frequency stability.

B. Linear State-Space Model

1) *Definition of Variables:* We define the following variables to express the system in state-space form :

- $x = \Delta f$: the system state (frequency deviation) ;
- $u = [P_{\text{bat}}, P_{\text{load}}, P_{\text{PV}}]$;
- $y = x$: the measured output (system frequency).

2) *General Form:* The equation becomes :

$$\dot{x} = \frac{1}{2H'} (u) \quad (4)$$

3) *State-Space Representation:* The standard form of a continuous linear system with disturbance is :

$$\dot{x} = Ax + Bu, \quad y = Cx + Du \quad (5)$$

By comparing with our equation, we identify the following matrices :

$$A = 0, \quad B = \left[\frac{1}{2H_{\text{eq}}}, -\frac{1}{2H_{\text{eq}}}, \frac{1}{2H_{\text{eq}}} \right], \quad C = 1, \quad D = 0.$$

Note : This two-state model can be useful if one wishes to include constraints on the battery's SoC (State of Charge) in the optimization process.

C. Assumptions and Simplifications

- The diesel generator is considered to provide a constant reference power ;
- The PV follows a predefined profile with no dynamic control ;
- Electrical losses in the lines are neglected ;
- The fast dynamics of the converters are assumed to be ideal ;
- Load and PV data are known in real time (no forecasting).

D. Discretization Process

Starting from the literal expressions of the matrices obtained in the previous step, we replaced the physical parameters with their numerical values :

$$H = 0.5 \quad \text{and} \quad f_{\text{nom}} = 50 \implies H' = \frac{H}{f_{\text{nom}}} = 0.01 \quad (6)$$

Substituting into the matrices :

$$A = 0, \quad B = [50 \quad -50 \quad 50], \quad C = 1, \quad D = 0.$$

These coefficients describe the continuous-time model. To obtain a discrete representation compatible with MPC, MATLAB's built-in function `c2d` was used :

```
sys      = ss(A, B, C, D);
Ts_disc = 1;
sys_disc = c2d(sys, Ts_disc);
```

With a sampling time of 1s, the discretization yielded :

$$\begin{aligned} A_d &= [50 \quad -50 \quad 50] \\ C_d &= [0 \quad 0 \quad 0] \end{aligned}$$

These discrete matrices are now ready to be integrated into the predictive controller (MPC).

III. MODEL PREDICTIVE CONTROL (MPC)

Model Predictive Control (MPC) is an optimal control technique used in multivariable dynamic systems. MPC is designed to optimize a cost function associated with a dynamic system over a time horizon, considering operational constraints of the process and the system's dynamic characteristics.

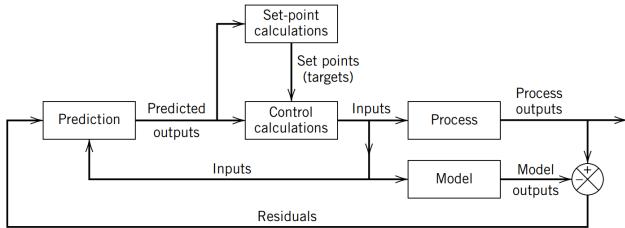


FIGURE 2 – MPC block diagram

Unlike traditional feedback control systems, the operation of MPC can be explained through three main blocks : a system model, an optimizer (used in set-point computation), and a controller (see Figure 1). In this context, a process model is used to predict the current state of the process. The residuals, resulting from the difference between actual and predicted outputs, serve as feedback signals for the prediction block, whose outputs are used for set-point and control calculations. In the optimizer, set-points for the controller are obtained by optimizing the cost function. This function can also define hard or soft constraints for manipulated and controlled variables. At the control stage, optimal control actions are determined so that the response reaches the reference value optimally.

