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Optimal Energy Management in multi-microgrids. A Scenario-Based MPC Approach

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Abstract— **In view of the advancements in microgrids technology, energy management plays an important role in optimizing energy resources and minimizing operational costs, however including distributed energy resources in the microgrids makes the system variability increase, then, an adequate control strategy is necessary for exploiting these resources appropriately. This study presents an intraday Energy Management System employing a Scenario-Based Model Predictive Controller in a multi-microgrid configuration. A hierarchical controller is proposed to minimize the economic cost of the deviations with respect to the day-ahead scheduling, in front of the uncertainty in renewable generation. The formulation guarantees a preset constraint violation probability, while simplifying the treatment of uncertainty. The results demonstrate that the approach outperforms the behavior of a deterministic Model Predictive Controller, reducing the economic costs by 16%. Moreover, it significantly reduces power deviations by up to 49%. This work highlights the potential of Scenario-Based Model Predictive Control as a promising tool for real-time multi-microgrid management, offering effective management of the uncertainty and guaranteeing probabilistic constraint satisfaction.**

I. INTRODUCTION

Over the past few years, the global energy demand has had a significant increase. Simultaneously, the adverse effects of climate change have intensified, demanding the reduction of our dependence on fossil fuels. The integration of renewable energy sources has emerged as a promising solution to address this pressing issue [1], and microgrids (MGs) have become popular due to their compatibility with Distributed Energy Resources (DERs). However, DERs introduce uncertainty into the grid, leading to congestion and imbalances. Consequently, the development of optimal Energy Management Systems (EMS) has become indispensable for effectively operating MGs. These systems play a crucial role in reducing the operational costs in both Day-Ahead (DA) and real-time [2].

Different approaches to optimal DA energy management have been studied, where the main goal is to minimize the cost of satisfying the energy demand, while guaranteeing the feasibility of the operations. For example, [3] presents a robust optimization framework to address DA operation planning for unbalanced three-phase MGs in a centralized way. Considering renewable energy systems uncertainties, in [4] a stochastic optimization approach is presented for the DA schedule. [5] proposes a DA dispatch strategy for a multi-microgrid system, offering centralized and ADMM distributed solutions. However, despite advancements in forecasting technology, prediction errors persist, introducing unbalances in intra-day operations. In fact, relying only on the DA solution, which often employs deterministic optimization methods, may prove suboptimal for real-time operations [6].

In modern EMS, a hierarchical structure is usually employed to minimize discrepancies between the scheduled plan and real-time outcomes, especially when large uncertainties are involved. [7] proposes a robust Model Predictive Controller (MPC) approach that combines the advantages of MPC and Robust Optimization (RO), allowing for the real-time energy dispatch of the MG while ensuring a reliable operation. [8] proposes an aggregator for optimally exploiting the flexibility in Electric Vehicle (EV) charging processes, to compensate for variations in Renewable sources. Likewise, [9] presents an optimal controller for a MG that maximizes the economic benefits while considering EV charge levels. This is achieved by formulating the problem as a stochastic chance-constrained optimization, which accounts for uncertainties in demand/generation predictions, EV state of charge, and connection/disconnection times.

Picking up on the hierarchical structure theme, a two-layer control scheme was put forward in [10] where the higher level optimizer runs at a slow timescale over a long time horizon and the lower level stochastic MPC runs at a faster pace, minimizing the difference between the planned energy exchange and the real one. In a similar way [11] presents a DA and intra-day multi-time scale model, using a light robust optimization program and an MPC, respectively.

Building on the concept of addressing uncertainties in optimization problems, [12] introduces a novel scenario-based MPC method that optimizes control inputs over a finite horizon while ensuring robust constraint satisfaction against a finite number of random scenarios representing the uncertainty and disturbances. Using the same concept, [13] developed a scenario-based MPC algorithm to deal with uncertainties in the energy planning of solar-thermal plants. In the same line, [14] proposes a scenario-based stochastic optimization model for determining the energy and flexibility dispatch within a residential MG. These studies collectively contribute to the ongoing exploration of effective strategies for addressing uncertainties in EMS.

