Decentralized Daily Scheduling of Smart Distribution Networks with Multiple Microgrids

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***Abstract*—Number of microgrids (MGs) are increasing in distribution systems. They behave more active than previous due to increasing of distributed generations (DG) and active loads. Therefore, it is necessary to consider them in distribution network daily scheduling. Central scheduling of distribution networks does not meet the privacy of MGs customers and it is vulnerable against cyber-attacks. Therefore, it is necessary to develop a decentralized daily scheduling model for distribution-connected resources to preserve the privacy of MGs. Moreover, the scheduling model must coordinate distribution-connected resources with transmission-connected resources. In this paper, a decentralized model for the daily scheduling of smart distribution networks resources is presented to preserve the privacy of MGs. Analytical Target Cascading (ATC) algorithm is used for optimization decomposition. The model considers controllable and non-controllable loads, distributed generations (DG), Renewable Energy Sources (RES) and Energy Storage Systems (ESS). In order to coordinate transmission and distribution connected resources, electricity price at each hour, at the transmission bus, which the distribution network is connected to, is modeled by a price conjecture curve. Base distribution network operator and Microgrids Operators (MGO) jointly compute an optimal schedule for the entire distribution network. The proposed method is applied to a 39-bus test distribution network and simulation results are discussed.**

Keywords—distribution network, microgrid, decentralized scheduling, centralized scheduling, daily schedule

NOMENCLATURE

Indices:

$t \in [t_1,...,T]$	Time (24 hours of a day)
g	Distributed Generation
b	Battery (ESS)
e	Renewable Resources
l	Loads (Fix, Curtailable, and Shiftable)
i , j , k	Bus
m	Microgrid (MG)

Sets:

G_i	Generators connected to bus *i*
B_i	Batteries connected to bus *i*
CL_i	Curtailable loads connected to bus *i*
SL_i	Shiftable loads connected to bus *i*
E_i	Renewable resources connected to bus *i*
N	Network buses
$N^{In,DSO}$	Internal buses of the base distribution network, which are not connected to MGs or transmission grid
$N^{B,DSO}$	Boundary buses of the base distribution network, which are connected to MGs or transmission grid
$N^{In,MG}$	Internal buses of MGs network, which are not connected to base distribution network

Variables:

$P_{ij,t}$	line power between bus *i* and bus *j* at hour t (MW)
$P_{DG\,g,t}$	DG's output power at hour t (MW)
$P_{RE\,e,t}$	RESs output power at hour t (MW)
$P_{Bt\,b,t}$	Batteries input/output power at hour t (MW)
$P^{R}_{C\,l,t}$	Reduced power of curtailable load at hour t (MW)
$P^{S}_{C\,l,t}$	Served power of curtailable load at hour t (MW)
$P_{S\,l,t}$	Shiftable load power at hour t (MW)
$P_{T-D,t}$	Purchased power from transmission grid at hour t (MW)
$\delta_{i,t}$	*i*th bus angel at hour t (rad)

Parameters:

$E_{Bt\,b,t}$	Stored energy in *b*th battery at hour t
$P^{D}_{D-M\,m,t}$	Exchanged power between *m*th MG and base distribution network at hour t, from the base distribution network's perspective (MW)
$P^{D*}_{D-M\,m,t}$	Optimal exchanged power from base distribution network's perspective, sent to *m*th MG at hour t (MW)
$P^{M}_{D-M\,m,t}$	Exchanged power between *m*th MG and base distribution network at hour t, from *m*th MG's perspective (MW)

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$P^{M*}_{D\text{–}M\ m,t}$	Optimal exchanged power from *m*th MG's perspective, sent to base distribution network at hour t (MW)
$\eta_{Bt\ b}$	The efficiency of *b*th battery
$\lambda_{m,t}$	Dual variable of relaxed constraint for *m*th MG at hour t
$\beta_{m,t}$	Penalty function parameter for *m*th MG at hour t
$P^{F}_{C\ l,t}$	Forecasted power of curtailable load at hour t (MW)
$P_{D\ l,t}$	Fix load power at hour t (MW)
$P^{F}_{S\ l,t}$	Forecasted power of shiftable load at hour t (MW)

I. INTRODUCTION

Due to the large scale penetration of renewable energy resources, many different changes have occurred in the power system. For example, changes made in customers consumption pattern due to the conversion of passive loads to active and responsive loads, development and increase of MGs all over the world, and conversion of traditional distribution networks to smart distribution networks. Therefore traditional centralized scheduling approaches are not appropriate. In this paper, decentralized scheduling for smart distribution networks with multiple MGs will be proposed.

