# Distributed Stochastic Model Predictive Control with Temporal Aggregation for the Joint Dispatch of Cascaded Hydropower and Renewables

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Abstract—This paper addresses the real-time energy dispatch of a hybrid system comprising cascaded hydropower plants, wind, and solar units, jointly participating in the day-ahead energy market under inflow, renewable generation, and price uncertainties. Traditional scenario-based stochastic model predictive control (MPC) faces severe computational bottlenecks due to the complexity arising from the temporal, asset, and scenario dimensions of this control problem. To address this, we propose a novel control scheme that combines time series aggregation (TSA) with distributed stochastic MPC. TSA is applied exclusively to the tail of the MPC prediction horizon to preserve real-time accuracy, while distributed optimization enables decomposition across assets and scenarios. Notably, the controller offers a formal performance guarantee through theoretically validated bounds on its approximation error. Simulations on a real-world case study confirm the controller's effectiveness, achieving a 42% reduction in execution time compared to centralized full-scale MPC.

*Index Terms*—Distributed stochastic model predictive control, time series aggregation, hydropower cascade, storage, complex systems.

# I. INTRODUCTION

The inherent stochasticity of variable renewable energy sources (vRES), such as wind and solar photovoltaic, has spurred increasing interest in their joint dispatch with controllable units [1]. Cascaded hydropower plants, which harness the water potential at multiple points along a river, have proven effective for this purpose [2]. By combining clean power generation, fast ramping capabilities, and the storage capacity of water reservoirs, cascaded hydropower plants coupled with vRES form a hybrid system capable of mitigating unforeseen power fluctuations internally, while effectively participating in energy trading [3] and providing ancillary services [4].

The efficient operation of such a hybrid system typically requires several decision-making stages, ranging from longterm planning to short-term operations and fast, reactive real-

Funded by the European Union (ERC, NetZero-Opt, 101116212). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them.

time control [5]. This paper focuses specifically on the latter stage of this sequential decision-making process.

The real-time control of hydropower plants typically operates at sub-hourly resolutions [6]. Among the available control schemes, model predictive control (MPC) [7] is the most widely employed in this context. However, when applied to the energy dispatch of cascaded hydropower-vRES (CH-vRES) hybrid systems, the high temporal resolution, the nonlinear hydropower dynamics, the hydraulic interdependencies within the cascade, and the complex interactions among heterogeneous units often render MPC computationally challenging [8]. This difficulty is further exacerbated by the various sources of uncertainty inherent in CH-vRES operations, such as water inflows, vRES generation, and market prices, typically modeled through scenarios of potential realizations [9]. The resulting stochastic MPC scheme [10] becomes intractable within the limited time available for computing real-time decisions.

To tackle this challenge, prior research has employed mathematical decomposition methods, such as dual decomposition [11], Benders decomposition [12], and augmented Lagrangian relaxation [13], to decompose the centralized MPC problem into subproblems that are solved iteratively in parallel while seeking convergence towards global optimality [14]. In the optimal dispatch of CH-vRES systems under uncertainty, existing approaches primarily focus on asset decomposition [15] (relaxing the hydraulic and power balance couplings among integrated assets) or scenario decomposition [16] (partitioning the problem across distinct scenarios). Few studies integrate both approaches within distributed stochastic MPC schemes.

Even when both asset and scenario decompositions are considered simultaneously [17], the resulting distributed scheme fails to scale with respect to the temporal dimension of the problem. Although decomposition methods could, in theory, decouple the intertemporal constraints of the water reservoirs to achieve temporal scalability, decomposing by time period would yield an impractically large number of subproblems.

Alternatively, time series aggregation (TSA) has proven effective for this task [18]. By condensing the input time series into a smaller set of representative periods, TSA yields an aggregated model that approximates the original full-scale model

while reducing computational complexity. Traditional TSA methods typically rely on clustering techniques to identify the representative periods based solely on the statistical features of the input data [19]. However, accurately representing the input space of an optimization model does not necessarily guarantee the accuracy of the aggregated model output [20]. This has sparked increasing interest in performance-guaranteed TSA methods, which focus on bounding the output error between the aggregated model and its full-scale counterpart [21]. Notably, ensuring performance guarantees in TSA under intertemporal storage constraints is particularly challenging, as the aggregated model must retain consistency with the full-scale temporal dynamics [22]. This challenge is amplified in CH-vRES problems, where the water reservoirs are characterized by both storage constraints and cascaded couplings.

To date, no approach has integrated performance-guaranteed TSA into a distributed stochastic MPC scheme to simultaneously enforce scalability across the temporal, asset, and scenario dimensions of the CH-vRES energy dispatch problem. This paper seeks to bridge this research gap.

The key contributions of this paper are as follows:

- We formulate the joint energy dispatch of cascaded hydropower plants and vRES as a scenario-based stochastic MPC problem. Then, we leverage TSA to derive a centralized stochastic MPC scheme with temporal aggregation, which maintains consistency with the full-scale intertemporal dynamics of the cascaded water reservoirs.
- By applying the alternating direction method of multipliers (ADMM) [23], the temporally aggregated centralized stochastic MPC scheme is decomposed across scenarios and assets, effectively decoupling the hydraulic and electrical coupling constraints of the CH-vRES system. This integration of MPC, TSA, and mathematical decomposition yields the proposed distributed stochastic MPC scheme with temporal aggregation, significantly reducing computational complexity across the temporal, asset, and scenario dimensions of the dispatch problem.
- We derive theoretically validated bounds on the approximation error incurred by the proposed controller relative to the original centralized, full-scale MPC scheme.

Finally, the effectiveness of the proposed controller is assessed through a case study involving the energy dispatch of a real-world CH-vRES hybrid system in France [24].

The remainder of the paper is structured as follows: Section II presents the problem, Section III details our distributed stochastic MPC scheme with temporal aggregation, Section IV discusses the results, and Section V concludes the study.

# II. PROBLEM STATEMENT

This section outlines the control problem considered.