In contrast to many existing approaches, including those previously mentioned, the Scenario-Based MPC (SC-MPC) strategy efficiently handles uncertainties, significantly reducing the number of scenarios needed to ensure a pre-

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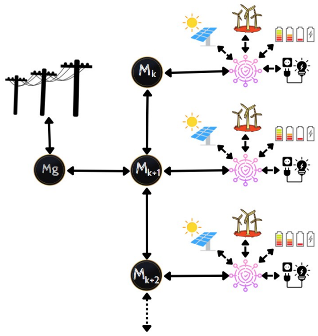


Fig. 1: Microgrid Scheme

defined constraint violation rate [12]. This paper presents an intra-day energy management approach based on a day-ahead schedule, employing SC-MPC methodology to manage uncertainties across a network of interacting MGs. The approach considers both economic cost deviations from the day-ahead plan and the expected value of required balancing power. The system comprises multiple MGs, each equipped with a set of DERs and capable of energy trading with the grid and other MGs, forming a multi-microgrid system. The proposed approach uses a hierarchical scheme for intra-day scheduling, employing a multi-objective optimization problem to track the day-ahead energy schedule and optimize balancing power requests, aiming to achieve robust behavior and improve tracking and cost efficiency.The main contributions are:

- A multi-objective optimization problem that simultaneously deals with the economic cost of the operations and the required balancing power.
- A framework to solve the proposed intra-day dispatch with a Scenario MPC approach.
- An efficient solution for managing the impact of sources uncertainty, enhancing the reliability and resilience of the multi-microgrid.

The paper is organized as follows. In Section 2, the model of the system is presented.The hierarchical scheme of the EMS and the formulation of the Scenario-Based MPC approach is described in section 3.Section 4 presents the analysis of results, followed by the conclusions in section 5.

II. System Dynamics and Constraints

This section briefly summarizes the multi-microgrid system presented in [5], properly adapting the model for the current analysis. The system configuration consists of multiple MGs. Each MG includes PV and Wind sources, Battery Energy Storage Systems (BESS), and uncontrollable loads, as shown in Fig. 1. Each MG is equipped with bidirectional meters (e.g., M_k) to monitor energy exchanges between them. At the same time, the interactions with the main grid are tracked by the meter M_g.

Each DER and load is linked to a predetermined forecast-based DA schedule, which guides the power generation and consumption profiles. In the models associated with the problem, index $k \in \Omega = 1, 2, ..., N$ represent the agents and the time index is given by $t \in \tau = 1, 2, ..., t_{end}$.

The optimization problem is subject to the following technical and electrical constraints:

- Power balance for each agent k,

$$\begin{aligned} PG^t_{buy_k} + P^t_{ES_{Dis k}} + P^t_{PV_k} + P^t_{WE_k} + \sum_{j=1}^{N} P^t_{buy_{k,j}} \quad (1) \\ = PG^t_{sell_k} + P^t_{ES_{Ch k}} + \overline{P^t_{CL_k}} + \sum_{j=1}^{N} P^t_{sell_{k,j}} \end{aligned}$$

where $PG^t_{buy_k}$ and $PG^t_{sell_k}$ are the power bought from and sold to the main grid by agent k at instant t, $P^t_{buy_{k,j}}$ and $P^t_{sell_{k,j}}$ are the power bought and sold by agent k to agent j, $\overline{P^t_{CL_k}}$ is the load forecast, $P^t_{ES_{Ch k}}$ and $P^t_{ES_{Dis k}}$ are the charge and discharge power of the BESS, $P^t_{PV_k}$ and $P^t_{WE_k}$ are the generated power from the PV and Wind sources, considering that it is possible to perform power curtailments if required.

- BESS dynamics,

$$\begin{aligned} SOC^{t+1}_{ES_k} = SOC^t_{ES_k} + \left(\frac{P^t_{ES_{Ch k}} * \eta_{ES_{Ch_k}} * \Delta_t}{Q_{max_k}}\right) \quad (2) \\ -\left(\frac{P^t_{ES_{Dis k}} * \Delta_t}{\eta_{ES_{Dis_k}} * Q_{max_k}}\right) \end{aligned}$$

$$SOC_{ES_{min k}} \leq SOC^t_{ES_k} \leq SOC_{ES_{max k}} \quad (3)$$

where the evolution of the State Of Charge (SOC) is considered with different charge and discharge efficiencies $\eta_{ES_{Ch_k}}$ and $\eta_{ES_{Dis_k}}$.