MGs are low-voltage distribution systems consisting of DGs, ESSs and controllable loads, which can be operated in either islanded or grid-connected modes. DGs include programmable DG units, such as diesel and microturbines and non-programmable DG units, such as wind turbines and photovoltaic. Controllable loads include shiftable loads and curtailable loads [1].

As it was mentioned before, scheduling of distribution network and MGs in a centralized manner does not meet the requirements. In centralized scheduling approaches a central entity will perform and determine the schedule of the entire system. As an example, in a distribution network, the distribution network operator (DNO) will act as the central entity, which has access to all information of generators and loads. We can mention, low flexibility, high computation burden, and vulnerability against cyber-attacks as disadvantages of centralized approaches.

In a decentralized approach, the centralized optimization is decomposed into several optimizations and the operator of each entity has its own optimization. Decentralized optimizations are solved iteratively using the exchange of limited information between entities. Less computing time due to parallel solving of optimizations, more immunity against cyber-attacks, and preserving customer's privacy can be noted as advantages of decentralized approaches.

Several decentralized algorithms have been proposed for the operation and the scheduling of distribution networks and MGs. In [1] a distributed optimal energy management for a MG, based on PCPM algorithm is proposed. Two local controllers and a central controller are assumed. Local controllers seek to minimize the cost of controllable loads and distributed generations. Central controller performs the OPF problem while minimizing power losses. The distributed problem is solved by exchanging information between the central controller and local controllers. A decentralized energy management system for networked MGs is presented in [2] based on the ADMM approach. Each entity's (MG or distribution network) objective function is to minimize its cost, individually. Special AC power flow model for radial distribution networks is used. The distribution network does not exchange any power with the upstream grid (transmission grid) and the decentralized problem is solved by exchanging active power between the distribution network and MGs. In this article only the effect of DGs are considered and the scheduling horizon is 1 hour. Authors in [3] present robust decentralized energy management for MGs. Reference [4] Focuses on the scheduling of a group of MGs in the distribution network. High penetration of renewable resources is assumed and based on ADMM decentralized algorithm an online scheduling considering minimum regret is presented. Energy management is proposed as a resource allocation problem in [5] and distributed algorithms are used for distributed allocations. A decentralized scheduling for a transmission network and several active distribution networks is presented in [6]. Dc power flow equations are used and the objective function is minimum cost. Also, the effect of controllable loads, distributed generations and energy storage systems are ignored in [6]. A decentralized decision-making algorithm for collaboration operation of electricity transmission and distribution system is represented in [7]. A bi-level optimization based on ATC algorithm is proposed in which the TSO and DSO OPF is solved in the upper and lower level, respectively. The effect of ESSs, RESs and, controllable and non-controllable loads are not considered in [7].

In this paper, a decentralized daily scheduling model for distribution-connected resources is proposed. The aim of this model is to preserve the privacy of MGs and coordinate distribution-connected resources with transmission-connected resources. The distribution network is portioned into MGs and the remaining part that is named Base Distribution Network (BDN). To keep the privacy of MGs, each MG optimizes its own objective function, while they seek to minimize the cost of the entire distribution network. In other words, Base Distribution Network Operator (BDNO) and MGOs cooperatively solve the problem. To solve the decentralized problem, while preserving the privacy, MGs exchange limited information with the base distribution network in an iterative manner. To coordinate distribution-connected resources with transmission-connected resources electricity price at the bus in which the under study distribution network is connected to, is modeled by a price conjecture curve at each hour.

The rest of this paper is organized as follows. Section II represents the proposed method, the centralized scheduling problem, the decentralized scheduling problem and the procedure of transforming the centralized problem to a decentralized one. In section III, numerical results and 39-bus test system are described, and Section IV provides the conclusion for the proposed optimization framework.

II. PROPOSED METHOD

In this section, first, the centralized form of scheduling problem is discussed. After that, the proposed method and decentralize form of the problem is represented.

