

Two-time-scale Congestion Management Scheme for Microgrid Integrated Distribution Networks

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Abstract—Microgrids (MGs) with high penetration of distributed generators may cause congestion in the distribution network during operation. To address this issue, this paper proposes a two-time-scale congestion management scheme for multiple MGs integrated distribution networks. Day-ahead hourly-scale dynamic congestion management (DCM) is formulated as a constrained optimization problem, which can be solved by utilizing the proposed alternating iterative method, with the privacy of both the distribution network and MGs being preserved. The sub-hourly-scale contract energy tracking aims at fully utilizing the controllable resources of the MGs to minimize the difference of the contract and actual exchanged energy between the MG and distribution network. Through coordination of the proposed two timescales of management schemes, the MGs integrated distribution networks can operate economically while avoiding the probable congestion predicament with high penetration of renewable energy. Simulation studies with a 13-bus system MGs integrated distribution network demonstrated this proposed approach is effective to manage the congestion problem in the distribution network, while the energy tracking approach can improve the welfare of the MGs engaged in energy contracts execution.

Index Terms—Alternating iterative method, congestion management, microgrids, renewable energy integration.

I. INTRODUCTION

THE distribution network (DN) is now facing power transfer capacity clapping with more and more Microgrids (MGs) being integrated into the power grids, further incurring voltage violations and thermal overloading [1], [2]. Congestion of the network occurs whenever the network is unable to accommodate all desired transactions due to physical constraint violations [3]. When multiple MGs are integrating into a DN, if not being properly managed, the limited power transfer capacity of DN will be simultaneously requested by these MGs from time to time. One may opt to reinforce

the infrastructures of the DN, yet it will significantly increase the capitalized cost. Hence, it is more imperative to develop an approach to coordinate multiple MGs within the DN for energy transactions while avoiding physically enhancing infrastructures of the DN [4]–[6].

Many methods have been proposed to solve the congestion management problem in transmission networks [7]. These congestion management methods can be categorized into two groups, direct control methods [6]–[10] and indirect control methods [11]–[13]. Generally, direct control methods are adopted in regulated energy markets while the indirect control method is commonly observed in deregulated markets. However, these methods can barely apply to DNs. There are two major differences between congestion problems in transmission networks and DNs. One of the differences lies that a transmission network is usually meshed topology, not radial topology. The other difference is that, as pointed in [14] for congestion management of a transmission network, it is required to consider the locational marginal price (LMP), but for the DN, the electricity price is equal all over the network due to regulation. Since there are a vast number of end-users in the DN, complete deregulation of the distribution market seems impractical, thus congestion management of the DN distinguishes it from the transmission network.

Several pieces of literature can be found regarding congestion management in the DN. The distribution locational marginal price (DLMP) method proposed in [15] for electrical vehicle charging is actually an extended form of the LMP used for transmission networks. In this method, the distribution system operator (DSO) determines the DLMPs while electric vehicle aggregators are treated as inactive price takers. The day-ahead dynamic tariff (DT) developed in [16] is also derived from LMP, and this DT is defined as the congestion component of the LMP. Kulmala *et al.* proposed a three-level hierarchical and distributed control concept for congestion management of DN, and their method needs to configure the control system of DN to be much the same as the transmission network, which is costly [17]. In [18], the authors suggested the optimal power flow (OPF) approach should be adopted to maintain integrity and stability of DNs. By considering that more than 90% of solar and wind plants are connected to distribution grids in Europe, the framework to develop a flexible service market for active management of distribution grids is discussed in [19], wherein the authors argued that day-ahead congestion management scheduling of MGs is more than necessary. Bai *et al.* proposed a DLMP based congestion management method that enables various distributed energy

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resources to bid in the day-ahead electricity market [20].

For existing methods of congestion management, some of them assume the DN market is fully deregulated while others suppose that energy users or MGs are inactive price takers that can only respond to the ex-ante price determined by DNs. In addition, information of these distributed energy users or MGs is, in most cases, required for carrying out an energy management schedule. This way of implementation, on one hand, is complicated or cost-ineffective since components in DN are not only owned by different entities but also are geographically scattered over the network. On other hand, since the DN tends to access inside information on them during optimization or operation, privacy of these users or MGs cannot be fully protected. Consequently, an advanced method, considering interaction of the DN and MGs while giving protection of the privacy for energy users or MGs, is desirable.

Another issue relates to congestion management of the DN is the scheduled or contract energy tracking. No matter what kind of methods are utilized, LMP, DLMP, or DT, the congestion of DN can only be avoided when price takers of the system can properly track their scheduled energy. To date, most congestion management methods only target generation or load schedule in the day-ahead time-scale level by using predicted data. However, due to the occurrence of generators' output clapping, change of load demand, and inaccuracy of forecast, the actual generation output and demand of the MGs may deviate from prediction or schedule when approaching settlement time, resulting in an energy difference between the schedule and actual transaction, i.e. unbalanced energy [19]. This deviation may lead to congestion during real-time operation and exposes the DN, MGs, and users to adverse states [21]–[23]. Consequently, the system operator usually enforces a high rate charge for imbalance energy. To minimize imbalance cost, the authors in [24] proposed a dynamic clustering method to procure flexibility from small-scale residential prosumers. Similarly, for MGs integrated into the DN, they should resort to their controllable resources to control energy imbalance to the contract during intra-day operation to avoid default. Hence, intra-day operation and day-ahead schedule of MG should coordinate with each other.

By and large, many approaches have been reported to handle the congestion management of DNs, commonly by applying DT [25], [26] and LMP methods [27] and their variations [28], [29]. Most of the methods assume the system operator can comprehend all the information and make a decision solely, which is not suitable for applications where prosumers require their privacy to be preserved. In recent years, the concept of peer-to-peer trading has been proposed for energy market applications [30], [31]. In [30], Liu *et al.* discussed a distributed day-ahead, peer-to-peer trading for multi-microgrid systems and Ullah *et al.* presented a peer-to-peer energy trading method in transactive markets considering physical network constraints [31]. However, due to the feature of the peer-to-peer communication technology, this kind of method may be significantly impacted by network condition and may pose challenges to real-world applications, which

require energy producers and consumers to respond to the environment in a timely manner.

On the other hand, the existing method, the schedule, and tracking are investigated separately. For example, the two-stage hierarchical congestion management method proposed by Luo *et al.* only targeted the day-ahead schedule [32]. The previously mentioned peer-to-peer energy trading approaches are also developed for the day-ahead schedule. To bridge the gap between day-ahead hourly schedule and sub-hourly energy tracking, this paper targets to develop a two-time scale (day-ahead hourly scale and intra-day sub-hourly scale) method that can address the congestion problem of the DN with the integration of MGs. The overarching goal of the proposed methodology is three-fold. First, it needs to enable entities of the system to optimize their welfare. Second, the privacy of each energy market participator should be preserved. Third, the contractors (MG) should follow a feasible and economic way to execute the corresponding contracts. To this end, day-ahead hourly-scale congestion management as a multi-constraint optimization problem is formulated for the first time, with DN and MGs having their own objectives and constraints that aim at optimizing their welfare. To preserve privacy of energy market participators, especially MGs, alternating iterative optimization is proposed in this paper to solve the formulated optimization problem. At last, to facilitate energy contract execution, scheduled contract energy tracking of MGs is proposed based on the optimal control approach. The proposed methodology mainly covers two phases of energy trading, i.e., scheduling (negotiation and optimization) and contract excitation (energy exchange and tracking), which fall into hourly and sub-hourly time scales, respectively.

The major contributions of this paper are summarized as follows:

- 1) A two-time-scale congestion management framework suitable for MGs integrated DNs is proposed for the first time, with the hourly-scale method targeting day-ahead DCM and the sub-hourly method aiming at intra-day energy tracking.
- 2) The day-ahead DCM problem is formulated as a serial of convex optimization problems, with the DN and MGs being treated as independent entities and the optimal solution is obtained with the DN and MGs alternatively optimizing their own objective functions via proper interactions among them.
- 3) Intra-day energy tracking of the MG is formulated as an optimal control problem with its final states being given by the schedule and its objective being minimizing its operation cost. This problem is solved by applying the Lagrangian multiplier method and rolling optimization techniques.

II. DAY-AHEAD HOURLY-SCALE DCM

An MG is connected to the DN as an individual entity, holding its own commissioned generation and load. Therefore, the energy market of the DN can be considered as the transaction and match among the main grid, DN, and MGs. Since most DNs are operated in radial topology, power transfer paths to accommodate the energy transactions are severely restricted. Accordingly, it is indispensable to determine the energy schedule in advance. As to the prosumers in the

DN, a long-term energy schedule (weekly or monthly) is not suitable since this kind of schedule is prone to be subject to unexpected changes compared to its counterpart in the transmission system. Consequently, a day-ahead hourly-scale schedule is a plausible option. MGs then can arrange their contracts with DN according to the day-ahead hourly schedule. During the energy exchange period, the MGs should follow their sealed contracts because 1) The part of the energy that goes beyond or below the contract will be charged at an extremely high rate, usually double or triple rate, e.g. the system operators in Germany charge double power exchange price for negative imbalance [33]; 2) The accumulated energy deviation of MGs from the contracts may cause congestion of the network that can be avoided if contracts are being exactly executed. Thereby, during the energy exchange period, the MGs should endeavour to track their energy contracts. The sequential operations of the proposed two-time-scale congestion management are shown in Fig. 1.