- Power curtailment in the PV and Wind sources,

$$0 \leq P^t_{PV_k} \leq \widehat{P^t_{PV_k}} \quad (4)$$

$$0 \leq P^t_{WE_k} \leq \widehat{P^t_{WE_k}} \quad (5)$$

$$t \in \tau, \quad k, j \in \Omega$$

which are limited by $\widehat{P^t_{PV_k}}$ and $\widehat{P^t_{WE_k}}$ respectively, that represents the maximum available power predicted on each system.

- Finally, the complementarity constraints on the power flows,

$$P^t_{sell_{k,j}} - P^t_{buy_{j,k}} = 0 \quad (6)$$

$$0 \leq PG^t_{buy_k} \leq PG_{buymax} * B^t_{sb_k} \quad (7)$$

$$0 \leq PG^t_{sell_k} \leq PG_{sellmax} * (1 - B^t_{sb_k}) \quad (8)$$

$$0 \leq P^t_{buy_{k,j}} \leq P_{buymax} * B^t_{sb_k} \quad (9)$$

$$0 \leq P^t_{sell_{k,j}} \leq P_{sellmax} * (1 - B^t_{sb_k}) \quad (10)$$

$$0 \leq P^t_{ES_{Ch k}} \leq P_{ES_{Chmax k}} * B^t_{es_k} \quad (11)$$

$$0 \leq P^t_{ES_{Dis k}} \leq P_{ES_{Dismax k}} * (1 - B^t_{es_k}) \quad (12)$$

$$t \in \tau, k \in \Omega$$

where (6) guarantees that the energy exchanges between MGs match, (7) to (10) prevent simultaneous energy selling and purchasing, (11) and (12) avoid charging and discharging the batteries at the same time. This is achieved through the use of binary decision variables ($B^t_{sb_k}$ and $B^t_{es_k}$).

III. intra-day Energy Management System

This section outlines the hierarchical EMS scheme for the system detailed in the preceding section, consisting of three distinct levels. The hierarchical approach aims to

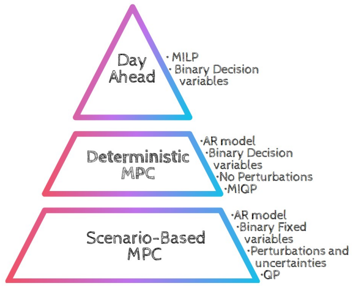


Fig. 2: Hierarchical EMS Scheme

create a robust framework for interacting and coordinating between the levels, ensuring the system's adaptability to changing conditions and effective performance optimization, as depicted in Figure 2.

At the first level, DA scheduling generates hourly consumption profiles for the entire day, informing subsequent levels of the hierarchy. DA scheduling is based on historical data or forecasted values of energy prices, power generation, and consumption. Formulated as a Mixed Integer Linear Programming (MILP) problem, it provides solutions with hourly intervals for decision variables, including binary variables. Further details on this optimization problem can be found in [5].

The second level employs a Deterministic MPC (D-MPC) approach, operating every fifteen minutes to adjust the DA schedule with high-frequency updates. This fast sampling rate enables dynamic responses, improving system performance, responsiveness, and stability. An Autoregressive (AR) model predicts the behavior of DERs affected by uncertainties like weather conditions, demand variability, price fluctuations, and load variations, leveraging historical data availability.

As a third level is proposed a SC-MPC to handle not only the dynamics but also uncertainties effectively, therefore it is possible to make more accurate predictions about future behaviors than in the D-MPC. This advanced approach not only enhances accuracy but also empowers the system to navigate uncertainties that might arise in real-time operation.

Both D-MPC and SC-MPC methods will be described in detail in the next two sub-sections, considering that the deviation economic cost is represented as the difference between the planned power exchange with the main grid in the DA and intra-day scheduling for each MG_k, as

$$J_{DC_k} = \sum_{t=t_{mpc}}^{t+T_{hzn}-1} \left[\left(PG^t_{buy_k} - \overline{PG^t_{buy_k}} \right)^2 * \overline{C^t_{buy}} - \left(PG^t_{sell_k} - \overline{PG^t_{sell_k}} \right)^2 * \overline{C^t_{sell}} \right] * \Delta_t \tag{13}$$

Where $\overline{PG^t_{buy_k}}$, $\overline{PG^t_{sell_k}}$ indicate the power exchanges with the main grid by agent k at instant t planned by the nominal DA schedule, and $\overline{C^t_{buy}}$ and $\overline{C^t_{sell}}$ are their unitary prices.