The goal is to determine the optimal dispatch of a hybrid system comprising wind and solar units jointly operated with cascaded hydropower. Wind and solar units are treated as purely stochastic, i.e., their output cannot be controlled, whereas hydropower discharges can be dispatched to regulate both power generation and water storage in the reservoirs.

The problem is formulated as a stochastic MPC subject to water inflow, vRES power generation, and price uncertainties. Following the rolling-horizon approach, at each time period  $t \in T$ , updated forecasts are incorporated, and the MPC scheme optimizes the dispatch over a prediction horizon K, indexed by k. At the subsequent period t+1, the optimization is repeated with the prediction horizon shifted forward by one time interval. We denote by  $t+k \mid t$  a control action computed for time t+k, based on the information available at time t.

Uncertainty forecasts, denoted by the hat symbol  $\hat{\cdot}$ , are defined over a set of scenarios  $\Omega$ , indexed by  $\omega$ . We consider a CH-vRES system participating in the day-ahead energy market. Since the dispatch is solved in real time, the day-ahead energy offer, denoted  $E_{t+k}$  (MWh) for time t+k, is a fixed input to the MPC. The controller seeks to minimize imbalance penalties arising from deviations between the actual output and the scheduled offer. A dual pricing settlement is assumed, distinguishing positive imbalances (MWh),  $\delta_{\omega,t+k|t}^{e\uparrow}$  (shortfalls relative to the offer), and negative imbalances (MWh),  $\delta_{\omega,t+k|t}^{e\downarrow}$  (excess injection), with associated predicted penalty prices ( $\in$ /MWh) denoted by  $\hat{\pi}_{\omega,t+k}^{\uparrow}$  and  $\hat{\pi}_{\omega,t+k}^{\downarrow}$ , respectively.

# III. METHODOLOGY

This section outlines the proposed methodology. Subsection III-A formulates the CH-vRES dispatch as a centralized stochastic MPC problem. Subsection III-B introduces its temporally aggregated form, which underpins the distributed scheme in Subsection III-C, and Subsection III-D establishes a performance guarantee for the proposed controller.

Sets, matrices, and vectors are denoted by boldface symbols. The cardinality of a set is denoted by  $|\cdot|$ , and the Euclidean  $(\ell_2)$  norm by  $||\cdot||_2$ . The zero vector in  $\mathbb{R}^m$  is denoted by  $\mathbf{0}^m$ .

### A. Centralized Stochastic Model Predictive Control

We consider a cascade of hydropower plants indexed by  $n \in \mathbb{N}$ . Each plant comprises a set of turbines for power generation, a barrage for water diversion, and a reservoir for water storage. For plant n, the cumulative turbine and barrage discharges (m³/s) at time t+k|t in scenario  $\omega$  are denoted by  $q_{n,\omega,t+k|t}^{\mathrm{tr}}$  and  $q_{n,\omega,t+k|t}^{\mathrm{br}}$ , respectively, while the reservoir forebay water level (m) is denoted by  $l_{n,\omega,t+k|t}$ . The optimal control problem is formulated with sampling time  $\Delta$  (s).

The forebay water level dynamics of reservoir n at time t+k|t in scenario  $\omega$  are governed by the reservoir surface area  $S_n$  (m²), the inflow  $q_{n,\omega,t+k|t}^{\rm in}$  (m³/s) and outflow  $q_{n,\omega,t+k|t}^{\rm out}$  (m³/s), and its initial water level  $L_n^0$  (m), as follows:

$$l_{n,\omega,t+k|t} = l_{n,\omega,t+k-1|t} + \frac{\left(q_{n,\omega,t+k|t}^{\text{in}} - q_{n,\omega,t+k|t}^{\text{out}}\right)\Delta}{S_n},$$

$$\forall n, \forall \omega, \forall k \in \mathbf{K} \setminus \{0\}, \quad (1)$$

$$l_{n,\omega,t|t} = L_n^0, \quad \forall n, \forall \omega.$$
(2)

The inflow comprises the sum of upstream plant discharges and uncertain external inflows  $\hat{Q}_{n,\omega,t+k}^{\rm ext}$  (m³/s) from the river tributaries, while accounting for the propagation delays (s) of

water discharged from the turbines and barrage, denoted by  $\tau_{n-1,n}^{\mathrm{tr}}$  and  $\tau_{n-1,n}^{\mathrm{br}}$ , respectively, as follows:

$$q_{n,\omega,t+k|t}^{\text{in}} = q_{n-1,\omega,t+k-\tau_{n-1,n}|t}^{\text{br}} + q_{n-1,\omega,t+k-\tau_{n-1,n}|t}^{\text{tr}} + \hat{q}_{n-1,\omega,t+k}^{\text{tr}} + \hat{q}_{n-1,\omega,t+k}^{\text{ext}}, \ \forall n \in \mathbf{N} \setminus \{0\}, \forall \omega, \forall k,$$
(3)

$$q_{0,\omega,t+k|t}^{\text{in}} = \hat{Q}_{0,\omega,t+k}^{\text{ext}}, \ \forall \omega, \forall k.$$
(4)

Similarly, the outflow is given by

$$q_{n,\omega,t+k|t}^{\mathrm{out}} = q_{n,\omega,t+k|t}^{\mathrm{br}} + q_{n,\omega,t+k|t}^{\mathrm{tr}}, \ \forall n, \forall \omega, \forall k. \tag{5}$$

The following ramp limit,  $\Delta_n^{\rm tr}$  (m<sup>3</sup>/s), is enforced:

$$\left| q_{n,\omega,t+k|t}^{\text{tr}} - q_{n,\omega,t+k-1|t}^{\text{tr}} \right| \leq \Delta_n^{\text{tr}}, \ \forall n, \forall \omega, \forall k \in \mathbf{K} \setminus \{0\}.$$
 (6)

