Revisiting robust model predictive control of renewable energy communities - a centralized intraday implicit tube formulation

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***Abstract*— Renewable Energy Communities management often faces significant operational uncertainty due to load variability and varying/unexpected renewable intermittency. This limits the effectiveness of classical day-ahead prediction strategies, which often increase costs due to imbalance penalties. This work revisits the robust control of Renewable Energy Communities using a centralized Model Predictive Control approach based on the robust tube paradigm. Starting from a simple photovoltaic panel and battery setup, an assumed available nominal day-ahead trajectory for a single prosumer is tracked by an intraday ancillary predictive controller that explicitly handles disturbances, physical storage dynamics, and input constraints. Robustness is studied by constructing state and input envelopes following a Monte Carlo analysis. Numerical applications in the presence of model disturbances highlight improved tracking and economic performance (despite imbalance penalties), while guaranteeing constraint satisfaction.**

I. Introduction

The increase in the decarbonization of electricity sources has enhanced the penetration of renewable energy markets, remodeling the current structures and operational strategies of the corresponding power systems [1]. In this context, Renewable Energy Communities (RECs) have emerged as a promising paradigm relying on decentralized power generation for local consumption and sharing among prosumers [2]. By enabling peer-to-peer energy exchanges, RECs aim to enhance prosumers' autonomy and reduce energy bills.

However, the decentralized and heterogeneous nature of RECs introduces significant challenges in terms of resource optimization. Community members typically exhibit diverse consumption profiles, generation capacities, and storage capabilities, which evolve and are subject to uncertainty [3]. Moreover, energy exchanges within the community must comply with physical constraints, market mechanisms, and regulatory frameworks [4], while ensuring fairness and economic efficiency among participants [5].

The optimization of energy resources in RECs, therefore, constitutes a multi-objective and multi-timescale problem. On the one hand, short-term decisions must balance supply and demand under uncertainty, accounting for renewable intermittency and demand fluctuations. On the other hand, longer-term objectives such as economic equity, billing reconciliation, and user satisfaction must be preserved across multiple market and billing periods [6]. These conflicting requirements call for advanced control and optimization strategies capable of handling constraints, uncertainty, and dynamic coupling between community members.

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Model-based optimization approaches, such as Model Predictive Control (MPC), have been widely adopted to address these challenges due to their ability to anticipate future system behavior while explicitly incorporating operational constraints [7]. Nonetheless, classical centralized MPC formulations may suffer from scalability issues and limited robustness in the presence of uncertainty [8]. This has motivated the exploration of alternative control paradigms, including robust MPC schemes [9] and learning-based approaches [10], to achieve efficient and reliable resource allocation within RECs [11].

In this work, we focus on a higher-level centralized intraday control layer, which coordinates the aggregated energy exchanges of the REC with the retailer, while assuming that prosumers may still implement local key repartition policies (for instance, using distributed control) for peer-to-peer energy balancing. The proposed framework therefore focuses on community-wide coordination rather than classical distributed local control at the individual prosumer level, aiming to ensure operational efficiency and constraint satisfaction while explicitly handling the intrinsic uncertainty and variability of renewable generation and load in community-based energy systems.

To address the limitations of classical MPC formulations, such as sensitivity to modeling errors and unknown external disturbances, which may lead to constraint violations and performance degradation, a robust tube MPC approach is considered, providing a systematic way to ensure robust constraint satisfaction by separating nominal day-ahead performance optimization from intraday feedback adjustments to unexpected but assumed-bounded disturbances [12]. The resulting measured state and input trajectories are steered to the nominal trajectories, reducing and bounding the dispersion of the disturbed trajectories, which form a "tube". This robustness design prevents excessive real-time deviations that would trigger imbalance settlements (and additional penalty costs) in day-ahead energy markets, a critical issue for conventional intraday MPC, which assumes perfect forecasts. These imbalance aspects are further studied in [13], where it is demonstrated that classical economic day-ahead/intraday MPC strategies fail to limit this undesired effect

Recent studies have highlighted that imbalance costs constitute a major operational challenge for RECs, especially under shorter market settlement periods where forecast errors directly translate into financial penalties [13]. Moreover, the interaction between energy communities and external retailers or balancing responsible parties can deteriorate overall balancing positions when local decisions neglect systemwide deviations [14].