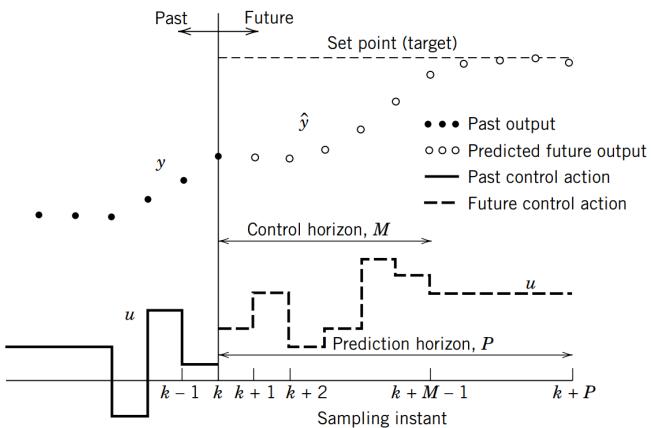


FIGURE 3 – Example of prediction horizon P and control horizon M

To achieve this goal, MPC uses a prediction horizon P and a control horizon M , as illustrated in Figure 2. Thus, at each time instant k , the above process is carried out by predicting the system behavior and optimizing,

using cost functions, the control actions for the next P steps. Among these, the next M control actions are implemented in the process. After instant k , the model is corrected using the difference between the predicted output $\hat{y}(k)$ and the real system output $y(k)$. Then, the optimization problem is solved again for the next P steps, and the next M control actions are computed.

To better understand, it is necessary to detail the functioning of the MPC controller, addressing the main steps of the process : The main objective of MPC is to minimize a cost function over a prediction horizon, which is a future period of interest. The cost function is defined based on the requirements and specifications of the system to be controlled. It can be written in the following general form :

$$J(x_0, U) = \sum_{k=0}^{N-1} (x_k^T Q x_k + u_k^T R u_k) + x_N^T Q_N x_N$$

Where :

- x_0 is the current state of the system ;
- $U = [u_0, u_1, \dots, u_{N-1}]$ is the vector of optimal control actions for the next N steps ;
- Q is a state weighting matrix penalizing the system state ;
- R is a control weighting matrix penalizing control actions ;
- Q_N is the terminal weighting matrix penalizing the state at the last step.

The weighting matrices Q , R , and Q_N are chosen by the controller designer and set the relative importance of the system variables in the cost function calculation.

The dynamic constraint of the system is given by the state equation :

$$x_{k+1} = Ax_k + Bu_k.$$

Equality constraints are incorporated into the optimization problem and can be written in matrix form as :

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} A & & & \\ A^2 & & & \\ \vdots & & & \\ A^N & & & \end{bmatrix} x_0 + \begin{bmatrix} B \\ AB \\ \vdots \\ A^{N-1}B \end{bmatrix} U.$$

Here, matrices A and B are those of the discretized state equation, and x_k and U are stacked vectors containing, respectively, the states and the control actions over the prediction horizon.

Furthermore, the state and control variables are subject to bounds :

$$\underline{x} \leq \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_N \end{bmatrix} \leq \bar{x}, \quad \underline{u} \leq U \leq \bar{u},$$

where \underline{x} and \bar{x} are the lower and upper bound vectors of the states, and \underline{u} and \bar{u} those of the control actions.

Thus, the MPC controller solves the above optimization problem to determine the vector of control actions U that minimizes the cost function while satisfying the equality and inequality constraints. Once the problem is solved, the first optimal action u_0 is applied to the system; then, at the next instant, the state x_0 is updated and the optimization problem is solved again.

IV. MPC IMPLEMENTATION

A. MPC for the Electrical Microgrid

In this project, a Model Predictive Controller (MPC) was chosen to ensure the dynamic control of frequency in an isolated microgrid. This microgrid includes a photovoltaic source, a variable load, and a battery energy storage system. The use of MPC is justified by its ability to anticipate disturbances (notably load and PV production) and to optimize battery control in real time. Unlike classical controllers, MPC explicitly takes into account system constraints such as battery power limits and permissible control variations, and allows a trade-off between regulation performance and control effort. The controlled output signal is the frequency deviation Δf , which the MPC aims to maintain at zero. The MPC thus acts as virtual inertia, stabilizing the grid against rapid load and production fluctuations.