A. Centralized Scheduling Problem

Consider the distribution system in Fig. 1. It consists of a distribution network that includes several MGs. In the centralized approach, it is assumed that BDNO schedules all DGs, active loads, and RESs, and ESSs that are located in the base distribution network and MGs. The objective function is minimizing the total costs of the base distribution network and MGs. Centralized scheduling problem can be formulated as follows:

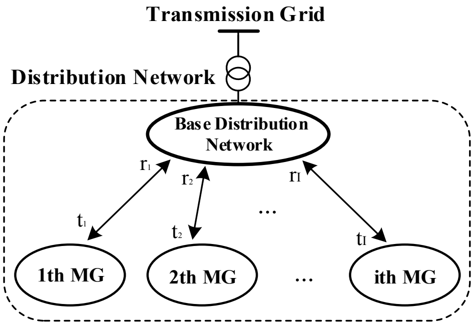

Fig. 1. Model Structure

$$\min \sum_{t\in T}(\mathrm{Cost}(P_{T-D,t})+\sum_{g\in G}\mathrm{Cost}(P_{DG\,g,t})+\sum_{l\in CL}\mathrm{Cost}(P^{R}_{C\,l,t}) + \sum_{l\in SL}\mathrm{Cost}(P_{S\,l,t}-P^{F}_{S\,l,t})+\sum_{b\in B}\mathrm{Cost}(P_{Bt\,b,t})) \tag{1}$$

$$-P_{ij}^{\max} \le \frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}} \le P_{ij}^{\max} \qquad \forall t\in T, \forall i,j\in N \tag{2}$$

$$\sum_{g\in G_i}P_{DG\,g,t}+\sum_{e\in E_i}P_{RE\,e,t}-\sum_{j\in N}\frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}}=\sum_{l\in D_i}P_{D\,l,t}+\sum_{l\in SL_i}P_{S\,l,t} + \sum_{l\in CL_i}P^{S}_{C\,l,t}+\sum_{b\in B_i}P_{Bt\,b,t} \qquad \forall t\in T, \forall i\in N \tag{3}$$

$$P_{T-D,t}+\sum_{g\in G_1}P_{DG\,g,t}+\sum_{e\in E_1}P_{RE\,e,t}-\sum_{j\in N}\frac{\delta_{1,t}-\delta_{j,t}}{X_{1j}}=\sum_{l\in D_1}P_{D\,l,t} + \sum_{l\in SL_1}P_{S\,l,t}+\sum_{l\in CL_1}P^{S}_{C\,l,t}+\sum_{b\in B_1}P_{Bt\,b,t} \qquad \forall t\in T \tag{4}$$

$$\sum_{t\in T}P_{S\,l,t}=\sum_{t\in T}P^{F}_{S\,l,t} \qquad \forall t\in T, \forall l\in SL \tag{5}$$

$$P^{\min}_{S\,l}\le P_{S\,l,t}\le P^{\max}_{S\,l} \qquad \forall t\in T, \forall l\in SL \tag{6}$$

$$P^{R,min}_{C\,l}\le P^{R}_{C\,l,t}\le P^{R,max}_{C\,l} \qquad \forall t\in T, \forall l\in CL \tag{7}$$

$$P^{F}_{C\,l,t}=P^{R}_{C\,l,t}+P^{S}_{C\,l,t} \qquad \forall t\in T, \forall l\in CL \tag{8}$$

$$P^{\min}_{DG\,g}\le P_{DG\,g,t}\le P^{\max}_{DG\,g} \qquad \forall t\in T, \forall g\in G \tag{9}$$

$$P^{\min}_{T-D}\le P_{T-D,t}\le P^{\max}_{T-D} \qquad \forall t\in T \tag{10}$$

$$E_{Bt\,b,t+1}=\eta_{Bt\,b}E_{Bt\,b,t}+P_{Bt\,b,t} \qquad \forall t\in T, \forall b\in B \tag{11}$$

$$P^{min}_{Bt\,b}\le P_{Bt\,b,t}\le P^{max}_{Bt\,b} \qquad \forall t\in T, \forall b\in B \tag{12}$$

$$E^{min}_{Bt\,b}\le E_{Bt\,b,t}\le E^{max}_{Bt\,b} \qquad \forall t\in T, \forall b\in B \tag{13}$$

$$E_{Bt\,b,T}\ge E^{T}_{Bt\,b} \qquad \forall b\in B \tag{14}$$

$$E_{Bt\,b,0}=E^{0}_{Bt\,b} \qquad \forall b\in B \tag{15}$$

In the aforementioned formulation, the objective function (1) consists of different costs. The first term represents the cost of purchasing power from the upstream grid, which is always greater than or equal to zero. This term of cost is dependent on the Locational Marginal Price (LMP) of transmission bus that the under study distribution network is connected to.