In recent literature, tube-based model predictive control has been applied to real-time energy management in prosumer microgrids, demonstrating enhanced robustness against renewable generation and load uncertainties while maintaining economic performance [15]. A flexible tube MPC regime for decentralized microgrid communities adjusts tube geometry in real time for robustness and economy. Distributed dynamic tube MPC frameworks have been introduced for multi-microgrid systems, addressing robust intraday scheduling with reduced conservatism [16]. Tube MPC has also been explored in battery-integrated microgrid energy management [17] and building energy management with PV and storage systems [18], highlighting its versatility in handling uncertainty and constraints in renewable contexts.

Despite the existence of tube MPC approaches for microgrid energy management, two important gaps remain in the context of Renewable Energy Communities (RECs): (i) a systematic comparison of robust MPC formulations, highlighting the trade-offs between robustness and operational performance, and (ii) a framework for centralized, upper-layer coordination at the community level, where a coordinator tracks day-ahead scheduled trajectories while ensuring constraint satisfaction under bounded disturbances, rather than relying on classical distributed local control at each prosumer.

This work addresses these gaps by proposing a centralized tube MPC formulation for RECs, adjusting the intraday trajectory within a predefined day-ahead reference, assumed to be computed offline by a nominal day-ahead optimization. A systematic comparison with classical intraday MPC under identical forecast uncertainty scenarios illustrates the trade-offs between robustness, operational performance, and exposure to imbalance penalties. Although the numerical study considers a single prosumer, the framework can be extended to a multi-prosumer REC by interpreting the day-ahead reference trajectories as the aggregated state and exchange profiles of the entire community. Validation is performed through Monte Carlo simulations, highlighting the ability of the proposed approach to maintain deviations within the designed tube and limit economic penalties due to forecast errors.

The remainder of this paper is organized as follows. Section II introduces the considered REC model and the corresponding production and consumption profiles. Section III is dedicated to the intraday classical and original tube MPC problem definitions, as well as a brief practical stability analysis. Section IV presents the numerical results and the robustness analysis. Conclusions are drawn in section V.

II. Renewable Energy Community Model

A. Overview

The considered Renewable Energy Community (REC) is composed of N prosumers, each equipped with a photovoltaic (PV) system generating a power $p^{pv}(k)$ (k is the discrete time variable), a battery with state of charge (SoC) $x(k)$,

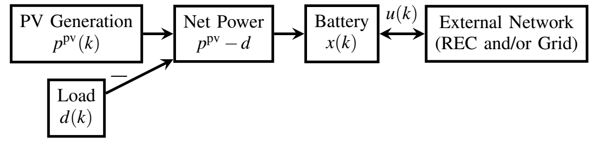

Fig. 1. Block representation of the compact prosumer model.

subject ot a specific load $d(k)$ and connected to the external network (grid). The control objective is to coordinate energy exchanges within the community, ensuring both operational efficiency and equitable distribution among prosumers.

Fig. 1 illustrates the compact prosumer model used throughout this work. The control input $u(k)$ represents the net power exchanged with the external network, while the battery absorbs the other net power residual between local PV generation and load consumption.

B. Time Structure

Comparably to the model of [6], two distinct time scales can, in general, be considered in Renewable Energy Communities:

- The market period, assimilated to the discrete-time index k, at which energy exchange decisions are taken and the system dynamics evolve.
- A longer billing horizon, typically composed of several market periods, over which economic fairness indicators may be evaluated.

In this work, however, we restrict the analysis to the intra-day (market-level) time scale. All control decisions and economic evaluations are therefore performed at the market period resolution, and no inter-day or billing-level fairness dynamics are explicitly modeled.

The introduction of a longer billing horizon, as in [6], would allow the definition of cumulative cost and equity variables across several days. Such an extension is conceptually straightforward but lies beyond the scope of the present intraday study.