A. Deterministic Model Predictive Controller

The D-MPC serves as an intermediary between the Day-Ahead and the SC-MPC. It is formulated as a Mixed Integer Quadratic Programming (MIQP) problem. It employs autoregressive models to predict the future behavior of DERs generation and operates with a sample time of fifteen minutes, rather than one hour, and uses binary variables to deal with the non-linearity of the problem. An AR model is used to represent the behavior of each DER. These models are estimated from historical information of each time-series and assume a linear behavior of the generated/consumed power, driven by white noise ε, i.e.,

$$Y_\tau = \sum_{i=1}^{I} \Phi_i * Y_{\tau-i} + \varepsilon_\tau \tag{14}$$

and I is the order of the model.

In the D-MPC, only the expected value of each uncertain DER is considered, based on the zero-mean assumption for ε, i.e., $\widehat{Y_\tau} = E[Y_\tau]$.

Considering that the aim of MPC is to optimize the system performance by repeatedly solving an optimization problem over a prediction horizon of N sample periods (N minutes intervals), the optimization problem for the D-MPC is

$$\begin{aligned} \underset{\substack{PG^t_{buy_k}, PG^t_{sell_k}, \\ P^t_{sell_{k,j}}, P^t_{buy_{j,k}}, \\ P^t_{ESDis_k}, P^t_{ESCh_k}, \\ P^t_{PV_k}, P^t_{WE_k}, \\ B^t_{es_k}, B^t_{sb_k}}}{\text{minimize}} \quad & \sum_{k=1}^{N} J_{DC_k} \\ \text{subject to} \quad & (1), (6), (7), (8), (9), (10), (11), \\ & (12), (2), (3), (4), (5) \end{aligned} \tag{15}$$

where the upper hat bounds in (4) and (5) are given by the AR models (14), N is the number of agents,t_{mpc} and T_{hzn} in (13) represent the current control interval time and the prediction horizon time respectively.

B. Scenario-based Model Predictive Controller

SC-MPC is a powerful method for addressing uncertainties in EMS, including factors such as power generation, consumption, and pricing. In contrast to deterministic or robust approaches, SC-MPC considers a set of possible scenarios to optimize the MPC problem while ensuring a desired bound on constraint violation probability, denoted as ϵ. This flexibility simplifies uncertainty treatment, providing robust solutions for real-time variations and disturbances in dynamic environments, ensuring reliable and efficient energy dispatch even amidst unexpected changes.

However, SC-MPC faces challenges in handling non-convex optimization problems, in particular the non-linearity introduced by integer variables. To manage this issue, the D-MPC located in the second level which does not directly handle uncertainties, plays an important role in fixing the binary variables, and transforming the SC-MPC into a convex Quadratic Programming (QP) problem, allowing the use of the methodology. To formulate the SC-MPC problem in the Intraday EMS, it is considered the stochasticity and fluctuations of power generation from DERs. Where each DER's power $P^t_{DER_i}$ comprises a deterministic component $\overline{P^t_{DER_i}}$ and an uncertain variable $\widetilde{P^t_{DER_i}}$.

By incorporating this term of uncertainty in the power balance equation, the equality cannot be guaranteed for all the possible realizations of the stochastic components, then, the balance equation should be relaxed to handle unknown power contributions. A deviation bound δ is added quantifying power balance deviations as

$$-\delta \leq \sum_{t}(\overline{P^{t}_{DER_i}} + \widetilde{P^{t}_{DER_i}}) \geq \delta \tag{16}$$

where the summation is performed over all the DERs in the MG, δ and a subset of the deterministic power components $\overline{P^{i}_{DER}}$ are decision variables. In addition, a binary function $M_t \rightarrow \{0,1\}$ is established to indicate the probability of exceeding these unbalance constraints, and it is established as a constraint as