The power output  $p_{n,\omega,t+k|t}^{\rm h}$  (MW) of the n-th hydropower plant in scenario  $\omega$  at time t+k is a function of the net hydraulic head  $h_{n,\omega,t+k|t}$  (m) of the associated reservoir:

$$p_{n,\omega,t+k|t}^{h} = 10^{-6} w g \eta_n q_{n,\omega,t+k|t}^{tr} h_{n,\omega,t+k|t},$$
 (7)

where w is the water density (kg/m<sup>3</sup>), g the gravitational acceleration (m/s<sup>2</sup>), and  $\eta_n$  the plant efficiency. The factor  $10^{-6}$  converts watts to megawatts. The head is given by

$$h_{n,\omega,t+k|t} = l_{n,\omega,t+k|t} - L_n^{\text{tlr}}, \ \forall n, \forall \omega, \forall k,$$
 (8)

where  $L_n^{
m tlr}$  is the tailrace water level (m) of reservoir n. The hydropower generation function (7) is nonconvex due to its bilinear dependence on the turbine discharge and head. To restore convexity, we apply the McCormick approximation [25], replacing the bilinear term with a convex envelope:

$$\frac{p_{n,\omega,t+k|t}^{h}}{C_n} \ge \underline{Q}_n^{tr} h_{n,\omega,t+k|t} + \underline{H}_n q_{n,\omega,t+k|t}^{tr} - \underline{Q}_n^{tr} \underline{H}_n, \quad (9)$$

$$\frac{p_{n,\omega,t+k|t}^{\text{h}}}{C_n} \ge \overline{Q}_n^{\text{tr}} h_{n,\omega,t+k|t} + \overline{H}_n q_{n,\omega,t+k|t}^{\text{tr}} - \overline{Q}_n^{\text{tr}} \overline{H}_n, \quad (10)$$

$$\frac{p_{n,\omega,t+k|t}^{h}}{C_n} \le \underline{Q}_n^{tr} h_{n,\omega,t+k|t} + \overline{H}_n q_{n,\omega,t+k|t}^{tr} - \underline{Q}_n^{tr} \overline{H}_n, \quad (11)$$

$$\frac{p_{n,\omega,t+k|t}^{h}}{C_n} \le \overline{Q}_n^{tr} h_{n,\omega,t+k|t} + \underline{H}_n q_{n,\omega,t+k|t}^{tr} - \overline{Q}_n^{tr} \underline{H}_n.$$
 (12)

Here,  $C_n=10^{-6}~w~g~\eta_n$ , while  $\underline{H}_n$  and  $\overline{H}_n$  are the minimum and maximum head values (m) of reservoir n, and  $\underline{Q}_n^{\rm tr}$  and  $\overline{Q}_n^{\text{tr}}$  its minimum and maximum turbine discharges (m<sup>3</sup>/s), respectively. The McCormick approximation, illustrated in Fig. 1 for a plant with 0.95 efficiency, is widely regarded as the most accurate relaxation for bilinear functions [25].

Let  $\underline{L}_n$  and  $\overline{L}_n$  be the minimum and maximum water levels (m) of reservoir n, and  $\underline{Q}_n^{\mathrm{br}}$  its minimum barrage discharge (m³/s). Moreover, let  $\underline{P}_n^{\mathrm{h}}$  and  $\overline{P}_n^{\mathrm{h}}$  denote the plant's minimum and maximum power generation (MW). The reservoir levels, hydropower generation, and discharges are bounded by:

$$\underline{L}_n \leq l_{n,\omega,t+k|t} \leq \overline{L}_n, (13) \quad \underline{Q}_n^{\text{tr}} \leq q_{n,\omega,t+k|t}^{\text{tr}} \leq \overline{Q}_n^{\text{tr}}, (14)$$

$$\underline{Q}_n^{\text{br}} \leq q_{n,\omega,t+k|t}^{\text{br}}, (15) \quad \underline{P}_n^{\text{h}} \leq p_{n,\omega,t+k|t}^{\text{h}} \leq \overline{P}_n^{\text{h}}. (16)$$

$$\underline{Q}_n^{\text{br}} \le q_{n,\omega,t+k|t}^{\text{br}}, \quad (15) \quad \underline{P}_n^{\text{h}} \le p_{n,\omega,t+k|t}^{\text{h}} \le \overline{P}_n^{\text{h}}. \quad (16)$$

The joint dispatch of wind and solar units, whose cumulative forecasted power generation in scenario  $\omega$  at time t + k is

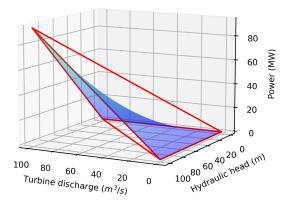


Fig. 1. Illustration of the McCormick approximation.

 $\hat{P}_{\omega,t+k}^{\mathrm{vRES}}$  (MW), together with the cascaded hydropower plants, is subject to the following energy balance constraint:

$$E_{t+k} = \sum_{n \in \mathbb{N}} p_{n,\omega,t+k|t}^{h} \Delta + \hat{P}_{\omega,t+k}^{\text{vRES}} \Delta + \delta_{\omega,t+k|t}^{e\uparrow} - \delta_{\omega,t+k|t}^{e\downarrow}, \ \forall \omega, \forall k.$$
 (17)

Let  $u_{n,t|t}$  denote the vector of control actions computed by the MPC scheme at time t for k = 0 and hydropower plant n. The decision variables are collected in the set z, defined as:

$$\boldsymbol{z} \coloneqq \left\{ \boldsymbol{u}_{n,t|t}, p_{n,\omega,t+k|t}^{\text{h}}, l_{n,\omega,t+k|t}, q_{n,\omega,t+k|t}^{\text{tr}}, q_{n,\omega,t+k|t}^{\text{br}}, q_{n,\omega,t+k|t}^{\text{br}}, \delta_{\omega,t+k|t}^{\text{e}\uparrow} \right\}_{n \in \boldsymbol{N}, \omega \in \boldsymbol{\Omega}, k \in \boldsymbol{K}}.$$

The goal is to minimize the objective function

$$F(z) := \sum_{\omega \in \Omega} \sum_{k \in K} \left( \hat{\pi}_{\omega,t+k}^{\uparrow} \delta_{\omega,t+k|t}^{\text{e}\uparrow} - \hat{\pi}_{\omega,t+k}^{\downarrow} \delta_{\omega,t+k|t}^{\text{e}\downarrow} \right)$$

$$+ \alpha \sum_{n \in N} \sum_{\omega \in \Omega} \sum_{k \in K} \left( l_{n,\omega,t+k|t} - L_{n,t+k}^{\text{ref}} \right)^{2}, \quad (18)$$

defined by two terms: a penalty for energy imbalances and a reference-tracking term to enforce desired reservoir water levels  $L_{n,t+k}^{\text{ref}}$  (m), accounting for unforeseen events or safety requirements. Here,  $\alpha \geq 0$  balances the two terms.