C. Prosumer Power Balance

At each market period k, the net power balance of prosumer $i \in \{1,\dots,N\}$ is:

$$p_i^{\mathrm{pv}}(k)+p_i^{\mathrm{dis}}(k)+p_i^{\mathrm{imp}}(k)= \ d_i(k)+p_i^{\mathrm{ch}}(k)+p_i^{\mathrm{exp}}(k) \quad (1)$$

where $p_i^{\mathrm{pv}}(k)$ denotes the photovoltaic generation, $d_i(k)$ the electricity demand, $p_i^{\mathrm{ch}}(k)$ and $p_i^{\mathrm{dis}}(k)$ the battery charging and discharging powers, and the remaining terms represent intra-community and grid exchanges, respectively indexed by "rec" and "grid" in the following:

$$p_i^{\mathrm{imp}}(k)=p_i^{\mathrm{imp,rec}}(k)+p_i^{\mathrm{imp,grid}}(k) \quad (2a)$$
$$p_i^{\mathrm{exp}}(k)=p_i^{\mathrm{exp,rec}}(k)+p_i^{\mathrm{exp,grid}}(k) \quad (2b)$$

Internal energy exchanges within the community are assumed to balance at each market period, ensuring that the total energy exported equals the total energy imported. Equation (1) expresses classical nodal energy conservation for a prosumer connected to storage and external markets.

In the proposed control implementation, a compact formulation is adopted. All external exchanges (REC and grid) are aggregated into a single net power variable

$$u_i(k) = p_i^{\text{imp}}(k) - p_i^{\text{exp}}(k) \tag{3}$$

where $u_i(k) > 0$ denotes net import and $u_i(k) < 0$ denotes net export. The battery power demanded by the prosumer is then implicitly defined as the residual required to satisfy energy balance:

$$\begin{aligned} p_i^{\text{bat}}(k) &= p^{\text{dis}}(k) - p^{\text{ch}}(k) \\ &= d_i(k) - p_i^{\text{pv}}(k) - u_i(k) \end{aligned} \tag{4}$$

Accordingly, the simplified balance of (1) becomes

$$p_i^{\text{pv}}(k) + u_i(k) + p_i^{\text{bat}}(k) = d_i(k) \tag{5}$$

which is used to implement the actual model.

Let $x_i(k)$ denote the battery state of charge (SoC) of prosumer i at instant (market period) k. The discrete-time dynamics are

$$x_i(k+1) = x_i(k) - T_s\, p_i^{\text{bat}}(k) \tag{6}$$

which, using (4), yields

$$x_i(k+1) = x_i(k) - T_s\big(d_i(k) - p_i^{\text{pv}}(k) - u_i(k)\big) \tag{7}$$

The battery is subject to operational constraints:

$$0 \le x_i(k) \le \bar{x}_i, \tag{8}$$
$$|p_i^{\text{bat}}(k)| \le \bar{p}_i^{\text{bat}} \tag{9}$$

where, $\bar{x}_i$ is the maximum storage capacity, $p_i^{\text{bat}}(k)$ is the instantaneous power demanded from the battery (positive for discharging, negative for charging), and $\bar{p}_i^{\text{bat}}$ is the maximum charging/discharging power.

The electricity demand and photovoltaic generation are described using representative daily profiles that capture typical trends and intra-day variations for residential prosumers. Let $k \in \{0,\dots,N_d - 1\}$ denote the discrete market period index over one day, where N_d is the number of market periods within a 24-hour horizon and Δt denotes the duration of one market period.

The residential electricity demand of household i is modeled as

$$d_i(k) = \bar{d} + A_d \sin\left(\frac{2\pi}{N_d}(k - k_{\text{shift}})\right) + \sigma_d \varepsilon_i(k), \tag{10}$$

where $\bar{d}$ represents the nominal residential demand level, A_d defines the magnitude of the daily modulation, k_{shift} introduces a phase shift aligning the demand peak with evening periods, and σ_d scales the stochastic fluctuations.

The random variable $\varepsilon_i(k) \sim \mathcal{N}(0,1)$ is assumed to be independent across households and market periods and captures short-term consumption variability.

The photovoltaic generation is modeled as

$$p_i^{\text{pv}}(k) = \begin{cases} \bar{p}^{\text{pv}} \exp\left(-\dfrac{(k - k_{\text{peak}})^2}{\sigma_{\text{pv}}^2}\right), & k_{\text{sunrise}} \le k \le k_{\text{sunset}}, \\ 0, & \text{otherwise}, \end{cases} \tag{11}$$

where $\bar{p}^{\text{pv}}$ denotes the installed PV capacity, k_{peak} corresponds to the market period of maximum solar irradiance, k_{sunrise} and k_{sunset} define the daylight interval in market periods, and σ_{pv}^2 controls the spread of the generation curve.