LMP of the upstream transmission bus depends on its demand and increases as the demand of the bus increases. In this paper, It is assumed that BDNO models LMP of hour t of the transmission bus by a linear curve, called Price Conjecture Curve [8] with the slope of m_t and intercept of $Lmp_{0,t}$. Modeling LMP as a function of demand coordinates the scheduling of distribution and transmission connected recourses. It also coordinates shiftable loads. For example, if many load shifts from peak to a specific hour, LMP of that hour increases, price conjecture curve identify the increase of price and scheduling distributes shiftable loads so that loads are supplied with minimum cost. Cost of purchasing power at hour t from the upstream grid can be formulated as bellow.

$$Cost(P_{T-D,t})=P_{T-D,t}Lmp_t=P_{T-D,t}(Lmp_{0,t}+m_tP_{T-D,t}) \quad \forall t\in T \tag{16}$$

The second term is the cost of DGs. The next two terms describe the costs of curtailable and shiftable loads, and the last term represents the degradation cost of ESSs. Cost of DGs, curtailable loads, shiftable loads and batteries are formulated as follows:

$$Cost_{DG}=\sum_{t}a_{DG\,g}P^{2}_{DG\,g,t}+b_{DG\,g}P_{DG\,g,t}+c_{DG\,g} \qquad \forall g\in G \tag{17}$$

$$Cost_{C\,l}=\sum_{t\in T}a_{C\,l}P^{R^2}_{C\,l,t}+b_{C\,l}P^{R}_{C\,l,t} \qquad \forall l\in CL \tag{18}$$

$$Cost_{S\,l,t}=\sum_{t\in T}a_{S\,l}(P_{S\,l,t}-P^{F}_{S\,l,t})^2+b_{S\,l}(P_{S\,l,t}-P^{F}_{S\,l,t}) \quad \forall l\in SL \tag{19}$$

$$Cost_{Bt\,b}=\sum_{t\in T}a_{Bt\,b}P^{2}_{Bt\,b,t}-\sum_{t=0}^{T-1}b_{Bt\,b}(P_{Bt\,b,t+1}P_{Bt\,b,t}) \quad \forall b\in B \tag{20}$$

Equation (17) represents the quadratic cost function of DGs, where $a_{DG\,g}$, $b_{DG\,g}$ and $c_{DG\,g}$ are constants. Equation (18) describes curtailable loads cost function, where $P^{R}_{C\,l}$ is the reduced part of the curtailable load and $a_{C\,l}$, $b_{C\,l}$ are constants. Equation (19) shows the shiftable loads cost function. Cost is applied to the difference of forecasted load at hour t and the power consumed by the shiftable load at hour t. Parameters $a_{S\,l}$ and $b_{S\,l}$ are fixed. The energy storage system cost is modeled as (20) [1].

Constraint (2) models line power limits, constraints (3) and (4) are power balance equations at distribution buses and transmission bus. Constraint (5) describes that the total power of shiftable loads should be equal to total forecasted shiftable loads. Constraints (6) and (7) are shiftable and curtailable loads power limits. Equation (8) guarantees that the sum of served and curtailed part of curtailable loads is equal to the forecasted value. Constraints (9) and (10) represents the generation limits of the programmable DGs and the limits of purchasing power from the transmission network. Constraints (11)-(15) model limits of energy storage systems. (11) Represents the dynamic of ESS. (12) Describes the ESS output power limit, which is less than maximum charging power and greater than maximum discharging power. Constraint (13) shows the ESS energy limit, (14) and (15) represent the ESS energy limits at the beginning and end of the scheduling horizon.

B. Decentralized Scheduling Problem

1. ATC Algorithm

ATC is a method for decomposing an optimization into two or more optimizations [9]. In the ATC method, an optimization problem is divided into a set of subproblems. These subproblems are hierarchically connected to each other. In other words, the ATC structure can be consist of several levels with at least one subproblem at each level. Subproblems in the higher level are called parents and the ones in the lower level are called children. In this structure, there is no horizontal connection between the subproblems at the same level. These subproblems (parents and children) are linked through coupling variables [10].