$$\mathbb{P}[\frac{1}{T}\sum_{t=1}^{T} M_t] \leq \epsilon \tag{17}$$

limiting the expected time-average of constraint violations until the specified desired violation parameter ϵ.Leveraging these premises, the problem can be solved by scenarios assuming that DERs uncertainty is generated independently and identically distributed, so SC-MPC provides strong solutions in a real-time, dynamic environment. Following [12], the number of scenarios required to guarantee a violation probability ϵ is,

$$N_{scn} = (\frac{DecisionVariables}{\epsilon}) - 1 \tag{18}$$

where the number of scenarios is directly associated with the dimension of the decision vector for the current sampling interval, not to the entire prediction horizon. Each MPC iteration generates N_{scn} different scenarios for each uncertain DER, each spanning T_{hzn} future time steps. These scenarios are created by simulating the AR model (14), where the variance of the white noise is estimated from historical data.

Then, considering the previous premises, the constraints related to the PV power source are reformulated as

$$0 \leq P^{t}_{PV_k} \leq \widehat{P^{t}_{PV_{k,scn}}} \tag{19}$$

$$\begin{aligned} -\delta^t \leq PG^{t}_{buy_k} + P^{t}_{ES_{Dis k}} + P^{t}_{PV_{k,scn}} + P^{t}_{WE_k} + \textstyle\sum_{j=1}^{N} P^{t}_{buy_{k,j}} \\ -PG^{t}_{sell_k} - P^{t}_{ES_{Ch k}} - \overline{P^{t}_{CL_k}} - \sum_{j=1}^{N} P^{t}_{sell_{k,j}} \leq \delta^t \end{aligned} \tag{20}$$

$$\delta^t \geq 0 \tag{21}$$

where the decision variable δ^t represents the balance power deviation at instant t. The scn sub-index refers to the scenario under consideration. Therefore, to mitigate the balance power deviation associated with the variations in the constraints, the balance power deviation cost component is introduced in the optimization problem as

$$J_\delta = \|\delta^t\|_2^2 * \Delta_t \tag{22}$$

Finally, the optimization problem for the SC-MPC is defined as

$$\begin{aligned} \underset{\substack{PG^{t}_{buy_k}, PG^{t}_{sell_k}, \\ P^{t}_{sell_{k,j}}, P^{t}_{buy_{j,k}}, \\ P^{t}_{ES_{Dis k}}, P^{t}_{ES_{Ch k}}, \\ P^{t}_{PV_k}, P^{t}_{WE_k}, \delta^t}}{\text{minimize}} \quad & J_\delta + \sum_{k=1}^{N} J_{DC_k} \\ \text{subject to} \quad & (6), (7), (8), (9), (10), (11), (12), (2), \\ & (3), (5), (19), (20), (21) \end{aligned} \tag{23}$$

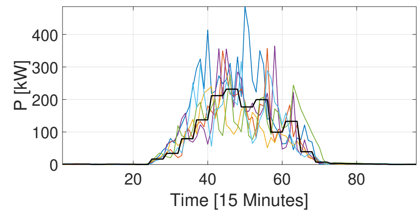


Fig. 3: Daily PV power Generation vs Day-Ahead prediction for Agent two

The resulting optimization problem is a QP problem, where the number of decision variables for each MG and time interval is related to the operation of local DERs, the power exchange with the main grid and other MGs, and the power balance deviations. On the other hand, the number of constraints corresponds to the power balance and technical limits of the DERs. The complexity of the problem grows linearly with the prediction horizon T_{hzn}, and the amount of constraints grows linearly with the number of scenarios N_{scn} required to guarantee a violation level ε in the stochastic problem. Note that the problem is convex and well structured, without binary variables, enabling it to scale with the number of agents and required scenarios.

IV. Analysis and Results

This section evaluates the performance of the intra-day EMS discussed in the previous section, using a configuration with three MGs, each one subject to different DER profiles. The operational parameters, data sets, and system characteristics are those presented in [5]. Nevertheless, taking into account that the objective is to assess the impact of uncertainty on the performance of the scenario MPC approach within the context of MG operation, this research introduces different data for the PV power sources and forecast models, considering that SC-MPC will deal only with the uncertainty in the PV power source.

For developing the AR model for the PV sources, historical data on PV generation in Bogotá, Colombia, was used. The data set was recorded with a sampling time of 2 seconds and averaged at 15-minute intervals, containing the information on PV generation for the year 2014 (35040 samples). Fig. 3 displays some daily power profiles and also the considered day-ahead prediction for agent 2. It is important to mention that Bogotá has almost the same sunlight throughout the year.