This Gaussian-shaped formulation produces a smooth and symmetric generation profile centered around midday in market-time coordinates, while ensuring zero production outside daylight periods.

III. Model Predictive Control of RECs

This section presents a predictive control framework for renewable energy communities (RECs), integrating prosumer-level energy balancing and robustness to forecast and system uncertainties.

A. Intraday Tube MPC Formulation

Under the assumption of available optimized day-ahead reference profiles of the battery SoC and control variable obtained by a nominal predictive controller, a second intraday ancillary MPC compensates disturbances $w(k)$ by computing, at each market period k, the sequence of actual battery control inputs $\{u_i(k+j|k)\}_{j=0}^{N_p-1}$ for prosumer $i = 1,\dots,N$ over a prediction horizon N_p. The corresponding optimization problem reads:

$$\begin{aligned} \min_{\{u_i(k+j|k)\}_{j=0}^{N_p-1}} \sum_{j=0}^{N_p-1} \Big[& Q\big(x_i(k+j|k) - z_{DA,i}(k+j)\big)^2 \\ & + R\big(u_i(k+j|k) - u_{DA,i}(k+j)\big)^2 \Big] \end{aligned} \tag{12}$$

subject to:

- Battery dynamics (prediction model):

$$\begin{aligned} x_i(k+j+1|k) = \ & x_i(k+j|k) \\ & - T_s\big(d_i(k+j) - p_i^{\text{pv}}(k+j) - u_i(k+j|k)\big), \\ & j = 0,\dots,N_p - 1, \end{aligned} \tag{13}$$

  with initial condition

$$x_i(k|k) = x_i(k). \tag{14}$$

- Battery operational constraints:

$$\begin{aligned} & x_{\min} \le x_i(k+j|k) \le x_{\max}, \\ & u_{\min} \le u_i(k+j|k) \le u_{\max}, \quad j = 0,\dots,N_p - 1. \end{aligned} \tag{15}$$

where $x_i(k+j|k)$ denotes the predicted battery SoC at future time $k+j$ based on the information available at k, $u_i(k+j|k)$ is the battery control input over the horizon, $d_i(k+j)$ is the net load demand, $p_i^{\text{pv}}(k+j)$ the PV production, $z_{DA,i}(k+j)$ and $u_{DA,i}(k+j)$ are the day-ahead reference trajectories, and

Q and R are the weighting factors balancing the tracking performance and control effort.

In practice, the day-ahead net demand forecast of each household is subject to uncertainties arising from photovoltaic generation forecast errors (irradiance variability), load prediction errors (behavioral variability), and model mismatches. These uncertainties lead to deviations between the scheduled day-ahead trajectory and each household's actual intraday net demand, yielding possible imbalance costs.

Let the actual net demand of household i be affected by an additive bounded disturbance $\delta_{d,i}(k)$, that is:

$$d_i^{\text{real}}(k) = d_i(k) + \delta_{d,i}(k) \tag{16}$$

with

$$|\delta_{d,i}(k)| \le \bar{\delta}_d \tag{17}$$

The boundedness of $\delta_{d,i}(k)$ is justified by physical and operational limits. Household electricity consumption is constrained by installed electrical capacity, while photovoltaic generation cannot exceed the nominal rating of the panels and remains limited by natural irradiance conditions. Historical forecast statistics or conservative engineering estimates provide a reasonable upper bound $\bar{\delta}_d$ on the deviation magnitude.

The real (disturbed) battery dynamics of household i therefore evolve as

$$x_i^{\text{real}}(k+1) = x_i^{\text{real}}(k) - T_s\big(d_i^{\text{real}}(k) - u_i(k)\big) \tag{18}$$

$$= x_i^{\text{real}}(k) - T_s\big(d_i(k) - u_i(k)\big) - T_s\delta_{d,i}(k) \tag{19}$$