During the Discussion/Optimization section depicted in Fig. 1, the DN and MGs aim at maximizing benefits on their own behalf, and MGs respond to price signals published by the DN during each round of discussion, till the market reaches equilibrium. This mechanism will be detailed in the sequential. The discussion period is set to be finished in an hour, and when it's done, the MGs set their energy tracking settings thereafter. It should be noted the Discussion/Optimization section is put to the time-span from 9:00–10:00, which is not a mandatory option as long as enough time is left for MGs for preparation.

A. Optimization Model of the DN

The objective of the DN is to maximize its own benefits while maintaining supply-demand balance. The objective function is given as:

$$\min \sum_{t=1}^T DP^t \times P_{DB}^t + \sum_{t=1}^T \sum_{i \in M} SP^{i,t} \times P_{MS}^{i,t} - \sum_{t=1}^T \sum_{i \in M} BP^{i,t} P_{MB}^{i,t} + \sum_{t=1}^T \sum_{j=1}^{n_d} f(P_{gj}^{D,t}) \quad (1)$$

where DP^t is the buying price from the main grid, P_{DB}^t is the power purchased from the main grid. M is the set of MGs, $SP^{i,t}$ is the selling price of MG_i , $BP^{i,t}$ is the power that MG_i sells to the distribution network, $P_{MB}^{i,t}$ is the buying price of MG_i , is the power that MG_i buys from the distribution network. n_d is the set of generators in the distribution network, $P_{gj}^{D,t}$ is the generation output of these generators and $f(\cdot)$ is

the corresponding cost function. T is the number of overall operation intervals.

For the DN, it should satisfy:

$$\begin{cases} P_{DB}^t + \sum_{i \in M} P_{gj}^{D,t} - P_D^t + \sum_{i \in M} P_{MS}^{i,t} - \sum_{i \in M} P_{MB}^{i,t} = 0 & (2a) \\ -T_k^{\max} \leq \sum_{i=1}^{n-1} PTDF_{k-i}(P_G^{i,t} - P_D^{i,t}) \leq T_k^{\max} & (2b) \\ P_{gj}^{D,\min} \leq P_{gj}^{D,t} \leq P_{gj}^{D,\max} & (2c) \\ -P_j^{Rd} \leq P_{gj}^{D,t} - P_{gj}^{D,t-1} \leq P_j^{Ru} & (2d) \end{cases}$$

Equation (2a) indicates the overall power balance of the DN, with P_D^t being the load connected to the distribution network. Inequality (2b) signifies the power flow constraint, with $T_k^{\max}$ being the thermal limits of the distribution line, and the power transfer distribution factor (PTDF) [34] for node i and branch k is recorded as $PTDF_{k-i}$. $P_G^{i,t}$ and $P_D^{i,t}$ are power generation and load at node i . $P_{gj}^{D,\min}$ and $P_{gj}^{D,\max}$ are the lower and upper generation bounds of the generators in the DN. The inequality (2d) denotes the ramp rate constraints of these generators, with P_j^{Ru} and P_j^{Rd} being ramp up and down rate of j^{th} generator in a specific interval.

It should be noted, the DC-power flow model is used in this paper with the assumption that loss of the system is neglectable compared with the overall load level. Notice, by using the PTDF constraint given in (2b) the proposed approach can indirectly signify the DC power flow constraint since the PTDF is defined according to the relationship between the nodal power and the branch power of the network. The detailed derivation of PTDF is provided in Appendix A.

B. Optimization Model of MGs

MGs, depending on their operating conditions, can be categorized into two modes, i.e., load mode and generation mode. An MG can have heterogeneous devices such as gas turbine generators (GTGs), wind generators (WGs), photovoltaic arrays (PVs), energy storage systems (ESSs), etc. Here, suppose some MG, say MG_1 , is operating in the load mode, and some MG, say MG_2 , is operating in the generator mode.

To maximize the benefits of MG_1 , the objective function can be expressed as:

$$\min \sum_{t=1}^T \sum_{i=1}^{m_i} f(P_g^{i,t}) + \sum_{t=1}^T \sum_{k \in G_w} C_k^{\text{wg}} (P_k^{\text{we},t} - P_k^{\text{wg},t}) + \sum_{t=1}^T BP^{i,t} P_{MB}^{i,t} \quad (3)$$

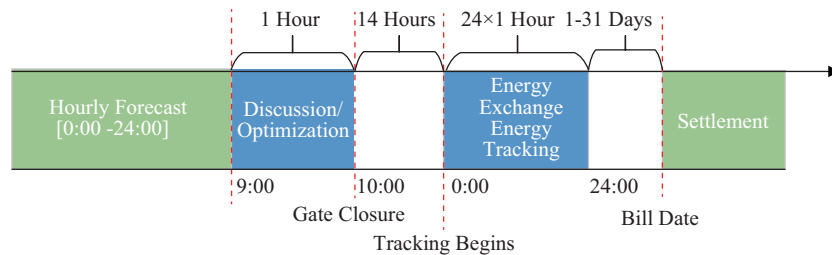


Fig. 1. Sequential operations of two-time-scale congestion management.

where m_i is the set of conventional generators (CGs) in MG_1 , G_w is the set of WGs and C_k^{wg} is the unit cost for wind energy curtailment. $P_g^{i,t}$ is the generation output of CGs in MG_1 . $P_k^{we,t}$ and $P_k^{wg,t}$ are the predicated and actual generation of WGs.

For the MG_1 , it should satisfy:

$$\begin{cases} \sum_{i \in MG_1} P_g^{i,t} + P_{MB}^{i,t} - P_L^{i,t} + \sum_{k \in G_w} P_k^{wg,t} = 0 & (4a) \\ P_g^{i,\min} \leq P_g^{i,t} \leq P_g^{i,\max} & (4b) \\ 0 \leq P_k^{wg,t} \leq P_k^{we,t}, k \in G_w & (4c) \\ -P_i^{\max} \leq P_g^{i,t} - P_g^{i,t-1} \leq P_i^{\max} & (4d) \\ P_{MB}^{i,t} \geq 0 & (4e) \end{cases}$$

Here, (4a) indicates the power balance within MG_1 should be maintained. $P_g^{i,\min}$ and $P_g^{i,\max}$ are the lower and upper generation bounds of CGs in MG_1 . The inequalities (4c) signifies the upper generation bounds of WGs. The inequality (4d) denotes the ramp rate constraint of CGs. Inequality (4e) gives that MG_1 buys energy from the DN.

Similarly, the objective function of MG_2 is given as:

$$\begin{aligned} \min \sum_{t=1}^T \sum_{i=1}^{n_i} f(P_g^{i,t}) + \sum_{t=1}^T \sum_{k \in G_s} C_k^{sg} (P_k^{se,t} - P_k^{sg,t}) \\ + AP^t \times E_n^t - \sum_{t=1}^T SP^{i,t} P_{MS}^{i,t} \end{aligned} \quad (5)$$

where n_i is the set of CGs in MG_2 , G_s is the set of PVs, C_k^{sg} is the unit cost due to disregard of solar energy. $P_g^{i,t}$ is the generation output of CGs in MG_2 . $P_k^{se,t}$ and $P_k^{sg,t}$ are the predicated and actual output of PVs. E_n^t is the charge or discharge power of ESS, and AP^t is the unit charge and discharge price of ESS. The constraints of MG_2 that should be considered are as follows:

$$\begin{cases} \sum_{i \in MG_2} P_g^{i,t} - P_{MS}^{i,t} - P_L^{i,t} + \sum_{k \in G_s} P_k^{sg,t} + E_n^t = 0 & (6a) \\ P_g^{i,\min} \leq P_g^{i,t} \leq P_g^{i,\max} & (6b) \\ 0 \leq P_k^{sg,t} \leq P_k^{se,t}, k \in G_s & (6c) \\ -P_i^{Rd} \leq P_g^{i,t} - P_g^{i,t-1} \leq P_i^{Ru} & (6d) \\ -E_{\max} \leq E_n^t \leq E_{\max} & (6e) \\ SOC_{\min} \leq SOC_{\text{init}} - \sum_{t=1}^T E_n^t \leq SOC_{\max} & (6f) \\ P_{MS}^{i,t} \geq 0 & (6g) \end{cases}$$

Here, (6a) indicates the power balance within MG_2 should be maintained. Inequality (6b) signifies the bounds for conventional generators while (6c) indicating the constraints of generation bounds for PVs. Inequality (6d) denotes the ramp rate constraint of CGs. Inequality (6e) shows that the both charge and discharge power of ESS should not exceed $E_{\max}$, while (6f) translates that SOC of the ESS should fall between $SOC_{\min}$ and $SOC_{\max}$ after T intervals' operation. Inequality (6g) indicates that MG_2 is set to sell energy to the DN.