The AR model that represents the PV system's dynamic response, derived from the data set mentioned before, is given by

$$\begin{aligned} M_{pv}(\tau+1) = 0.42 * M_{pv}(\tau) + 0.11 * M_{pv}(\tau-1) \\ +0.15 * M_{pv}(\tau-2) + 0.05 * M_{pv}(\tau-3) \\ +0.04 * M_{pv}(\tau-4) + \varepsilon_{M_{pv}}. \end{aligned} \tag{24}$$

where the variance of the white noise $\varepsilon_{M_{pv}}$ driving the uncertainty model is $972kW^2$. It is to generate the scenarios in the SC-MPC.

Given the 15-minute sampling rate of the data, both D-MPC and SC-MPC are configured to operate with 96 steps

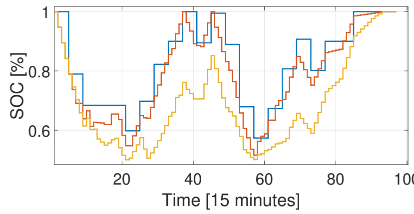


Fig. 4: Evolution of SOC of agent two for DA (blue), D-MPC (red) and SC-MPC (yellow) solutions.

per day. Moreover, when analyzing the behavior of the PV data, a prediction horizon time T_{hzn} of five hours is employed, equivalent to 20 MPC steps. The desired limit on the constraint violation probability ϵ is set as 0.1. The D-MPC and SC-MPC approaches, as formulated in (15) and (23), were implemented and simulated using MATLAB in conjunction with the YALMIP optimization modeling toolbox [15]. The optimization problems were solved using the CPLEX solver.

Since D-MPC acts as an intermediary to set the binary variables, it manages the energy exchange status between agents. This process supports the principle of complementarity, ensuring that the energy exchange between agents fulfills the system's operational constraints.

The behavior of the BESS State-of-Charge (SOC) serves as an indicator of the proper management of the MGs across DA, D-MPC, and SC-MPC. Figure 4 illustrates the SOC evolution for agent two, showing similar waveforms across all methods. However, by analyzing the statistical mean values, see Table I, SC-MPC exhibits the biggest deviation from DA, attributed to uncertainty handling. This highlights the methodology's capability to leverage BESS flexibility for real-time MGs performance optimization.

TABLE I: SOC - Performance measures for DA, D-MPC and SC-MPC solutions

	DA[SOC%]	$D-MPC$[SOC%]	$SC-MPC$[SOC%]
Agent One	0.82	0.81	0.73
Agent Two	0.83	0.79	0.69
Agent Three	0.83	0.71	0.67

Fig. 5 compares the hourly DA nominal cost with the effective economic cost of D-MPC and SC-MPC, excluding power deviation costs. The MPC solutions are consistent with respect to the DA. While controllers react to real-time data, an increase in economic cost is expected, although limited. Table I provides mean dispatch economic cost values for the three approaches, with D-MPC costs around 18% higher than DA. However, with SC-MPC incorporation, the increment is just 2.2%. These findings indicate that combining D-MPC and SC-MPC outperforms a single deterministic control strategy.

Once the dispatch economic costs are compared, the subsequent analysis examines the impact of power deviation. This parameter reflects the difference between the energy generated and consumed at a specific time, given by (20). After obtaining the results, the value of the balance power deviation bound (δ_R^t) for each approach DA, D-MPC, and SC-MPC is evaluated, given the real PV consumption. Fig. 6 describes the behavior of δ_R^t through the day showing fewer power deviations with MPC approaches. Table III presents mean δ_R^t values for each approach, where it is appreciated that as the hierarchical scheme is going forward, the values are showing a progressive decrease as the hierarchical scheme advances. This reduction signifies a positive outcome for intra-day EMS performance. With the D-MPC approach, power deviation decreased by 7.7%, and incorporating SC-MPC reduced up to 49% in the studied case.