Defining the induced state disturbance

$$w_i(k) = -T_s\delta_{d,i}(k) \tag{20}$$

the disturbed dynamics can be written compactly as

$$x_i^{\text{real}}(k+1) = x_i^{\text{real}}(k) - T_s\big(d_i(k) - u_i(k)\big) + w_i(k) \tag{21}$$

where the disturbance $w_i(k)$ satisfies the bound

$$|w_i(k)| \le \bar{w}, \qquad \bar{w} = T_s\bar{\delta}_d \tag{22}$$

The intraday MPC (12), under bounded disturbance assumption, can be interpreted as a robust tube MPC [19], i.e., steering the nominal day-ahead input/state profiles in a limited neighborhood (tube) of the nominal trajectories. Persistent forecast biases or systematic deviations cannot be absorbed by the nominal reference, forcing the controller to apply corrective actions that may be unnecessarily large to satisfy constraints, inducing conservatism and poor tracking performance. To address this issue, an enhanced tube formulation is introduced in the next subsection, improving practical flexibility and, indirectly, economic performance by limiting large excursions and imbalance costs.

B. An Improved Tube MPC Formulation

To mitigate the effect of persistent forecast errors, an additional excursion of the nominal day-ahead reference trajectory z_{DA} is allowed by an optimization variable D_z, in the spirit of [20] and [21], where the additional degree of freedom on the initial nominal state improves the controller performance without altering its robustness.

Moreover, a deviation bound $\Delta_X > 0$ is introduced to restrict the admissible neighborhood around the shifted reference, thereby penalizing large excursions.

At each market period k, the following new problem is solved:

$$\begin{aligned} \min_{\{u(k+j)\}_{j=0}^{N_p-1},\, D_z(k)} \quad & \ell(x,u,D_z) \\ \text{s.t.} \quad & \text{(13)–(15)}, \\ & D_z(k) \in [-\delta_z, \delta_z], \\ & Q,R,P > 0, \end{aligned} \tag{23}$$

with

$$\begin{aligned} \ell_k(x,u,D_z(k)) = \sum_{j=0}^{N_p-1} \Big[& Q\big(x(k+j) - z_{\text{DA}}(k+j) - D_z(k)\big)^2 \\ & + R\big(u(k+j) - u_{\text{DA}}(k+j)\big)^2 \\ & + P\Big(\max\Big(0,\ |x(k+j) - (z_{\text{DA}}(k+j) + D_z(k))| - \Delta_X\Big)\Big)^2\Big]. \end{aligned} \tag{24}$$

and P is the weight of the large state excursion penalization term, while δ_z defines the maximum absolute allowed shift of the state nominal trajectory. The robust optimization problem is therefore solved over the same prediction horizon and under the same state and input limits, with the additional design elements D_z (decision variable) and Δ_X (setting parameter).

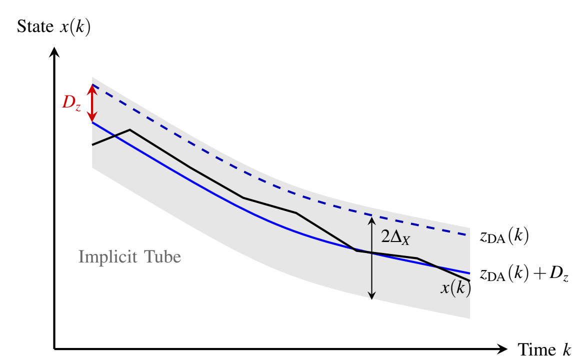

Fig. 2. Illustration of the robust tube MPC formulation. The nominal day-ahead trajectory z_{DA} is shown as a dashed line, the shifted nominal trajectory $z_{\text{DA}} + D_z$ as a solid blue line, and the admissible tube with width Δ_X is shaded. The actual battery SoC $x(k)$ (solid black line) fluctuates due to intraday disturbances but is steered to the nominal trajectory z_{DA}.

The effects of adaptive nominal reference shifting and bounded-deviation penalization are illustrated in Fig. 2.

C. Practical Stability Analysis

The proposed MPC formulation (23) enhances robustness through cost shaping rather than a classical explicit ancillary feedback law [19]. Stability is therefore established in the sense of uniform ultimate boundedness (UUB) with respect to an implicit tube set [22].

Let the tracking error be defined as

$$e_k = x(k) - z_{\mathrm{DA}}(k), \tag{25}$$

we define the modified error as

$$\tilde{e}_k = e_k - D_z(k) \tag{26}$$

where D_z satisfies the boundedness constraint from (23).