The centralized (full-scale) stochastic MPC scheme solves the following quadratic programming (QP) problem at time tover the prediction horizon K:

$$\min_{\mathbf{z}} F(\mathbf{z}) \tag{19a}$$

s.t. 
$$(1) - (6), (8), (17),$$
 (19b)

$$(13) - (16), (9) - (12), \forall n, \forall \omega, \forall k,$$
 (19c)

$$\left[q_{n,\omega,t|t}^{\text{br}}, q_{n,\omega,t|t}^{\text{tr}}\right]^{\top} = \boldsymbol{u}_{n,t|t}, \ \forall n, \forall \omega.$$
 (19d)

Following the rolling-horizon approach, only the first control action  $u_{n,t|t}$ ,  $\forall n$ , is implemented at each time period, and the horizon is shifted forward by one period at time t+1.

B. Centralized Stochastic Model Predictive Control with Temporal Aggregation

Solving the full-scale nonlinear stochastic energy dispatch model (19) at high temporal resolution is computationally

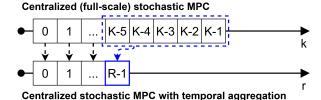


Fig. 2. Illustration of the proposed TSA method.

intensive due to the presence of intertemporal dynamics, multiple sources of uncertainty, and hydraulic cascade couplings. To alleviate this complexity, TSA is employed to construct a temporally aggregated approximation of (19), defined over a reduced set of representative periods (or clusters) R, indexed by r. When the number of clusters satisfies  $|R| \ll |K|$ , the aggregated model yields significant computational savings.

Let  $K_r \subseteq K$  denote the set of time periods assigned to cluster  $r \in R$ , with cardinality  $K_r := |K_r|$ . The optimization model (19) is reformulated over the representative periods R. For notational compactness, we write  $k \to r$  to denote that the full-scale constraints, variables, and parameters in (19), originally defined over K, are now expressed over R, with the input time series averaged over each representative period.

We group the aggregated model's decision variables in  $\bar{z}$ :

$$\begin{split} \bar{\boldsymbol{z}} \coloneqq \left\{ \boldsymbol{u}_{n,t|t}, p_{n,\omega,t+r|t}^{\text{h}}, l_{n,\omega,t+r|t}, q_{n,\omega,t+r|t}^{\text{tr}}, q_{n,\omega,t+r|t}^{\text{br}}, \\ h_{n,\omega,t+r|t}, \delta_{\omega,t+r|t}^{\text{e}\downarrow}, \delta_{\omega,t+r|t}^{\text{e}\uparrow} \right\}_{n \in N} \underset{v \in \Omega}{\underset{r \in R}{\text{re}}}. \end{split}$$

The aggregated counterpart of F(z) in (18) is defined as

$$\bar{F}(\bar{z}) := \sum_{\omega \in \Omega} \sum_{r \in R} \sum_{k \in K_r} \left( \pi_{\omega, t+k}^{\uparrow} \delta_{\omega, t+r|t}^{e\uparrow} - \hat{\pi}_{\omega, t+k}^{\downarrow} \delta_{\omega, t+r|t}^{e\downarrow} \right) 
+ \alpha \sum_{n \in N} \sum_{\omega \in \Omega} \sum_{r \in R} \left( l_{n, \omega, t+r|t} - \sum_{k \in K_r} \frac{L_{n, t+k}^{ref}}{K_r} \right)^2.$$
(20)

The centralized stochastic MPC scheme with temporal aggregation solves the following QP problem at time t, defined over the representative periods R:

$$\min_{\bar{F}} \bar{F}(\bar{z}) \tag{21a}$$

s.t. 
$$(1) - (6), (8), (17), (19d), \text{ with } k \to r,$$
 (21b)

$$(13) - (16), (9) - (12), \text{ with } k \to r, \forall n, \forall \omega, \forall r. (21c)$$

At each time period t, the dispatch is optimized over the prediction horizon K, with only the first action, computed at time t|t (i.e., k=0), being executed. Let K:=|K| and R:=|R|. To ensure accuracy in the immediate control decision, the proposed TSA method retains full resolution for the first R-1 periods of K, aggregating the remaining K-R+1 periods (the tail of the horizon) into one, as shown in Fig. 2.

C. Distributed Stochastic Model Predictive Control with Temporal Aggregation

The original centralized MPC scheme (19) involves three types of coupling constraints: (i) intertemporal coupling arising from the reservoir dynamics (1)–(2); (ii) asset coupling

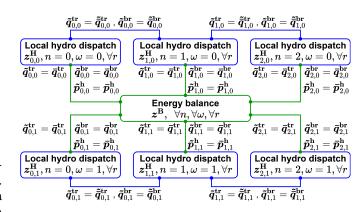


Fig. 3. The proposed decomposition in (22), with |N| = 3 and  $|\Omega| = 2$ .

induced by the hydraulic (3)–(4) and electrical (17) coupling constraints; and (iii) scenario coupling due to non-anticipativity constraints (19d). While the temporally aggregated MPC scheme (21) reduces the temporal dimensionality via TSA, asset and scenario couplings remain unaddressed, hindering scalability. To address this limitation, we develop a consensus ADMM-based decomposition of (21).