C. Alternating Iterative Optimization-based Solution Method

For both the DN and MGs, the cost function for CGs can be represented using a quadratic function [35]:

$$\begin{aligned} f(P_{gj}^{D,t}) &= a_j^D (P_{gj}^{D,t})^2 + b_j^D P_{gj}^{D,t} + c_j^D \\ f(P_g^{i,t}) &= a^i (P_g^{i,t})^2 + b^i P_g^{i,t} + c^i \end{aligned} \quad (7)$$

Thereby, the optimization problem for either the DN or the MG is transformed to a constrained convex optimization problem given in (1, 2), (3, 4), or (5, 6). Since there is no global variable in the DCM problem, and the variables in the constraints in a specific interval only have a coupling relationship with the previous interval, thus optimization models of both the DN and MGs can be decoupled w.r.t. the time axis.

By introducing a penalty function, the Lagrangian function [36] for the distribution network optimization in (1, 2) is given as:

$$\begin{aligned} L_D(P_{DB}, P_{MB}^i, P_{MS}^i, P_{gj}^D, \lambda_E, \bar{\lambda}_C, \underline{\lambda}_C, \bar{\lambda}_g, \underline{\lambda}_g, u, v, w, z) \\ = DP \times P_{DB} + \sum_{i \in M} SP^i P_{MS}^i \\ - \sum_{i \in M} BP^i P_{MB}^i + \sum_{j=1}^{n_d} f(P_{gj}^D) \\ - \lambda_E \left(P_{DB} + \sum_{i \in M} P_{gj}^D - P_D + \sum_{i \in M} P_{MS}^i - \sum_{i \in M} P_{MB}^i \right) \\ - \sum_{k=1}^{n_b} \bar{\lambda}_{ck} \left(\sum_{i=1}^n PTDF_{k-i} (P_G^i - P_D^i) + u_k - T_k^{\max} \right) \\ - \sum_{k=1}^{n_b} \lambda_{ck} \left(\sum_{i=1}^n PTDF_{k-i} (P_G^i - P_D^i) - v_k + T_k^{\max} \right) \\ - \sum_{j=1}^{n_g} \bar{\lambda}_{gj} (P_{gj}^D + w_j - P_{gj}^{D,\max}) \\ - \sum_{j=1}^{n_g} \lambda_{gj} (P_{gj}^D - z_j - P_{gj}^{D,\min}) - \mu \sum_{k=1}^{n_b} \log(u_k) \\ - \mu \sum_{k=1}^{n_b} \log(v_k) - \mu \sum_{j=1}^{n_g} \log(w_j) - \mu \sum_{j=1}^{n_g} \log(z_j) \end{aligned} \quad (9)$$

In (10), u_k , v_k , w_k and z_k are slack variables corresponding to inequality constraints and μ is the penalty function coefficient. λ_E , $\bar{\lambda}_{ck}$, $\underline{\lambda}_{ck}$, $\bar{\lambda}_{gj}$ and $\underline{\lambda}_{gj}$ are Lagrangian multipliers, and they can associate with corresponding prices: λ_E is defined as the energy price, $\bar{\lambda}_{ck}$ is the forward flow congestion price, $\underline{\lambda}_{ck}$ is the backward flow congestion price, $\bar{\lambda}_{gj}$ is the difference between the upper bound marginal cost of the generator and the energy price, and $\underline{\lambda}_{gj}$ is the difference between the lower bound marginal cost of the generator and the energy price.

For MG_1 , the Lagrangian function can be written as:

$$\begin{aligned} L_M(P_{MB}^1, P_g^i, P_k^{wg}, \bar{\lambda}_g, \underline{\lambda}_g, \bar{\lambda}_{wg}, \underline{\lambda}_{wg}, u, v, w, z, \chi, \lambda_{E_1}, \Delta_{MB}) \\ = BP^1 P_{MB}^1 + \sum_{i=1}^{m_1} f(P_g^i) + \sum_{k \in G_w} C_k^{wg} (P_k^{we} - P_k^{wg}) \\ - \lambda_{E_1} \left(\sum_{i \in MG_1} P_g^i + P_{MB}^1 - P_L^1 + P_k^{wg} \right) \end{aligned}$$

$$\begin{aligned}
& - \sum_{i=1}^{m_i} \bar{\lambda}_{gi}(P_g^i + u_i - P_g^{i\max}) \\
& - \sum_{i=1}^{m_i} \lambda_{gi}(P_g^i - v_i - P_g^{i\min}) - \bar{\lambda}_{wg}(P_k^{wg} + w_k - P_k^{we}) \\
& - \lambda_{wg}(P_k^{wg} - z_k) - \lambda_{MB}(P_{MB} - \gamma_k) - \mu \sum_{i=1}^{m_i} \log(u_k) \\
& - \mu \sum_{i=1}^{m_1} \log(v_k) - \mu \log(w_k) - \mu \log(z_k) - \mu \log(\chi)
\end{aligned} \quad (10)$$

And for MG₂, the Lagrangian function is:

$$\begin{aligned}
L_M(P_{MS}^2, P_g^i, P_k^{sg}, E_n, \bar{\lambda}_g, \lambda_g, \bar{\lambda}_{sg}, \lambda_{sg}, \bar{\lambda}_{E_n}, \lambda_{E_n}, \\
u, v, p, q, r, s, \chi, \lambda_{E_2}, \lambda_{MS}) \\
= -SP^2 P_{MS}^2 + \sum_{i=1}^{m_2} f(P_g^i) + \sum_{k \in G_s} C_k^{sg}(P_k^{se} - P_k^{sg}) \\
+ AP^t \times E_n^t \\
- \lambda_{E_2} \left(\sum_{i \in MG_2} P_g^i - P_{MS}^i - P_L^i + P_k^{sg} + E_n \right) \\
- \sum_{i=1}^{m_2} \bar{\lambda}_{gi}(P_g^i + u_i - P_g^{i\max}) \\
- \sum_{i=1}^{m_2} \lambda_{gi}(P_g^i - v_i - P_g^{i\min}) - \bar{\lambda}_{sg}(P_k^{sg} + p_k - P_k^{se}) \\
- \lambda_{sg}(P_k^{sg} - q_k) - \bar{\lambda}_{E_n}(E_n + r_n - E_{\max}) \\
- \lambda_{E_n}(E_n - s_n + E_{\max}) - \lambda_{MS}(P_{MS} - \chi) \\
- \mu \sum_{i=1}^{m_2} \log(u_k) - \mu \sum_{i=1}^{m_2} \log(v_k) - \mu \log(p_k) \\
- \mu \log(q_k) - \mu \log(r_n) - \mu \log(s_n) - \mu \log(\chi) \quad (11)
\end{aligned}$$

The parameters in (10) and (11) are defined in a similar way as that in (9). We can solve the equations of the Karush-Kuhn-Tucker (KKT) conditions for the Lagrangian functions given in (9), (10), and (11), to obtain the corresponding optimal solutions for the DN and MGs, correspondingly.

During each round of optimization, the DN will calculate the expected energy exchange with MGs, i.e., P_{MB}^i and P_{MS}^i , aiming at maximizing its own benefits. The MG, on the other hand, will adjust its controllable resources to maximize its own welfare, which yields its declared buying or selling amount. To distinguish these terms with the calculated values of the DN, we denote them with $P_{MB}^{i,m}$ and $P_{MS}^{i,m}$. During the discussion period, the DN updates the buying and selling prices according to [37]:

$$\begin{cases} SP^i[k+1] = SP^i[k] - \alpha(P_{MS}^{i,m} - P_{MS}^i) \\ BP^i[k+1] = BP^i[k] + \alpha(P_{MB}^{i,m} - P_{MB}^i) \end{cases} \quad (12a)$$

$$\quad (12b)$$

Here, α is the step size. By applying the price update mechanism given in (12), the DN can regulate energy selling or buying from MGs. If the declared buying energy of MGs is greater than DN expected, the DN will try to increase the selling price SP^i , and vice versa. Then the DN and MGs alternatively optimize their own welfares to obtain the updated

$P_{MS}^i, P_{MB}^i, P_{MS}^{i,m}, P_{MB}^{i,m}$. This alternating iterative optimization process will terminate when the following conditions are satisfied:

$$\left| P_{MS}^{i,m} - P_{MS}^i \right| < \varepsilon, \quad \left| P_{MB}^{i,m} - P_{MB}^i \right| < \varepsilon \quad (13)$$

where ε is a predefined small number.

Note, if (13) is satisfied, the buying or selling prices also converge, hence the market reaches equilibrium.

The overall alternating iterative optimization-based solution method can be summarized as follows.

Step 1: DN estimates the net power generation or load of each MG and sets the buying and selling prices for MGs.

Step 2: DN informs MGs of the prices for buying or selling.

Step 3: Each MG optimizes its generation according to its own operating conditions, i.e., the overall generation and load demand, then sends its intermediate power schedule back to the DN.

Step 4: DN adjusts the prices for buying and selling according to the unbalanced amount of the power between its own estimates and the declared amount of the MGs and updates selling and buying prices for each MG according to (13).