Let the optimal value function at time k be defined as

$$V_k(x_k) = \min_{\substack{\{u_{k+j|k}\}_{j=0}^{N_p-1},\\ D_{z|k}}} \sum_{j=0}^{N_p-1} \ell\left(x_{k+j|k}, u_{k+j|k}, D_{z|k}\right), \tag{27}$$

subject to the system dynamics and constraints from (23). Note that the time index is changed to variable lower indices for compactness.

We assume that recursive feasibility of the problem (23) holds since the disturbance-induced state deviation over one sampling period is bounded by $\bar{w}$, which can be compensated by the control action.

Due to the boundedness of D_z and the dead-zone parameter Δ_X, we define the target error set

$$\mathcal{E} := \{e \in \mathbb{R}^n \mid \|e\| \leq \delta_z\}, \tag{28}$$

and the enlarged set

$$\mathcal{E}_\Delta := \{e \in \mathbb{R}^n \mid \mathrm{dist}(e, \mathcal{E}) \leq \Delta_X\}. \tag{29}$$

Since Q and P are positive, there exists $\alpha > 0$ such that for all admissible (x, u, D_z),

$$\ell_k \geq \alpha\, \mathrm{dist}(e_k, \mathcal{E}_\Delta)^2. \tag{30}$$

This follows from the fact that: (i) deviations smaller than δ_z can be compensated by D_z, (ii) deviations smaller than Δ_X fall inside the dead-zone, and (iii) outside $\mathcal{E}_\Delta$ the quadratic penalties grow radially unbounded.

Considering the standard horizon-shifting argument for MPC (see [19], Corollary 1 of Proposition 3), one can construct a feasible candidate at time $k+1$ by shifting the optimal sequence and appending a feasible terminal input.

Under bounded disturbances (22), there exists $\gamma > 0$ such that

$$V_{k+1} - V_k \leq -\alpha \mathrm{dist}(e_k, \mathcal{E}_\Delta)^2 + \gamma \bar{w}^2. \tag{31}$$

Standard perturbed Lyapunov arguments (see [22]) imply that there exists

$$r_w = \sqrt{\frac{\gamma}{\alpha}}\, \bar{w}, \tag{32}$$

such that

$$\mathrm{dist}(e_k, \mathcal{E}_\Delta) \leq r_w \quad \text{for all sufficiently large } k. \tag{33}$$

Therefore, the tracking error satisfies

$$\|e_k\| \leq \delta_z + \Delta_X + r_w \quad \text{for sufficiently large } k. \tag{34}$$

The closed-loop system is thus uniformly ultimately bounded with respect to the implicit set $\mathcal{E}_\Delta$. The ultimate bound depends explicitly on the disturbance magnitude $\bar{w}$, the tube width parameter δ_z, the dead-zone parameter Δ_X, and the weighting coefficients Q and P. Although asymptotic convergence cannot be guaranteed due to persistent disturbances, the trajectories remain confined within a bounded neighborhood of the day-ahead reference trajectory.

D. Intraday Economic Evaluation

Although the MPC controllers are not designed to optimize economic objectives directly, it is informative to quantify the resulting costs, including penalties for deviations from day-ahead forecasts. The instantaneous cost at market period k for prosumer i is defined as

$$c_i(k) = \pi^{\mathrm{buy}} u_i^+(k) + \pi^{\mathrm{sell}} u_i^-(k) + \lambda_{\mathrm{pen}} |d_i(k) - u_i(k)|, \tag{35}$$

where u_i^+ and u_i^- denote charging and discharging ($u_i^- = u_i$ if $u_i < 0$ and 0 otherwise) powers, and λ_{pen} is a penalty coefficient for imbalance. The penalty coefficients, chosen for the sake of illustration, are set to $\pi^{\mathrm{buy}} = 0.30$ €/kWh, $\pi^{\mathrm{sell}} = 0.10$ €/kWh, and $\lambda_{\mathrm{pen}} = 0.50$ €/kWh.

The cumulative intraday cost over the horizon T is

$$C_i = \sum_{k=0}^{T-1} c_i(k) \tag{36}$$

providing a post-simulation economic assessment of each control strategy.