All coupling constraints in (21) involve the *global variables*  $\boldsymbol{q}^{\mathbf{tr}}_{n,\omega}\coloneqq \begin{bmatrix} q^{\mathrm{tr}}_{n,\omega,t|t},\ldots,q^{\mathrm{tr}}_{n,\omega,t+r|t},\ldots,q^{\mathrm{tr}}_{n,\omega,t+R-1|t} \end{bmatrix}^{\top},\ \boldsymbol{q}^{\mathbf{br}}_{n,\omega}\coloneqq \begin{bmatrix} q^{\mathrm{br}}_{n,\omega,t|t},\ldots,q^{\mathrm{br}}_{n,\omega,t+r|t},\ldots,q^{\mathrm{br}}_{n,\omega,t+R-1|t} \end{bmatrix}^{\top},\ \text{ and }\ \boldsymbol{p}^{\mathbf{h}}_{n,\omega}\coloneqq \begin{bmatrix} p^{\mathbf{h}}_{n,\omega,t|t},\ldots,p^{\mathbf{h}}_{n,\omega,t+r|t},\ldots,p^{\mathbf{h}}_{n,\omega,t+R-1|t} \end{bmatrix}^{\top}.$  These are collected in the global variable vector  $\boldsymbol{z}^{\mathbf{G}}_{n,\omega}$ , defined as

$$\boldsymbol{z}_{n,\omega}^{\mathbf{G}}\!\coloneqq\!\!\left[\boldsymbol{q}_{n-1,\omega}^{\mathbf{tr}},\boldsymbol{q}_{n-1,\omega}^{\mathbf{br}},\boldsymbol{q}_{n,\omega}^{\mathbf{tr}},\boldsymbol{q}_{n,\omega}^{\mathbf{br}},\boldsymbol{p}_{n,\omega}^{\mathbf{h}},\boldsymbol{q}_{n,\omega}^{\mathbf{tr}},\boldsymbol{q}_{n,\omega}^{\mathbf{br}},\boldsymbol{p}_{n,\omega}^{\mathbf{h}}\right]^{\top}\!.$$

To enable decomposition, we introduce *local copies* of the global variables in  $z_{n,\omega}^{\mathbf{G}}$ , grouped in  $\tilde{z}_{n,\omega}^{\mathbf{G}}$ :

$$\tilde{\boldsymbol{z}}_{n,\omega}^{\mathbf{G}}\!\coloneqq\!\!\left[\tilde{\boldsymbol{q}}_{n-1,\omega}^{\mathbf{tr}},\tilde{\boldsymbol{q}}_{n-1,\omega}^{\mathbf{br}},\tilde{\bar{\boldsymbol{q}}}_{n,\omega}^{\mathbf{tr}},\tilde{\bar{\boldsymbol{q}}}_{n,\omega}^{\mathbf{br}},\tilde{\boldsymbol{p}}_{n,\omega}^{\mathbf{h}},\bar{\boldsymbol{q}}_{n,\omega}^{\mathbf{tr}},\bar{\boldsymbol{q}}_{n,\omega}^{\mathbf{br}},\bar{\boldsymbol{p}}_{n,\omega}^{\mathbf{h}}\right]^{\top}\!\!.$$

By duplicating these variables, the centralized problem (21) is reformulated as the following consensus problem:

$$\min_{\bar{z}} \bar{F}(\bar{z}) \tag{22a}$$

s.t. 
$$\mathbf{z}^{\mathbf{B}} \in \mathbf{\Xi}(\boldsymbol{\beta}),$$
 (22b)

$$\boldsymbol{z}_{n,\omega}^{\mathbf{H}} \in \Gamma_{n,\omega}(\boldsymbol{\theta}_{n,\omega}), \ \forall n, \forall \omega,$$
 (22c)

$$\mathbf{z}_{n,\omega}^{\mathbf{G}} = \tilde{\mathbf{z}}_{n,\omega}^{\mathbf{G}} : \boldsymbol{\lambda}_{n,\omega}, \, \forall n, \forall \omega.$$
 (22d)

This decomposition yields two classes of subproblems: (i) the *energy balance subproblem* (22b), with decision variables

$$\boldsymbol{z}^{\mathbf{B}}\!\coloneqq\!\!\left\{\!\boldsymbol{u}_{n,t|t},\!\delta_{\omega,t+r|t}^{\mathrm{e}\downarrow},\!\boldsymbol{\delta}_{\omega,t+r|t}^{\mathrm{e}\uparrow},\!\boldsymbol{\bar{p}}_{n,\omega}^{\mathbf{h}},\!\boldsymbol{\bar{q}}_{n,\omega}^{\mathbf{tr}},\!\boldsymbol{\bar{q}}_{n,\omega}^{\mathbf{br}}\right\}_{n\in\boldsymbol{N},\omega\in\boldsymbol{\Omega},r\in\boldsymbol{R}},$$

and feasible set  $\Xi(\beta)$ , defined by (17), (14)–(16) (with  $k \to r$ ), and (19d), with parameters  $\beta$ ; and (ii)  $|N| \times |\Omega|$  local hydropower dispatch subproblems (22c), with decision variables

$$\boldsymbol{z}_{n,\omega}^{\mathbf{H}} \! := \! \left\{ \! l_{n,\omega,t+r|t}, \! h_{n,\omega,t+r|t}, \! \tilde{\boldsymbol{q}}_{n,\omega}^{\mathbf{tr}}, \! \tilde{\boldsymbol{q}}_{n,\omega}^{\mathbf{tr}}, \! \tilde{\boldsymbol{q}}_{n,\omega}^{\mathbf{br}}, \! \tilde{\boldsymbol{q}}_{n,\omega}^{\mathbf{br}}, \! \tilde{\boldsymbol{p}}_{n,\omega}^{\mathbf{h}} \! \right\}_{r \in \boldsymbol{R}},$$

and feasible set  $\Gamma_{n,\omega}(\boldsymbol{\theta}_{n,\omega})$ , defined by (1)–(6), (8), (13)–(16), and (9)–(12) (with  $k \to r$ ), with parameters  $\boldsymbol{\theta}_{n,\omega}$ . Consistency between global and local variables is ensured by the consensus constraints (22d), with associated dual variables:

$$oldsymbol{\lambda}_{n,\omega}\!\coloneqq\!\!\left[\!ar{oldsymbol{\lambda}}_{n-1,\omega}^{\mathbf{tr}}, ar{oldsymbol{\lambda}}_{n-1,\omega}^{\mathbf{br}}, ar{ar{ar{\lambda}}}_{n,\omega}^{\mathbf{tr}}, ar{ar{ar{\lambda}}}_{n,\omega}^{\mathbf{hr}}, ar{ar{\lambda}}_{n,\omega}^{\mathbf{hr}}, ar{\lambda}_{n,\omega}^{\mathbf{hr}}, ar{\lambda}_{n$$