Step 5: Repeat the above steps until the market-clearing price is reached, i.e., supply-demand balance is achieved, and prices of each interval are all converged.

It is worth to pointing out, in the proposed day-ahead dynamic approach, the DN regulates the energy consumption of the MGs via the proper setting of the price signals. The interaction of the DN and MGs follows the above five-step procedures, which is also illustrated in Fig. 2.

III. SCHEDULED CONTRACT ENERGY TRACKING OF MGs

As discussed previously, the aim of the sub-hourly contract energy tracking of an MG is to minimize the energy difference between the schedule and actual generation, that is to say, in the end of each contract interval (one hour), the actual yield of the MG should be controlled to reach the predetermined scheduled value. Here, an interval of one hour is further divided into 4 sub-hourly epochs with each epoch lasting 15 min to solve this optimal control problem. Fig. 3 shows the schematic diagram of this optimal control problem.

For the MG, the hourly reference of exchanged energy with the DN in a specific dispatch interval, say, interval T , is given by the day-ahead scheme and it is denoted with E^T , as shown in Fig. 3. Generation references of the controllable generators of the MG are updated every 15 min such that actual energy yield will match the energy contract at the end of the dispatch interval. Mark the four epochs in one hour with numbers from 0 to 3. In Fig. 3, $E_m(k|T)$ ($k = 0, 1, 2, 3$) denotes the energy that should be accumulated by the MG in the remaining epochs at the beginning of the k^{th} epoch of interval T and $E_a(k|T)$ denotes the actual net energy yield of the MG at the end of epoch k . At the beginning of epoch 0, the MG predicts its load curve and the renewable generation for the coming hour (4 epochs), then sets the optimized generation references according to energy difference $E_m(0|T)$. Similarly, at the beginning of epoch 1, the MG predicts the load curve and the renewable generation in the following 45 min (3 epochs)

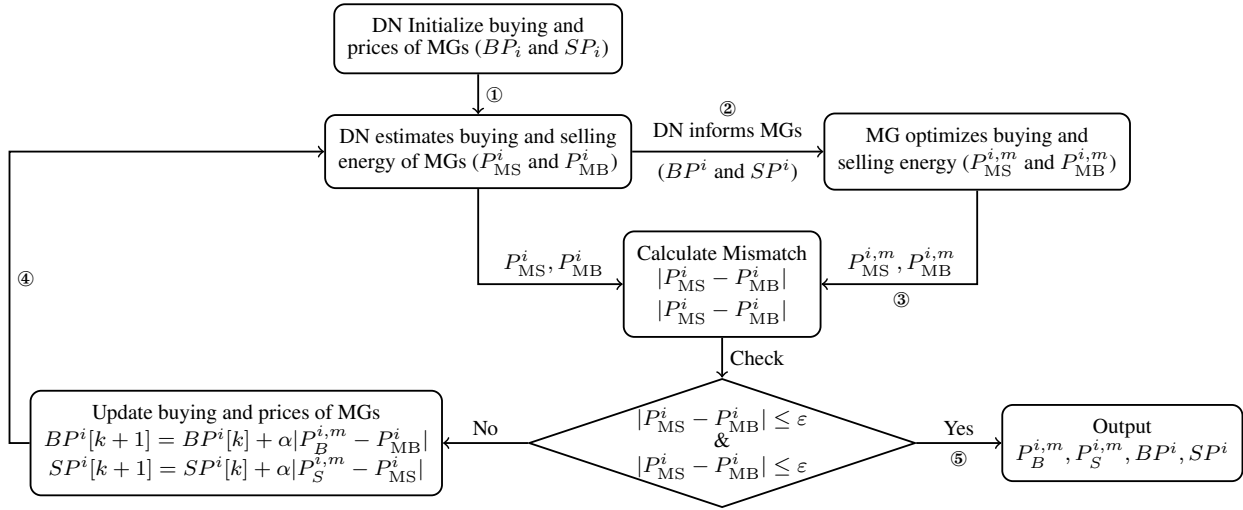


Fig. 2. Structure of day-ahead hourly optimization framework.

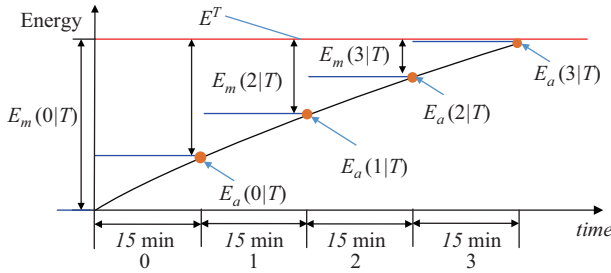


Fig. 3. Optimal control diagram within one hour.

and optimizes generation settings. The same logic applies to epochs 2 and 3. Here, for the duration of an epoch being 15 min, one needs to solve the optimal control problem at every beginning of the epoch, with a total of four times in an hour. In the following context, the solution method to this optimal control problem will be developed based on the Lagrangian multiplier method.

At the beginning of epoch k , the predicted net energy produced by the uncontrollable components in the MG for the remaining epochs is the summation of the energy produced by the renewable generators and energy consumed by loads, and we denote it with $E_{\text{pre}}(k|T)$. Accordingly, the energy that needs to be provided by controllable generators is:

$$E_g(k|T) = E_m(k|T) - E_{\text{pre}}(k|T) \quad (14)$$

In (14), $E_m(k|T)$ can be calculated as:

$$E_m(k|T) = E^T - E_a(k-1|T) \quad (15)$$

where $E_a(k-1|T)$ is the actual accumulated exchanged energy of MG with DN from epoch 0 to epoch $k-1$.

At the beginning of every epoch, the $E_g(k|T)$ can be calculated according to (14) and (15), the MG then initiates another round of optimization to obtain the optimal generation settings of its controllable generators according to the following developed method.

Without loss of generality, it is assumed that an hour is divided into N epochs, with each epoch being $60/N$ minutes.

Starting from k^{th} epoch, energy accumulated from the following epoch t ($t = 1, 2, \dots, N-k$) can be expressed in a discrete form as:

$$E(t) = E(t-1) + \mathbf{1}^T \mathbf{P}_G(t) \quad (16)$$

where $\mathbf{1}$ is the column vector of all ones, $\mathbf{P}_G(t) = [P_{G1}(t), P_{G2}(t), \dots, P_{Gn_g}(t)]$ is the vector composed of the power output of the controllable generators, with n_g being the number of these controllable generators.

Obviously, the initial value, $E(0)$, is equal to zero. Starting from k^{th} epoch, there are $N-k$ epoch left for the MG to accumulate energy, and the final state, $E(N-k)$ should equal the predicted reference, $E_g(k|T)$. These two constraints can be summed up as:

$$\begin{cases} E(0) = 0 \\ E(N-k) = E_g(k|T) \end{cases} \quad (17a) \quad (17b)$$

The goal of optimal control is to track the energy reference with minimal cost. Here, cost is the overall generation cost of the controllable generators in the MG and the cost function of the generator is the same as that given in (8), which is rewritten as:

$$f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad (i = 1, 2, \dots, n_g) \quad (18)$$

The overall generation cost can be written as:

$$J = \sum_{t=0}^{n-k} \sum_{i=1}^{n_g} f_i(P_{Gi}[t]) \quad (19)$$

Therefore, the sub-hourly contract energy tracking problem for MG is formulated as an optimal control problem to minimize the performance index J given in (19). To solve this optimal control problem, we first provide the corresponding auxiliary functional to this optimal problem:

$$J_0 = \sum_{t=0}^{n-k} \left\{ \sum_{i=1}^{n_g} f_i(P_{Gi}[t]) - \lambda(t+1)[E(t) + \mathbf{1}^T \mathbf{P}_G(t) - E(t+1)] \right\} \quad (20)$$

Define L_t and L_{t-1} as:

$$L_t = \sum_{i=1}^{n_G} f_i(P_{Gi}[t]) - \lambda(t+1)[E(t) + \mathbf{1}^T \mathbf{P}_G(t) - E(t+1)] \quad (21)$$

$$L_{t-1} = \sum_{i=1}^{n_G} f_i(P_{Gi}[t-1]) - \lambda(t)[E(t-1) + \mathbf{1}^T \mathbf{P}_G(t-1) - E(t)] \quad (22)$$

Then, the Euler-Lagrange equation corresponding to the optimal control problem is given as:

$$\begin{cases} \frac{\partial J_0}{\partial E(t)} = \frac{\partial L_t}{\partial E(t)} + \frac{\partial L_{t-1}}{\partial E(t)} = 0 \\ \frac{\partial J_0}{\partial P_{Gi}(t)} = \frac{\partial L_t}{\partial P_{Gi}(t)} + \frac{\partial L_{t-1}}{\partial P_{Gi}(t)} = 0 \end{cases} \quad (23a)$$

$$(i = 1, 2, \dots, n_G) \quad (23b)$$

Since $\partial L_t / \partial E(t) = -\lambda(t+1)$, $\partial L_t / \partial E(t) = \lambda(t)$; $\partial L_t / \partial P_{Gi}(t) = a_i P_{Gi}(t) + b_i - \lambda(t+1)$, $\partial L_{t-1} / \partial P_{Gi}(t) = 0$, (23) can be rewritten as:

$$\begin{cases} \lambda(t+1) - \lambda(t) = 0 \\ 2a_i P_{Gi}(t) + b_i - \lambda(t+1) = 0 \end{cases} \quad (24a)$$

$$(24b)$$

Solving (24) yields:

$$\lambda(t) = \lambda^* = \text{cons.} \quad (25)$$

$$P_{Gi}(t) = (\lambda^* - b_i) / 2a_i \quad (26)$$

Substituting (25) and (26) in (16) yields:

$$E(t+1) = E(t) + \lambda^* \sum_{i=1}^{n_G} \frac{1}{2a_i} - \sum_{i=1}^{n_G} \frac{b_i}{2a_i} \quad (27)$$