B. MPC Implementation in the Control Chain

The MPC controller was implemented in SIMULINK using the discretized state-space model. The matrices A , B , C , and D are imported into a MATLAB script where the MPC object is created using the `mpc()` function.

The controller is configured as follows :

- Prediction horizon : 6 minutes (360 steps of 1 s);
- Control horizon : 20 s;
- Sampling time : 1 s;
- Constraints : on battery power and ramp rate (maximum variation);
- Weights : in the cost function to penalize frequency deviations and control variations.

Script excerpt :

```
%>>> %% MPC OBJECT (for the MPC Controller)
Ts_ctrl = 1; % controller runs every 1 s

% Signal classification:
% column 1 = MV (Pbat),
% columns 2-3 = MD (Pload, Ppv)
plant = c2d(sys, Ts_ctrl);
```

```
plant = setmpcsignals(plant,'MV',1,'MD',[2 3])

mpcobj = mpc(plant, Ts_ctrl);

mpcobj.PredictionHorizon = 360; % 6 min
mpcobj.ControlHorizon = 20;

% Constraints on the MV (Pbat)
mpcobj.MV(1).Min = -Pbat_max;
mpcobj.MV(1).Max = Pbat_max;
mpcobj.MV(1).RateMin = -5e3;
mpcobj.MV(1).RateMax = 5e3;

% Weights
mpcobj.Weights.OV = 100;
mpcobj.Weights.MV = 0.1;
mpcobj.Weights.MVRate = 1;

disp('initialisation_MPC completed: ...
mpcobj created and ready.'');
```

The signals connected to the MPC block in SIMULINK are :

- mv (manipulated variable) : power injected by the battery P_{bat} ;
- mo (measured output) : frequency deviation Δf to be brought to zero;
- md (measured disturbances) : load power P_{load} and PV production P_{PV} ;
- ref (setpoint) : setpoint of the measured output, set to 0 to maintain $\Delta f = 0$.

This configuration allows the MPC to anticipate disturbances and generate an optimal control command to compensate for imbalances in real time, while respecting the physical constraints of the storage system.

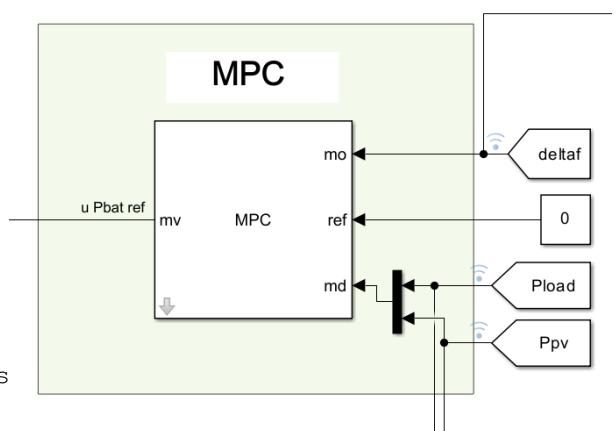


FIGURE 4 – MPC implemented in the control system

V. SIMULATION RESULTS

In this section, we examine the results obtained by the system integrated with MPC, and compare them to the performance of the initial system using droop control alone.

A. Impacts on Reference Tracking

To evaluate the effectiveness of both approaches, we compare their ability to track a reference. For this purpose, we show the evolution of the grid frequency and its variation in both cases.

1) Droop Only: The results show a tracking error that increases over time, with a frequency deviation that starts non-zero and continues to grow during the simulation.

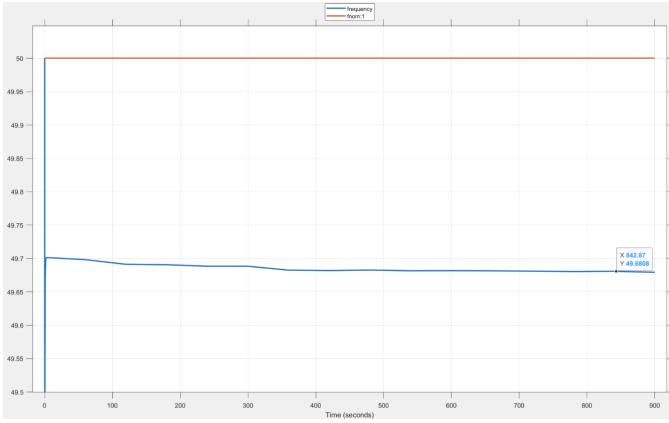


FIGURE 5 – Frequency f evolution with droop only.