The decomposition in (22) yields  $|N| \times |\Omega| + 1$  (temporally aggregated) subproblems, which are solved in parallel within the proposed distributed MPC scheme. Fig. 3 illustrates this decomposition, where multiple copies of the same global variables are assigned to the subproblems, forming a bipartite graph whose edges represent the consensus constraints (22d).

Reformulating the centralized problem (21) as the consensus problem (22) makes it solvable via consensus ADMM [23]. Let  $\bar{F}'\left(z^{\mathbf{B}}\right)$  denote the first term in (20), and  $\bar{F}_{n,\omega}''\left(z_{n,\omega}^{\mathbf{H}}\right)$  the second term for plant n in scenario  $\omega$ . Let  $\rho$  be the ADMM step size, and let  $i \in \mathbf{I}$  denote the iteration index, with  $I \coloneqq |\mathbf{I}|$ . Define  $\mathbf{A} \in \mathbb{R}^{8R \times 8R}$  as a diagonal matrix with a  $5R \times 5R$  identity matrix in the top-left block and zeros elsewhere, and  $\mathbf{B} \in \mathbb{R}^{8R \times 8R}$  as a diagonal matrix with a  $3R \times 3R$  identity matrix in the bottom-right block and zeros elsewhere. Applying ADMM to (22) yields the following iterative steps, executed at each time  $t \in \mathbf{T}$  over the aggregated prediction horizon  $\mathbf{R}$  within the proposed **distributed stochastic MPC scheme with temporal aggregation**.

Step I. Local primal variable update:

$$\boldsymbol{z}_{n,\omega}^{\mathbf{H}^{i+1}} \coloneqq \underset{\boldsymbol{z}_{n,\omega}^{\mathbf{H}} \in \Gamma_{n,\omega}}{\operatorname{argmin}} \left\{ \bar{F}_{n,\omega}^{"} \left( \boldsymbol{z}_{n,\omega}^{\mathbf{H}} \right) + \left( \mathbf{A} \boldsymbol{\lambda}_{n,\omega}^{i} \right)^{\top} \tilde{\boldsymbol{z}}_{n,\omega}^{\mathbf{G}} + \frac{\rho}{2} \left\| \mathbf{A} \left( \tilde{\boldsymbol{z}}_{n,\omega}^{\mathbf{G}} - \boldsymbol{z}_{n,\omega}^{\mathbf{G}^{i}} \right) \right\|_{2}^{2} \right\}, \forall n, \forall \omega, (23)$$

$$\boldsymbol{z}^{\mathbf{B}^{i+1}} := \underset{\boldsymbol{z}^{\mathbf{B}} \in \Xi}{\operatorname{argmin}} \left\{ \bar{F}'\left(\boldsymbol{z}^{\mathbf{B}}\right) + \sum_{n \in \boldsymbol{N}} \sum_{\omega \in \boldsymbol{\Omega}} \left( \left(\mathbf{B} \boldsymbol{\lambda}_{n,\omega}^{i}\right)^{\top} \tilde{\boldsymbol{z}}_{n,\omega}^{\mathbf{G}} + \frac{\rho}{2} \left\| \mathbf{B} \left( \tilde{\boldsymbol{z}}_{n,\omega}^{\mathbf{G}} - \boldsymbol{z}_{n,\omega}^{\mathbf{G}^{i}} \right) \right\|_{2}^{2} \right) \right\}. \tag{24}$$

Step II. Global primal variable update:

$$\mathbf{q}_{n,\omega}^{\mathbf{tr}\ i+1} := \frac{1}{3} \left( \tilde{\mathbf{q}}_{n,\omega}^{\mathbf{tr}\ i+1} + \tilde{\bar{\mathbf{q}}}_{n,\omega}^{\mathbf{tr}\ i+1} + \bar{\mathbf{q}}_{n,\omega}^{\mathbf{tr}\ i+1} \right), \forall n, \forall \omega, \quad (25a)$$

$$\mathbf{q}_{n,\omega}^{\mathbf{br}\ i+1} := \frac{1}{3} \left( \tilde{\mathbf{q}}_{n,\omega}^{\mathbf{br}\ i+1} + \tilde{\bar{\mathbf{q}}}_{n,\omega}^{\mathbf{br}\ i+1} + \bar{\mathbf{q}}_{n,\omega}^{\mathbf{br}\ i+1} \right), \forall n, \forall \omega, \quad (25b)$$

$$\mathbf{p}_{n,\omega}^{\mathbf{h}\ i+1} := \frac{1}{2} \left( \tilde{\mathbf{p}}_{n,\omega}^{\mathbf{h}\ i+1} + \bar{\mathbf{p}}_{n,\omega}^{\mathbf{h}\ i+1} \right), \forall n, \forall \omega. \quad (25c)$$

Step III. Dual variable update:

$$\lambda_{n,\omega}^{i+1} \coloneqq \lambda_{n,\omega}^{i} + \rho \left( \tilde{\boldsymbol{z}}_{n,\omega}^{\mathbf{G}^{i+1}} - \boldsymbol{z}_{n,\omega}^{\mathbf{G}^{i+1}} \right), \ \forall n, \forall \omega.$$
 (26)