By applying (17), one can have:

$$E(N-k) = (N-k) \left(\lambda^* \sum_{i=1}^{n_G} \frac{1}{2a_i} - \sum_{i=1}^{n_G} \frac{b_i}{2a_i} \right) \quad (28)$$

and λ^* is calculated as:

$$\lambda^* = \left(\frac{E(N-k)}{N-k} + \sum_{i=1}^{n_G} \frac{b_i}{2a_i} \right) / \left(\sum_{i=1}^{n_G} \frac{1}{2a_i} \right) \quad (29)$$

The optimal control law then is given as:

$$P_{Gi}(t) = \left(\frac{E(N-k)}{N-k} + \sum_{i=1}^{n_G} \frac{b_i}{2a_i} - b_i \sum_{i=1}^{n_G} \frac{1}{2a_i} \right) / \left(2a_i \sum_{i=1}^{n_G} \frac{1}{2a_i} \right) \quad (30)$$

and the corresponding optimal trajectory of the energy is:

$$E(t) = \frac{E(N-k)}{N-k} t \quad (31)$$

As can be seen from (31), the optimal control law results in equal distribution of energy within the follow-up epochs. Assume there are n epochs left to accumulate the energy of E , the quantity of the energy that should be accumulated in each epoch satisfies:

$$\Delta E(1) = \Delta E(2) = \dots = \Delta E(n) = E/n \quad (32)$$

As can be seen from (24b), generation of the controllable generators is allocated such that marginal costs of them ($\dot{f}(P_{Gi}) = 2a_i + b_i$) are all the same in the following epochs, i.e.:

$$\dot{f}(P_{G1}) = \dot{f}(P_{G2}) = \dots = \dot{f}(P_{Gn_g}) = \lambda^*(t) \quad (33)$$

At the beginning of a specific epoch, the optimal control law maintains the generation settings of controllable generators unchanged in subsequent epochs, yielding a shape of horizontal lines of generation references for these generators, with the load being shared among them via equal marginal cost principle. Yet, due to prediction error of the renewable load, the actual accumulated energy in the coming epoch will not be the same as expected. Consequently, generation references of these generators are constantly updated according to the *status quo* of MG when a new epoch begins. In each epoch, the generators are controlled in a way such that compensating the energy difference accumulated in the previous epoch is taken into consideration. Hence, at the end of the interval (also the end of the epoch), the energy difference can be controlled to fall in a relatively small range since the only prediction error of the last epoch can contribute to the energy tracking difference.

This proposed two-time-scale congestion management method is implemented in such a way that day-ahead hourly-scale DCM issues the contract energy order, while the intra-day sub-hourly-scale energy tracking follows the order. Through cooperation of these two schemes with different temporal scales, congestion of the DN during operation can be avoided.

IV. CASE STUDIES

Configuration of a 13-bus distribution system is shown in Fig. 4. DN is connected to the main grid from bus#13. To test our proposed scheme for congestion management, we added two MGs in the DN, along with two distributed generators. The two MGs, MG₁ and MG₂, are connected at bus#4 and bus#8 whilst the two generators (G#1 and G#2) are installed at bus#7 and bus#12, respectively. MG₁ has one controllable generator (G#3) and one renewable wind generator (WG) and MG₂ has three controllable generators (G#4, G#5, and G#6), one PV and ESS. The ramp rates (up/down) of all the controllable generators are 0.2 MW/h. The thermal limit of distribution lines is 2.0 MW, and the maximum power exchange between DN and the main grid is 2.0 MW.

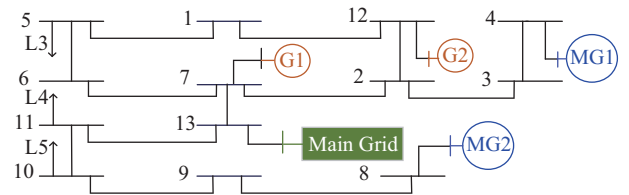


Fig. 4. A 13-bus distribution system with two MGs.

The parameters of generators are provided in Table I. The hourly load profiles for the DN and MGs in one day are shown

TABLE I
GENERATOR PARAMETERS OF THE GENERATORS

Gen.#	Cost function			Lower bound (MW)	Upper bound (MW)
	<i>a</i>	<i>b</i>	<i>c</i>		
G#1	3.60	900	0	0.4	2.0
G#2	3.30	915	0	0.4	2.0
G#3	2.70	870	0	0.4	2.0
G#4	2.55	855	0	0.3	1.5
G#5	2.85	870	0	0.24	1.2
G#6	3.00	885	0	0.24	1.2

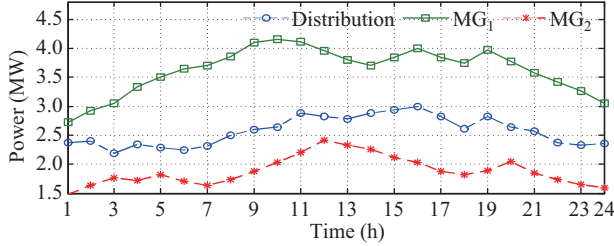


Fig. 5. Load profiles for the Distribution Network and MGs.

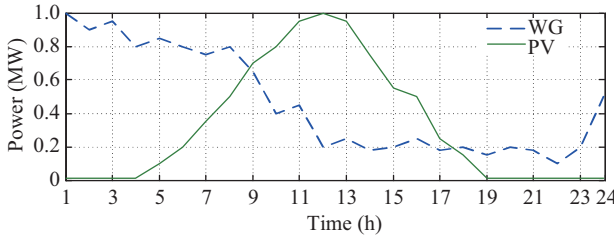


Fig. 6. Predicted power output of WG and PV.

in Fig. 5. Predicted power output of WG in MG₁ and PV in MG₂ are shown in Fig. 6. In this test case, buying price from the main grid is 103.33 \$/(MWh), and unit cost for wind and solar power curtailment is 100 \$/(MWh).

A. Alternating iterative optimization

Consider that, at the end of interval 5, outputs of the generators G#1, G#2, G#3, G#4, G#5, and G#6 are 0.81, 0.66, 1.63, 1.50, 1.16, and 0.85 MW, with generations of WG and PV being 0.85 and 0.1 MW, respectively. Predicted generations for WG and PV are 0.80 and 0.20 MW. Initial BP and SP are set to 95.46 \$/(MWh) and 94.59 \$/(MWh), which are the clearing prices for interval 5.

As shown in Fig. 7, after seven rounds of discussions, the energy mismatches for both buying and selling transactions decrease to around zero, and corresponding selling and buying prices converge, consequentially (Fig. 8). In this scenario, congestion occurs on branch 8–9, and evolution of the congestion price during optimization is shown in Fig. 9.

Congestion of this branch limits the power MG₂ can sell. At the beginning of the discussion, selling energy of MG₂ is greater than buying energy of the DN since the thermal limit of branch 8–9 restrains the overall energy DN can procure. Accordingly, DN decreases the selling price of MG₂ until the energy mismatch between them is wiped out.

It should be noted that decreasing the selling price here is equivalent to raising the congestion price. As can be derived

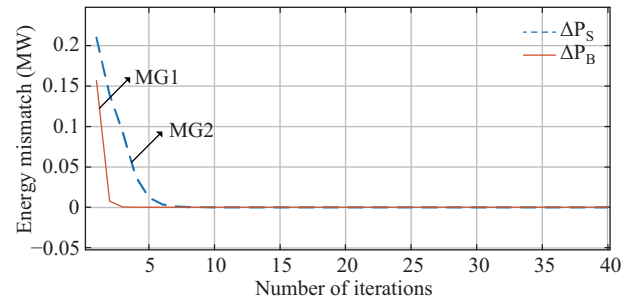


Fig. 7. Update of buying and selling prices for MGs during optimization.

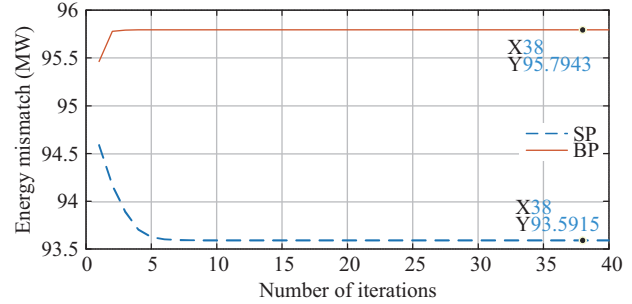


Fig. 8. Evolution of energy selling and buying price during optimization.