It should be noted that the MPC focuses solely on trajectory tracking and robustness to intraday disturbances, with no explicit community-level economic coordination or billing-period aggregation. Hence, the above cost is used only as a performance metric, with full economic optimization left for future work.

IV. Numerical Results

The proposed robust tube MPC was evaluated through Monte Carlo simulations ($N = 100$) on a single prosumer with PV generation and battery storage over a 24-hour horizon. The nominal day-ahead schedule assumed perfect forecasts, while intraday control faced bounded Gaussian disturbances ($|w(k)| \leq 0.7$ kW). The classical MPC solves (12) with over a horizon $N = 8$ with $T_s = 1$h, $Q = 10$, $R = 1$, $P = 10^4$, and battery limits $u_{\min} = -3$ kW, $u_{\max} = 3$ kW. The original tube MPC solves (24) with the same parameter setting, with $\delta_Z = 1.5$ kWh and $\Delta_X = 3$ kWh. These parameters were selected through preliminary tuning to balance tracking performance and robustness to forecast errors. Figure 3 shows the tracking errors and control actions. The shaded corridors depict the 5^{th} to 95^{th} percentile corridors across simulations. The classical tube MPC exhibits wider dispersion (mean width 2.26 kWh) with peak deviations exceeding ± 2 kWh, whereas the original tube MPC keeps deviations within a tighter envelope (mean width 1.02 kWh), reducing dispersion by 55% thanks to D_z. Tighter control actions translate into lower imbalance costs: the ideal day-ahead forecast, according to (36), amounts to 8.33 €, while the classical tube MPC yields 9.05 ± 0.42 €, and the original tube MPC 8.62 ± 0.25 €.

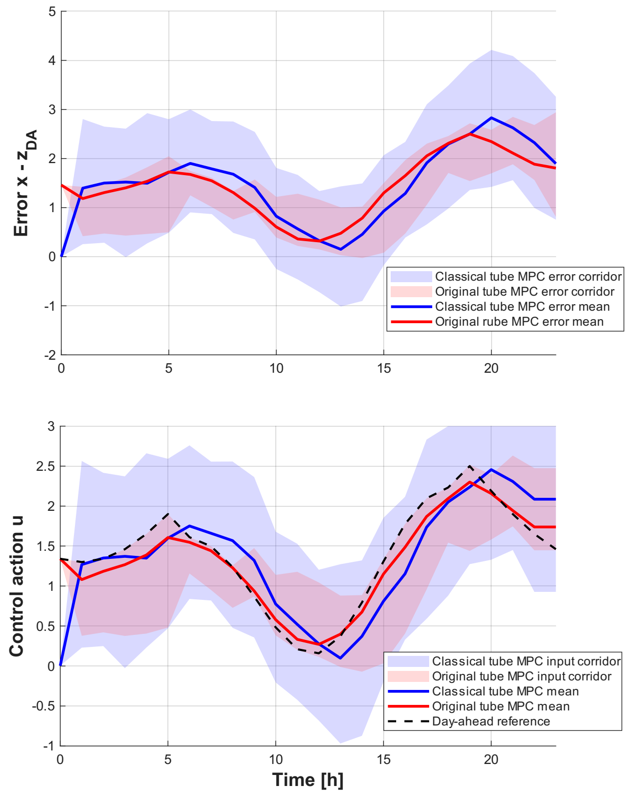

Fig. 3. Tracking error and corresponding corridor evolutions with time.

Although illustrated for a single prosumer, the formulation extends directly to a multi-prosumer REC if z_{DA} and u_{DA} represent aggregated profiles. Explicitly accounting for local peer-to-peer exchanges could further reduce bills, with distributed local control handling internal trades and the centralized MPC ensuring community-level robustness and global power balance.

V. Conclusion

An enhanced tube MPC formulation has been proposed, effectively managing intraday uncertainties of energy production and consumption in a Renewable Energy Community (REC). The additional day-ahead shifting variable, combined with a large deviation penalty, significantly reduces the operational deviations and, in turn, the economic imbalance while respecting battery and power constraints. Although the numerical validation focuses on a single prosumer, the framework naturally extends to a multi-prosumer REC using aggregated day-ahead reference trajectories, and further work entails combining the proposed strategy with a distributed control for beneficial local peer-to-peer energy exchange. Future research will also consider stronger photovoltaic intermittency induced by adverse weather conditions.

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