D. Objective Function Error Bounds

The MPC scheme in Subsection III-C employs consensus ADMM to obtain a distributed, temporally aggregated solution to the centralized problem (21). Since (21) is convex, the

Algorithm 1 Performance-Guaranteed Distributed Stochastic Model Predictive Control with Temporal Aggregation

```
Input: \alpha, \beta, \gamma, \{\theta_{n,\omega}\}_{n\in N,\omega\in\Omega}, \rho, \epsilon^{\rm thr}, \bar{F}^{\rm thr}, R^0, J, I.

Output: Bounds \{F^{{\rm UB}^\star}, F^{{\rm LB}^\star}\}, and control \{u_{n,t|t}^\star\}_{n\in N}.
      1: j \leftarrow 0, R^j \leftarrow R^0, \epsilon^j \leftarrow +\infty;
     2: Invoke the high-level routine:
     3: while \epsilon^j > \epsilon^{\text{thr}} and j < J do
                              Assign the time periods k \in K to \{K_r^j\}_{r \in R^j} using
               the TSA method of Subsection III-B with R^j clusters; i \leftarrow 0, \ \left\{ \boldsymbol{z}_{n,\omega}^{\mathbf{G}^0} \leftarrow \mathbf{0}^{8R}, \boldsymbol{\lambda}_{n,\omega}^0 \leftarrow \mathbf{0}^{8R}, \forall n, \forall \omega \right\}, \ \bar{F}^0 \leftarrow +\infty;
     5:
                            Invoke the low-level routine:

while 100 \left| \frac{\bar{F}^{i+1} - \bar{F}^{i}}{\bar{F}^{i+1}} \right| > \bar{F}^{\text{thr}} \text{ and } i < I \text{ do}
\left\{ \bar{F}', \bar{F}''_{n,\omega}, \tilde{z}_{n,\omega}^{\mathbf{G}^{i+1}} \right\}_{n \in \mathbf{N}, \omega \in \Omega} \leftarrow \text{Solve (23)-(24)};
\left\{ u_{n,t|t}^{i+1}, z_{n,\omega}^{\mathbf{G}^{i+1}} \right\}_{n \in \mathbf{N}, \omega \in \Omega} \leftarrow \text{Solve (25)};
     9:
   10:
                                            \bar{F}^{i+1} \leftarrow \bar{F}' + \sum_{n \in \mathbf{N}} \sum_{\omega \in \mathbf{\Omega}} \bar{F}''_{n,\omega};
   11:
                                             i \leftarrow i + 1;
                              end while
   13:
                               \begin{aligned} & \boldsymbol{u}_{n,t|t}^{\star} \leftarrow \boldsymbol{u}_{n,t|t}^{i}, \text{ and } \bar{F}^{\star} \leftarrow \bar{F}^{i}; \\ & F^{\text{PRJ}} \leftarrow \text{Solve the centralized (full-scale) stochastic} \end{aligned} 
   15:
               problem (19) with \boldsymbol{u}_{n,t|t} = \boldsymbol{u}_{n,t|t}^{\star}, \forall n; \triangleright \text{In parallel } \forall \omega

F^{\text{LB}^{j+1}} \leftarrow \bar{F}^{\star}, and F^{\text{UB}^{j+1}} \leftarrow \min \left( F^{\text{UB}^{j}}, F^{\text{PRJ}} \right);

\epsilon^{j+1} \leftarrow 100 \frac{F^{\text{UB}^{j+1}} - F^{\text{LB}^{j+1}}}{F^{\text{UB}^{j+1}}}, \text{ and } R^{j+1} \leftarrow R^{j} + \gamma;
  16:
   17:
 19: end while
20: F^{\mathrm{UB}^{\star}} \leftarrow F^{\mathrm{UB}^{j}}, F^{\mathrm{LB}^{\star}} \leftarrow F^{\mathrm{LB}^{j}}, \text{ and } \left\{ \boldsymbol{u}_{n,t|t}^{\star} \right\}_{n \in \boldsymbol{N}};
```

ADMM-based solution converges to the optimal objective function value of the centralized problem (21) [23]. However, as (21) is itself an approximation (obtained via TSA) of the original full-scale model (19), additional analysis is required to quantify the approximation error relative to (19).

To address this issue, we provide a performance guarantee for the proposed controller in the form of upper and lower bounds, denoted by  $F^{\rm UB}$  and  $F^{\rm LB}$ , respectively, on its approximation error. This is achieved by leveraging the theoretical properties of (21), which always provides a lower bound on the optimal objective function value of the full-scale model (19), as demonstrated in [26]. To compute the upper bound, the full-scale model (19) is solved with the first-stage decisions  $u_{n,t|t}$  fixed to those derived from the aggregated model (21). Notably, once these decisions are fixed, (19) can be solved in parallel for each scenario. The proposed **performance-guaranteed distributed stochastic MPC scheme with temporal aggregation** is outlined in Algorithm 1.

Algorithm 1 consists of two distinct routines executed iteratively until convergence at each time period  $t \in T$ . The *high-level routine* computes the aggregated counterpart (21) of the full-scale model (19), using R representative periods, initially set to  $R^0$  and iteratively increased by a parameter  $\gamma$  over a

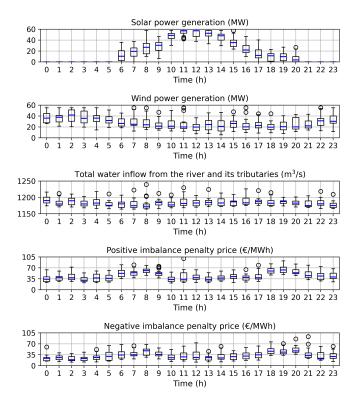


Fig. 4. Boxplots of hourly uncertainty realizations. Each boxplot characterizes the distribution of values observed at a given hour: the box spans the interquartile range, the blue line indicates the median, the whiskers extend to the 10th and 90th percentiles, and outliers are shown as individual points.