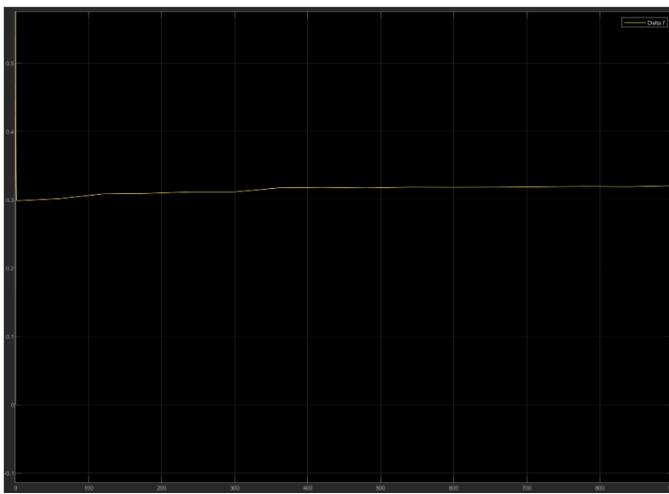


FIGURE 6 – Frequency deviation Δf evolution with droop only.

2) Droop + MPC: The plots show that the MPC model is better able to track the reference. It maintains 50 Hz throughout the simulation with zero steady-state error.

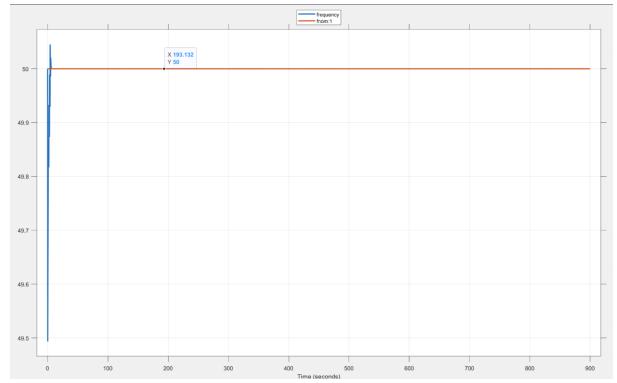


FIGURE 7 – Frequency f evolution with droop + MPC.



FIGURE 8 – Frequency deviation Δf evolution with droop + MPC.

B. Control Signal and Power Demand

The control signal generated by the MPC, represented by $P_{\text{bat_ref}}$, corresponds to the active power the battery must inject or absorb to compensate for imbalances in the microgrid. Analyzing this signal helps assess the relevance of the control and its adherence to the system's physical constraints.

First, we observe that $P_{\text{bat_ref}}$ evolves progressively and continuously, without abrupt changes (Figure 9). This indicates a smooth and anticipative behavior of the MPC controller, capable of effectively reacting to variations in load and PV production.

Next, the maximum value reached by $P_{\text{bat_ref}}$ in the studied scenario is around 28 kW. This value is acceptable, being well below the battery's maximum power (50 kW). Moreover, compared to the diesel generator power ($P_{g,nom} = 128$ kW), this demand is reasonable, representing about 22 % of the generator's capacity. This shows that the MPC does not impose excessive demand on the battery and remains within realistic operating ranges.