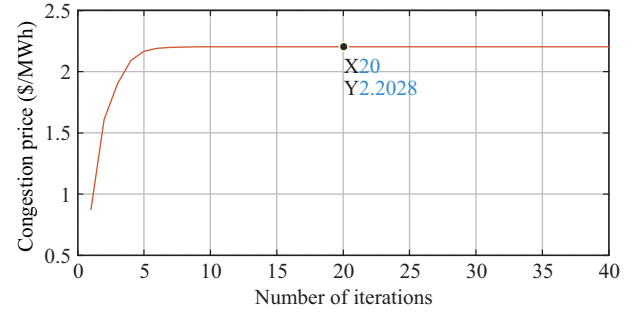


Fig. 9. Evolution of congestion price during optimization.

from KKT conditions of Eq. (9), the congestion price and selling price satisfy:

$$SP^i - \lambda_E - \sum_{k=1}^{n_b} (PTDF)_{i-k}^T (\bar{\lambda}_{ck} + \underline{\lambda}_{ck}) = 0 \quad (34)$$

As congestion occurs only on branch 8–9, Eq. (34) can be further be simplified as:

$$SP^i + \underline{\lambda}_{ck} = \lambda_E \quad (35)$$

Here, the power transfer distribution factor relates to line 8–9 and node #9 is -1 , and forwarding congestion $\bar{\lambda}_{ck}$ is zero since power only flows backward (i.e. from node #9 to node #8) in this scenario. As can be observed in Fig. 9, the converged congestion price and selling prices are 2.20 \$/(MWh) and 93.59 \$/(MWh), accordingly, the converged energy price for DN should be $93.59 + 2.20 = 95.79$ \$/(MWh), as shown in the figure.

Update of the power output setting for generators during the optimization process is shown in Fig. 10. By using the converged values of G#1–G#6 shown in the figure, one can

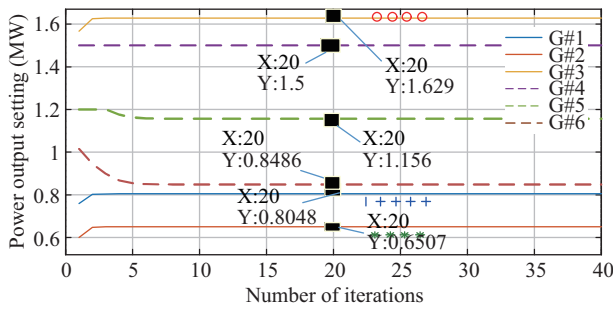


Fig. 10. Update of power output settings for generators.

calculate the corresponding marginal prices of them, which are 95.79, 95.79, 95.79, 93.15, 93.59, 93.59 \$/(MWh), respectively. Note that, the observed marginal prices of the generators in the distribution network (G#1, G#2) are all the same, which equal the energy price. The marginal price of G#3 in MG1 also equals the energy price, which is the buying price of MG1 (BP). Under this circumstance, MG2 buys a portion of energy to meet its load demand, at the price of 95.79 \$/(MWh) to maximize its overall benefits. The marginal prices of the G#5 and G#6 are the same, which are the selling price of MG2 (SP). The marginal price of G#4 is less than SP because its power output has been clapped at its upper bound of 1.5 MW.

It is worth to pointing out that, during optimization, DN only needs the declared quantities of buying or selling energy of MGs, and MGs on the other hand only receive price signals from the DN. MGs are entitled to discretionary decision-making with no privacy being revealed. In this case, the optimized operation costs for the DN, MG1, and MG2 are \$224.67, \$272.06, and \$135.79, resulting in a total cost of \$632.52, as shown in Fig. 11.

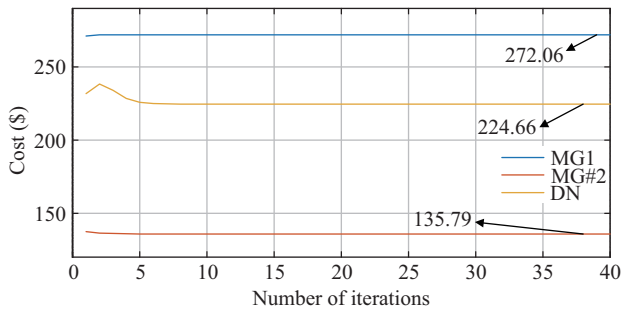


Fig. 11. Change of objective function values of MGs and DN.

To demonstrate the effectiveness of the proposed method, integrated optimization of both the DN and MGs by using the interior-point (IP) method discussed in [37] is also conducted for comparison. Optimized results of the proposed method are the same as results obtained by using IP, which shows the proposed method is effective at finding the optimal solution.

B. Day-ahead dynamic congestion management

In this case, only one branch (branch #8–#9) may reach its thermal limits, thus congestion prices corresponding to other branches are zero. Congestion prices corresponding to branch #8–#9 in 24-hour intervals are shown in Fig. 12.

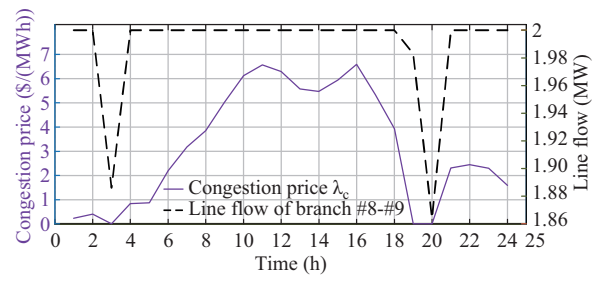


Fig. 12. Congestion prices corresponding to branch #8–9 of 24 hours.

Note that, congestion prices in intervals 3, 19, and 20 are also zero for this branch since its line flow does not reach the bound, as shown in Fig. 12. It can also be observed that congestion prices are high when PV output is large. This is because the MG2 maintains a relatively low generation cost and it always tends to sell energy to the DN via branch #8–#9. Accordingly, when PV generation is high, the only line that can be used for selling becomes too crowded, thus, congestion prices at these intervals are higher.

Day-ahead cleared buying and selling prices for the MGs are shown in Fig. 13. The buying price of MG1 (BP) is the same as the energy price, as discussed previously. This price increases significantly in peak hours as the load of the DN and MG1 during these periods is heavy. The selling price of MG2 is low during peak hours since the increase of congestion price, similar to the logic introduced in the previous subsection. One can observe a price spike emerges at interval 19 (19:00) and this price is the buying price of the DN from the main grid (103.3 \$/(MWh)). The causes of this price spike are threefold. First, the MG2 decreases its energy selling of MG2 to the amount of 0.017 MW due to the decrease of PV generation and increase of load. Second, load peaks of the DN and MG1 concur at 19:00. Since G#3 already reaches its upper load, its power shortage of 0.271 MW needs to be accommodated by buying energy from the DN. Lastly, the load of the DN is increased by 0.204 MW, which adds to the total power shortage of 0.492 MW, counting the decrease of energy selling of MG2 plus the increase of energy buying of MG1. Limited by the ramp rate, the G#1 and G#2 in the DN can provide the maximum of 0.4 MW generation incrementally. Accordingly, the remaining 0.092 MW power has to be procured from the main grid with the price of 103.3 \$/MW, which is the energy price of the DN, as well as the buying price of the MG1. One can find more details for this phenomenon from Figs. 14 and 15.

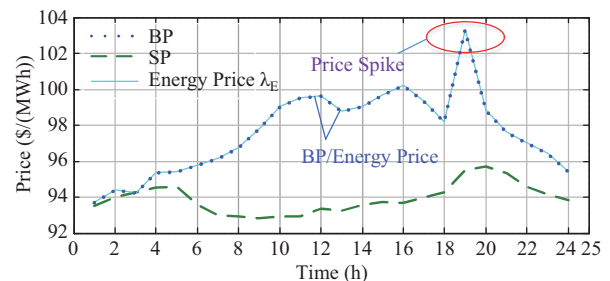


Fig. 13. Day-ahead buying and selling prices of MGs.

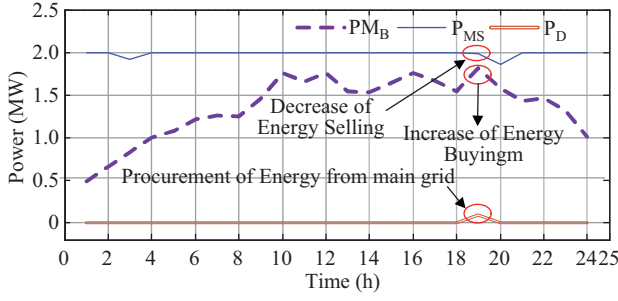


Fig. 14. Energy transactions among multiple entities.