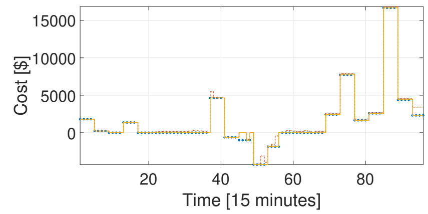


Fig. 5: Dispatch economic cost of DA (blue), D-MPC (red) and SC-MPC (yellow) approaches

TABLE II: DA, D-MPC and SC-MPC Dispatch Cost Comparison

DA [k$]	$D-MPC$ [k$]	$SC-MPC$ [k$]
327.56	386.48	334.75

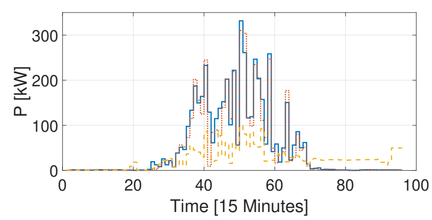


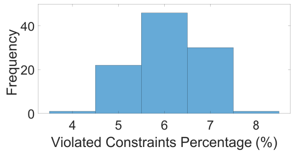
Fig. 6: Power Deviation Comparison DA (blue), D-MPC (red) and SC-MPC (yellow)

TABLE III: Mean power balance deviations for DA, D-MPC and SC-MPC solutions

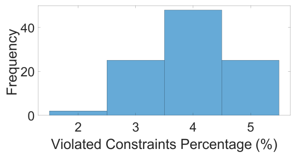
DA [kW]	$D-MPC$ [kW]	$SC-MPC$ [kW]
50.17	46.30	25.58

To validate SC-MPC effectiveness and its performance in intra-day EMS, predicted power balance deviations (δ^t) generated from (20) for each step are compared with actual deviations (δ_R^t) mentioned previously. The simulation is conducted 100 times to evaluate the SC-MPC accuracy as the primary tool in intra-day EMS. The sample mean of M_t is evaluated to analyze the statistical performance, taking into account the different white noise realizations in the PV source scenarios.

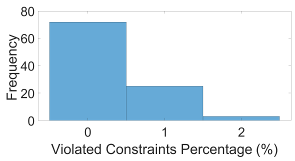
Fig. 7 displays the simulation results, each subfigure represents a different MG. The Y-axis represents the frequency of each constraint violation level, while the X-axis from (17)



(a)



(b)



(c)

Fig. 7: Violated Constraints Percentage (%), (a) MG_1 (b) MG_2 (c) MG_3

depicts the sample probability of the constraint violation. As expected, all simulations consistently remained below the imposed 10% constraint violation limit, demonstrating effective constraint management with SC-MPC methodology.

In the hierarchical scheme with DA, D-MPC, and SC-MPC, each strategy enhances the capabilities of the preceding one, leading to improved performances. Among these, SC-MPC stands out for its capability in managing random power deviations within the MGs, by using multiple scenarios in an efficient convex optimization framework, which enables it to effectively handle unpredictable fluctuations in power sources.

V. Conclusions

This work presented a hierarchical scheme for intra-day management in multi-microgrid energy systems, employing the Scenario-Based Model Predictive Control (SC-MPC) approach. The controller incorporates two concurrent MPC strategies: deterministic MPC for binary decision variables and scenario-based MPC for handling uncertainty from non-controllable DERs.

A simulation using real PV generation data is used to evaluate the performance and capabilities of the solution, demonstrating the promising potential of SC-MPC for optimizing real-time multi-microgrid operations. Performance evaluation involved three distinct MGs with varying DER profiles and dynamic conditions, comparing hourly dispatch economic costs among DA, D-MPC, and SC-MPC, as well as power deviation management. SC-MPC significantly reduces dispatch economic costs by up to 16% compared to the deterministic case.

Furthermore, the SC-MPC significantly reduces power deviations by up to 49% with the validation data, highlighting its potential as a real-time MG management tool for handling uncertainty, optimizing operations, and ensuring stability. SC-MPC consistently maintains constraint violations below the requested 10% threshold, further enhancing system reliability. In summary, SC-MPC offers a promising solution for optimizing MG operations, delivering cost savings, improved power deviation management, and robust constraint compliance. In future research, a sensitivity analysis will evaluate the impact of uncertainties associated with different DERs and the influence of seasonality on dynamic models. Additionally, exploring the feasibility of a distributed solution to parallelize scenario analysis with the aim of enhancing efficiency.

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