Finally, this control strategy ensures a harmonious distribution of effort among the different sources in

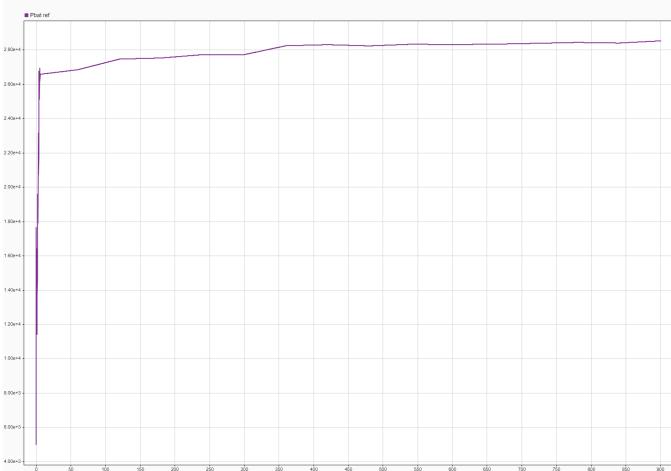


FIGURE 9 – Evolution of $P_{\text{bat_ref}}$.

the microgrid, while maintaining frequency within an acceptable range.

C. Energy Analysis

The total energy consumed by the battery during the simulation was estimated to be about 7 kWh (Figure 10). This amount is approximately 35 times its nominal capacity set at 200 Wh in the model. This highlights that, within the scope of this simulation, the battery acts as a virtual inertia device, without considering its real energy limitations.

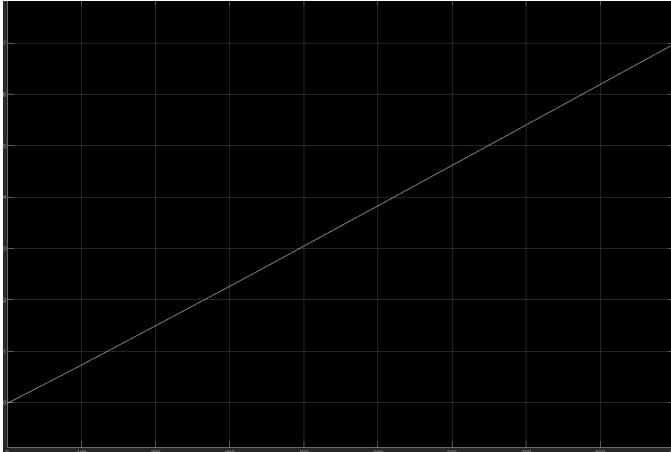


FIGURE 10 – Energy (kWh) \times Time (s)

This intentional simplification allows for evaluating the dynamic efficiency of the MPC controller in response to load disturbances, but it does not accurately reflect the energy behavior of a real system. A more precise model should incorporate the battery's state-of-charge (SoC) constraints, especially for operational implementation.

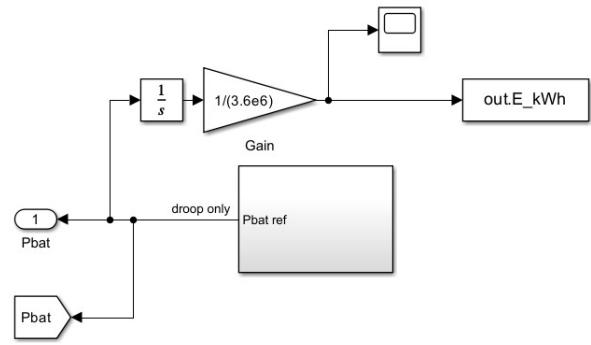


FIGURE 11 – Simulink path used to determine the energy consumed

VI. CONCLUSION

The use of MPC in this microgrid context showed overall satisfactory behavior. The controller effectively stabilized the grid frequency, even in the presence of rapid load and production variations. The control signal remained within realistic ranges, without causing excessive demand on the battery, confirming the coherence of the model and the chosen parameters.

However, these results were obtained in a simplified context, without accounting for some important physical constraints such as the state of charge (SoC) or uncertainties related to forecasts. Furthermore, the inertial role attributed to the battery does not fully reflect the real energy limitations of a storage system.

Thus, although the observed performance validates the interest of an MPC approach for frequency control, its integration into a more realistic environment would require incorporating aspects such as SoC management, power ramp limits, and robustness against unmodeled disturbances. Nevertheless, MPC remains a promising solution, offering a flexible and rigorous framework to address the stability challenges of modern electrical grids.

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