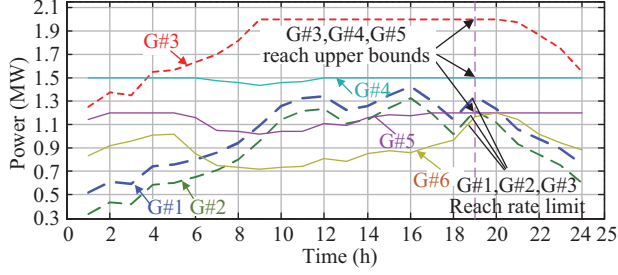


Fig. 15. Power generation settings of generators for 24-hour intervals.

From the analysis above, one can find the proposed day-ahead hourly-scale DCM can regulate energy transactions between the DN and MGs via congestion prices to avoid overloading of the distribution lines. It should be noted the obtained generation settings of the MGs here are used to generate energy contracts. However, actual power output for the intra-day scale will vary according to the actual load and renewable generation conditions.

C. Day-ahead Dynamic Congestion Management

Take interval 6 (from 5:00 am–6:00 am) for example to demonstrate the contract energy tracking of MG2. According to the day-ahead schedule, the contracted energy selling of MG2 is 2.0 MWh. The predicted energy consumed by the load is 1.705 MWh with the predicted energy provided by the PV being 0.2 MWh, resulting in a net load of 1.505 MWh. The original settings of generators for G#4, G#5, and G#6 are 1.5, 1.156, and 0.849 MW, providing a total energy of 3.505 MWh.

The predicted load profiles and actual load profiles are shown in Fig. 16. By applying the proposed sub-hourly energy tracking method, the power outputs and marginal cost of the generators of MGs in an hour are shown in Figs. 17 and 18, respectively.

It can be seen from the figure, G#4's output still reaches its upper bound of 1.5 MW whereas the output of G#5 and G#6 slightly deviate from the day-ahead schedules. Consequently, the marginal costs of G#5 and G#6 vary in a range from 93.45 \$/(MWh) to 93.56 \$/(MWh) and they are kept in accord by the MG2 to minimize overall generation cost.

The trajectories of the sold energy and exchanged power are shown in Fig. 19. Here, at the end of this interval, the actual traded energy is locked to 1.997 MWh, with a difference of only 3 kWh. The exchanged power fluctuates around 2 MW,

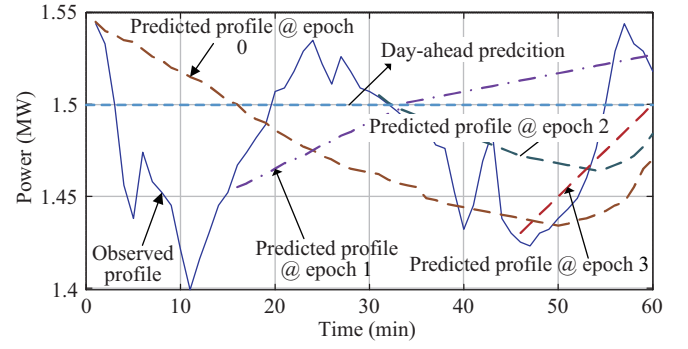


Fig. 16. Actual and predicted net load profiles.

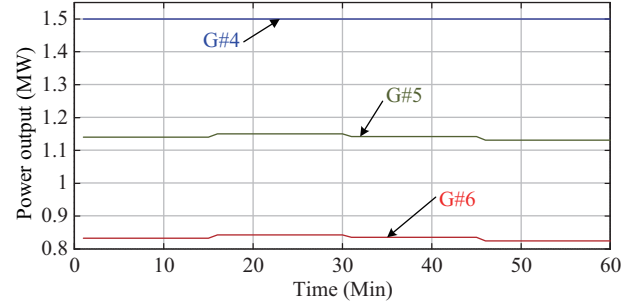


Fig. 17. Power output of generators of MG2 during tracking.

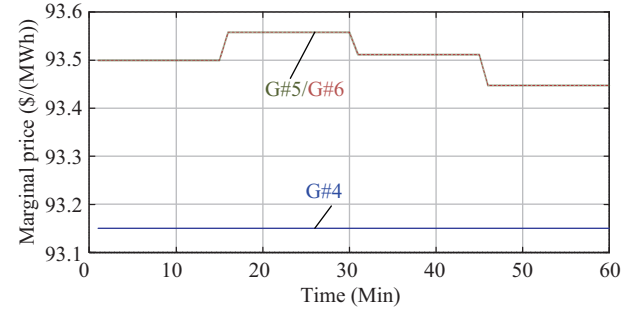


Fig. 18. Marginal prices generators in MG2 during tracking.

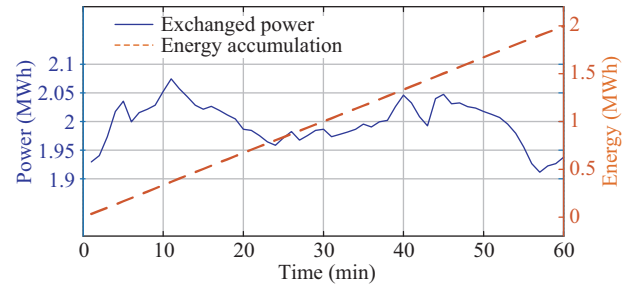


Fig. 19. Contract energy tracking trajectory of MG2.

with a maximum deviation of 0.08 MW (4%). Since the day-ahead scheme has determined the energy schedule by taking in congestion, following the schedule implicates that power exchange among MGs and DN can be maintained in the predetermined ranges, thus possible congestion due to MGs' deviating from the apriorism settings can be avoided. During tracking, MG always keeps an optimal allocation of load among generators to minimize its overall generation cost. Note

that, the MGs regulate or control their resources independently here, and do not need to provide their information to the DN.

To further investigate the benefits of applying the proposed energy tracking approach, another policy named proportional energy sharing with scheduled energy tracking is applied. For this tracking, the sharing proportion of each period is fixed at the beginning of each tracking period such that generators only respond to load change according to the previously measured load imbalance. Comparison results are shown in Table II. It can be seen the proposed method, on one hand, can reduce generation cost in an hour to the minimum level; on the other hand, can minimize scheduled energy tracking error, which can further avoid the penalty caused by the energy contract violation. Thus, the proposed approach can improve economic benefits of the MG in the long run.

TABLE II
COMPARISON RESULTS WITH PROPORTIONAL SHARING TRACKING

Method	Cost (\$/h)	Energy exchange (MWh)	Mismatch (MWh)	Error	Total cost (\$)
Proposed	301.49	1.997	0.003	0.015%	301.49
Proportional	302.23	2.105	0.105	5.2%	312.04

From the analysis of the case studies, one can find out by coordinating the day-ahead dynamic congestion management and intra-day contract energy tracking, the proposed integrated two-time-scale congestion management scheme can properly regulate the energy transactions between the MGs and DN while ensuring optimal power tracking of generators in the MGs.

In this paper, two MGs are integrated into DN and the alternating iterative optimization method can obtain comparable optimal results as the IP method. The logic is that the optimization problem for the hourly-scale DCM problem is a constrained convex optimization problem. The proposed solution method is equivalent to solving multiple decomposed sub-optimization problems where the optimization of DN and each MGs is formulated as a sub-optimization problem. The termination criteria provided in (13) can be treated as a requirement that all sub-optimization problems need to reach a consensus. As long as the optimal of the problem exists, it is unique due to convexity, and the gradient-based algorithm will generally converge. However, with more MGs being considered, the proposed approach will generally take a longer time to converge, as this negotiations among MGs and DN need more steps to reach a consensus.

The DC power flow model is used for the distribution network here, since this paper mainly focuses on the energy transaction and active power management. It should be pointed out that, AC power flow can be integrated into the proposed framework and the reactive schedule/control scheme can also be incorporated in the proposed approach. Voltage and network loss are important concerns, which can be regulated by adjusting reactive power control devices such as transformer with tap changer, capacitor banks and generators with controllable reactive power output. However, due to the non-linearity of AC power flow model, finding an optimal solution method to the AC power flow-based optimization problem in a timely

manner will be challenging. This could be an interesting and important research topic in the future.

V. CONCLUSION

This paper proposes a two-time-scale congestion management scheme for the congestion management of the DN with multiple MGs/DN. The day-ahead hourly-scale DCM schedules the optimal energy transactions between MGs and DN by considering the physical constraints of them. The intra-day sub-hourly-scale contract energy tracking method ensures MG follow the schedule in an optimized manner to avoid the possible occurrence of congestion due to deviation from the schedule. Case studies show the alternative optimization process of the DCM is actually the price negotiation between DN and MGs, which can provide a schedule without the occurrence of congestion. This energy tracking method requires MGs to fully mobilize their dispatchable resource to fulfill the sealed contracts to avoid the contract default, as well as the occurrence of congestion during operation. The proposed method can also preserve privacy and the right of control of the MGs and is promising for energy management of MGs integrated DNs.

APPENDIX A

The analysis through (19) to (33) is provided to illustrate the physical characteristics of the contract tracking of MGs by relaxing the constraints of generation bound and ramp rate of the generation. To signify the generation bounds, the constraints should include:

$$P_{Gi}^{\min} \leq P_{Gi}^t \leq P_{Gi}^{\max} \quad (A1)$$

where $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ are the lower and upper bounds of the generator i in a MG, with P_{Gi}^t being the corresponding generation at time t .