maximum of J iterations indexed by j. This aggregated model serves as input to the low-level routine, which solves (21) in a distributed manner using ADMM. Once the maximum number of iterations is reached, or if the ADMM converges (when the variation in the objective function falls below a threshold  $\bar{F}^{\mathrm{thr}}$ ) the objective value  $\bar{F}^{\star}$  (serving as a lower bound) and the optimal control actions  $u_{n,t|t}^{\star}$  (first-stage decisions) are returned to the high-level routine. An upper bound is then computed as described above. The high-level routine checks if the optimality gap (the difference between the upper and lower bounds) is below a threshold  $\epsilon^{\rm thr}$ . If so, the algorithm terminates; otherwise, it proceeds to the next iteration. Thus, Algorithm 1 integrates MPC, TSA, and mathematical decomposition to control the CH-vRES system, while simultaneously reducing computational complexity across the temporal, asset, and scenario dimensions of the dispatch problem.

# IV. SIMULATION RESULTS AND DISCUSSION

This section presents the simulations. Subsection IV-A discusses the case study and Subsection IV-B the results.

# A. Case Study Description

We consider a hybrid CH-vRES configuration that mimics a real-world system in France [13], using input data, forecasts, and parameters that replicate those of the actual system [24]. Three cascaded hydropower plants are considered with generation capacities of 160 MW, 120 MW, and 180 MW;

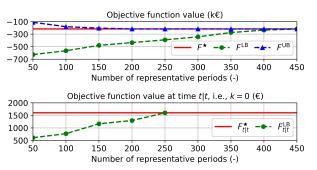


Fig. 5. Objective function bounds computed via Algorithm 1.

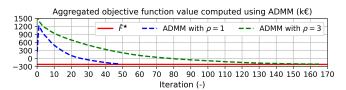


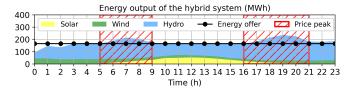
Fig. 6. Example of convergence of the low-level (ADMM-based) routine within Algorithm 1 for different values of the step size parameter  $\rho$ .

turbine discharge limits of [110; 1600], [60; 1200], and [140; 2200] m<sup>3</sup>/s; and minimum barrage discharges of 50 m<sup>3</sup>/s each. Reservoir levels range in [120; 123], [110; 112], and [95; 98] m, with tailrace levels at 115, 105, and 94 m, and surface areas of 3.13, 2.95, and 2.34 km<sup>2</sup>, respectively. All plants operate at 90% turbine efficiency, with water propagation times of 100 s (turbine) and 60 s (barrage), and a ramping limit of 300 m<sup>3</sup>/s. The initial reservoir levels are set to their respective minima. The water level references in (18) are fixed at the midpoint of their admissible ranges. The hydropower cascade is integrated with 60 MW solar and 60 MW wind units. In Algorithm 1, the parameters are set as follows:  $\alpha = 10$ ,  $\epsilon^{thr} = 1\%$ ,  $\bar{F}^{\rm thr} = 0.001\%, R^0 = 50, \gamma = 50, \rho = 1, J = 12, \text{ and}$ I=2000. The controller operates under multiple uncertainties (Fig. 4) over a 3-month simulation, with 2-minute resolution, a 24-hour prediction horizon, and 40 scenarios updated at each MPC step. To highlight the real-time performance, the energy offer is fixed at 165 MWh. The simulations are conducted on an Intel i7 CPU with 32 GB RAM using Gurobi 12.0.1.

### B. Numerical Results

An example of upper and lower bounds computed using Algorithm 1 is shown in Fig. 5. The algorithm converges to an optimality gap below 1% within 9 iterations with 450 representative periods, yielding a 37.5% reduction in temporal dimensionality relative to the original 720-period prediction horizon. As the upper bound corresponds to a feasible dispatch solution, it typically converges faster than the lower bound. Notably, only 250 representative periods are needed to recover the exact optimal cost  $(F_{t|t}^{\star})$  of the first MPC step, resulting in a 65% reduction in temporal dimensionality without loss of fidelity in the control action executed at time t|t, i.e.,  $u_{t,t|t}$ .

As detailed in Subsection III-D, Algorithm 1 utilizes an ADMM-based low-level routine to iteratively approximate the centralized controller's optimal decisions. Fig. 6 illustrates the



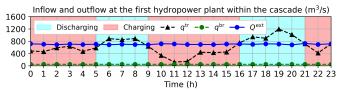


Fig. 7. Example of ex-post CH-vRES system dispatch using Algorithm 1.

routine's execution with two different  $\rho$  values, highlighting the sensitivity of the ADMM performance to parameter tuning. In the best case, the routine converges within 50 iterations.

Notably, Algorithm 1 reduces the average per-iteration MPC execution time to 262.2 seconds, compared to 453.4 seconds for the centralized full-scale MPC, yielding a **42% reduction in execution time** achieved by the proposed distributed stochastic MPC scheme with temporal aggregation.

Finally, Fig. 7 illustrates an example of ex-post CH-vRES system dispatch under Algorithm 1, where the proposed distributed MPC with temporal aggregation effectively coordinates the reservoir discharge  $(q^{\rm tr} > Q^{\rm ext})$  to maximize the output during peak price periods and recharge  $(q^{\rm tr} < Q^{\rm ext})$  during low-price or high vRES power generation periods.

# V. CONCLUSION AND FUTURE WORK

This paper presents a distributed stochastic MPC with temporal aggregation for the real-time energy dispatch of a CH-vRES hybrid system in the day-ahead market. The proposed approach improves upon centralized, full-scale stochastic MPC schemes by simultaneously reducing computational complexity across the temporal, asset, and scenario dimensions of the dispatch problem, while providing a theoretically validated performance guarantee. Simulations on a real-world system show that the proposed controller efficiently coordinates the heterogeneous assets within the hybrid system and reduces execution time by 42% relative to centralized full-scale MPC. Future work will address nonconvex dynamics and enhance the proposed TSA method toward exact TSA [20].

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