Furthermore, considering the ramp rate of the generator, the following constraint should also be included:

$$-R_{Gi} \leq P_{Gi}^{t+1} - P_{Gi}^t \leq R_{Gi} \quad (A2)$$

By introducing the slack variables, inequality constraints provided in (A2) can be translated to equality constraints as follows:

$$\begin{cases} P_{Gi}^t + u_i = P_{Gi}^{\max} \\ P_{Gi}^t - v_i = P_{Gi}^{\min} \\ P_{Gi}^{t+1} - P_{Gi}^t + w_{Gi} = R_{Gi} \\ P_{Gi}^{t+1} - P_{Gi}^t - z_{Gi} = -R_{Gi} \end{cases} \quad (A3)$$

The auxiliary function corresponding to the optimal contract tracking problem can be written as:

$$\begin{aligned} J_0 = & \sum_{t=0}^{n-k} \left\{ \sum_{i=1}^{n_G} f_i(P_{Gi}[t]) \right. \\ & - \lambda(t+1) [E(t) + \mathbf{1}^T \mathbf{P}_G(t) - E(t+1)] \\ & \left. - \sum_{i=1}^{n_G} \bar{\lambda}_{Gi}(t+1) [P_{Gi}(t) + u_i - P_{Gi}^{\max}] \right\} \end{aligned}$$

$$\begin{aligned}
& - \sum_{i=1}^{n_G} \underline{\lambda}_{Gi}(t+1) [P_{Gi}(t) - v_i - P_{Gi}^{\min}] \\
& - \sum_{i=1}^{n_G} \bar{\lambda}_{rampi}(t+1) [P_{Gi}(t+1) - P_{Gi}(t) + w_i - R_{Gi}] \\
& - \sum_{i=1}^{n_G} \underline{\lambda}_{rampi}(t+1) [P_{Gi}(t+1) - P_{Gi}(t) - z_i + R_{Gi}] \Big\} \\
& \quad \quad \quad (A4)
\end{aligned}$$

Under this circumstance, L_t and L_{t-1} are defined as follows:

$$\begin{aligned}
L_t &= \sum_{i=1}^{n_G} f_i(P_{Gi}[t]) \\
& - \lambda(t+1) [E(t) + \mathbf{1}^T \mathbf{P}_G(t) - E(t+1)] \\
& - \sum_{i=1}^{n_G} \bar{\lambda}_{Gi}(t+1) [P_{Gi}(t) + u_i - P_{Gi}^{\max}] \\
& - \sum_{i=1}^{n_G} \underline{\lambda}_{Gi}(t+1) [P_{Gi}(t) - v_i - P_{Gi}^{\min}] \\
& - \sum_{i=1}^{n_G} \bar{\lambda}_{rampi}(t+1) [P_{Gi}(t+1) \\
& - P_{Gi}(t) + w_i - R_{Gi}] \\
& - \sum_{i=1}^{n_G} \underline{\lambda}_{rampi}(t+1) [P_{Gi}(t+1) \\
& - P_{Gi}(t) - z_i + R_{Gi}] \\
L_{t-1} &= \sum_{i=1}^{n_G} f_i(P_{Gi}[t-1]) \\
& - \lambda(t) [E(t-1) + \mathbf{1}^T \mathbf{P}_G(t-1) - E(t)] \\
& - \sum_{i=1}^{n_G} \bar{\lambda}_{Gi}(t) [P_{Gi}(t-1) + u_i - P_{Gi}^{\max}] \\
& - \sum_{i=1}^{n_G} \underline{\lambda}_{Gi}(t) [P_{Gi}(t-1) - v_i - P_{Gi}^{\min}] \\
& - \sum_{i=1}^{n_G} \bar{\lambda}_{rampi}(t) [P_{Gi}(t) - P_{Gi}(t-1) + w_i - R_{Gi}] \\
& - \sum_{i=1}^{n_G} \underline{\lambda}_{rampi}(t) [P_{Gi}(t) - P_{Gi}(t-1) - z_i + R_{Gi}] \\
& \quad \quad \quad (A6)
\end{aligned}$$

The Euler-Lagrange equation corresponding to this constrained optimal control problem still follows (23). By applying (A4), (A5), and (A6), the Euler-Lagrange equation is rewritten as the following equation:

$$\lambda(t+1) - \lambda(t) = 0 \quad (A7a)$$

$$\begin{aligned}
2a_i P_{Gi}(t) + b_i - \lambda(t+1) - \bar{\lambda}_{Gi}(t+1) \\
- \underline{\lambda}_{Gi}(t+1) + \bar{\lambda}_{rampi}(t+1) \\
+ \underline{\lambda}_{rampi}(t+1) - \bar{\lambda}_{rampi}(t) - \underline{\lambda}_{rampi}(t) = 0 \quad (A7b)
\end{aligned}$$

$$E(t) + \mathbf{1}^T \mathbf{P}_G(t) - E(t+1) = 0 \quad (A7c)$$

$$\mathbf{P}_G(t) + \mathbf{u} - \mathbf{P}_G^{\max} = 0 \quad (A7d)$$

$$\mathbf{P}_G(t) - \mathbf{v} - \mathbf{P}_G^{\min} = 0 \quad (A7e)$$

$$\mathbf{P}_{Gi}(t+1) - \mathbf{P}_{Gi}(t) + \mathbf{w} - R_{Gi} = 0 \quad (A7f)$$

$$\mathbf{P}_{Gi}(t+1) - \mathbf{P}_{Gi}(t) - \mathbf{z} + R_{Gi} = 0 \quad (A7g)$$

$$-\mathbf{U} \bar{\lambda}_G(t+1) - \mu \mathbf{e} = 0 \quad (A7h)$$

$$\mathbf{V} \underline{\lambda}_G(t+1) - \mu \mathbf{e} = 0 \quad (A7i)$$

$$-\mathbf{W} \bar{\lambda}_{ramp}(t+1) - \mu \mathbf{e} = 0 \quad (A7j)$$

$$\mathbf{Z} \underline{\lambda}_{ramp}(t+1) - \mu \mathbf{e} = 0 \quad (A7k)$$

For each step of control, the control action of each generator in the MG is obtained by solving (A7).

APPENDIX B

By using the power transfer distribution factor (PTDF) the DC-power flow constraint is indirectly considered in the optimization problem. Detailed analysis is provided as follows.

Note, with DC-power flow, the power flow equation can be denoted as:

$$\mathbf{B} \times \boldsymbol{\theta} = \mathbf{P}_G - \mathbf{P}_D \quad (B1)$$

where $\mathbf{B}$ is the imaginary part of the admittance matrix of the system, which is an $(n-1) \times (n-1)$ matrix excluding the slack bus, with n being the total number of the buses; $\mathbf{P}_G = [P_{g1}^D, P_{g2}^D \cdots P_{gm}^D, 0, 0 \cdots]^T$ is an $(n-1)$ -dimensional power generation vector; and $\mathbf{P}_D = [0, 0 \cdots P_{Lm+1}, P_{Lm+1}, \cdots P_{Ln-1}]^T$ is an $(n-1)$ -dimensional net load vector.

Obviously, $\boldsymbol{\theta}$ can be given as:

$$\boldsymbol{\theta} = \mathbf{B}^{-1}(\mathbf{P}_G - \mathbf{P}_D) \quad (B2)$$

Define the impedance matrix $\mathbf{Z} = \mathbf{B}^{-1}$, and $\hat{\boldsymbol{\theta}} = [\boldsymbol{\theta}^T 0]^T$, $\hat{\mathbf{P}}_G = [\mathbf{P}_G^T 0]^T$, $\hat{\mathbf{P}}_D = [\mathbf{P}_D^T P_{Ln}]^T$, $\hat{\mathbf{Z}} = \begin{bmatrix} \mathbf{B}^{-1} & 0 \\ \mathbf{1}^T & 1 \end{bmatrix}$, the associated equation based on (B2) can be expressed as:

$$\hat{\boldsymbol{\theta}} = \hat{\mathbf{Z}}(\hat{\mathbf{P}}_G - \hat{\mathbf{P}}_D) \quad (B3)$$

Accordingly, the power flow of the branch between nodes i and j in the distribution network, P_{ij}^D can be expressed as:

$$P_{ij}^D = B_{ij}(\theta_i - \theta_j) \quad (B4)$$

Denote the branch-node incidence matrix as $\mathbf{A}$, then (B4) can be rewritten in a matrix form as:

$$[\mathbf{P}_{ij}^D] = \text{Diag}\{B_{ij}\} \mathbf{A} \hat{\boldsymbol{\theta}} \quad (B5)$$

Substituting (B3) in (B5) yields:

$$[\mathbf{P}_{ij}^D] = \text{Diag}\{B_{ij}\} \mathbf{A} \hat{\mathbf{Z}} (\hat{\mathbf{P}}_G - \hat{\mathbf{P}}_D) \quad (B6)$$

Then, the PTDF can be calculated as:

$$\text{PTDF} = \text{Diag}\{B_{ij}\} \mathbf{A} \hat{\mathbf{Z}} \quad (B7)$$

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