Coupling variables are named target variables (*t)* from parents' perspective and response variables (*r)* from the children's perspective. In this paper, the BDNO acts as parent and MGs play the role of children. The BDNO solves its optimization problem, determines the target variables and propagate them down to MGOs. Each MG's operator solves its own optimization problem based on the received information from the BDNO and determines the response variables. The problem is solved iteratively until the difference between these variables (targets and responses) get close to zero.

To model these variables in the optimization of each subproblem, a set of consistency constraints are defined. After that, these consistency constraints are relaxed in the objective function of each subproblem [9]. In [11] the ATC algorithm is briefly discussed and an exponential penalty function is represented for relaxing the consistency constraints. For convex optimization problems, it is proven that the ATC algorithm converges to the optimal point [12]. For a non-convex problem, selecting a quadratic penalty function for relaxing the consistency constraints in the subproblems, where the quadratic terms act as local convexifiers, mitigates non-convexity [10].

2. Solution Procedure

The algorithm solving procedure is as follows:

1. **Initialization**: initializing λ , β and r . λ is the lagrangian coefficient of consistency constraint, β is the penalty function multiplier and r is the set of response variables, $k=0$
2. **While** $|t-r|>\varepsilon$, $k=k+1$
3. **Solving** (23) by BDNO and determining *t* (set of target variables).
4. **Propagating** down the target variables to MGs by BDNO.
5. **Solving** (29) by MGOs and determining *r* (set of response variables).
6. **Sending** response variables to the BDNO by MGOs.
7. **Updating** λ and β using (21) and (22).

$$\lambda^{(k+1)}=\lambda^{(k)}+2\beta^{(k)}\circ\beta^{(k)}\circ c^{(k)} \tag{21}$$

$$\beta^{(k+1)}=\alpha\beta^{(k)} \tag{22}$$

9. **End while**

In the above formulation, $\alpha\geq 1$ is necessary for convex functions. In order to increase the speed of convergence, $2\leq\alpha\leq 3$ is usually considered [13]. For more information about ATC algorithm, [10] and [14] can be useful.

Consider the distribution system of Fig. 1. In the decentralized approach, operators of each entity (BDN and MGs) solve their own optimization problem, while exchanging limited information, to minimize the costs of the entire distribution network cooperatively.

For this purpose, the centralized problem that was represented before is decomposed into a bi-level optimization. In the proposed model, at first level, the scheduling problem of BDN is solved in which the purchasing power from the upstream grid, generations and loads schedule and exchanging power with MGs are determined. At the second level, MGs optimizations are solved in parallel.

Base Distribution Network Optimization

$$\begin{aligned}\min \ & \sum_t (\mathrm{Cost}(P_{T-D,t}) + \sum_{g\in G^{BDN}} \mathrm{Cost}(P_{DG\ g,t}) + \\ & \sum_{l\in CL^{BDN}} \mathrm{Cost}(P^R_{C\ l,t}) + \sum_{l\in SL^{BDN}} \mathrm{Cost}(P_{S\ l,t} - P^F_{S\ l,t}) + \\ & \sum_{b\in B^{BDN}} \mathrm{Cost}(P_{Bt\ b,t})) + \sum_t (\sum_{m\in MG} \lambda_{m,t}(P^{M*}_{D-M\ m,t} - P^D_{D-M\ m,t}) + \\ & \left\|\beta_{m,t}\cdot(P^{M*}_{D-M\ m,t} - P^D_{D-M\ m,t})\right\|_2^2)\end{aligned} \tag{23}$$

$$-P_{ij}^{\max}\leq\frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}}\leq P_{ij}^{\max} \qquad \forall t\in T,\forall i,j\in N^{BDN} \tag{24}$$

$$\begin{aligned}&\sum_{g\in G_i^{BDN}} P_{DG\ g,t} + \sum_{e\in E_i^{BDN}} P_{RE\ e,t} - \sum_{j\in N^{BDN}} \frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}} = \sum_{l\in D_i^{BDN}} P_{D\ l,t} + \\ &\sum_{l\in SL_i^{BDN}} P_{S\ l,t} + \sum_{l\in CL_i^{BDN}} P^S_{C\ l,t} + \sum_{b\in B_i^{BDN}} P_{Bt\ b,t} \quad \forall t\in T,\forall i\in N^{In,BDN}\end{aligned} \tag{25}$$

$$\begin{aligned}&\sum_{g\in G_i^{BDN}} P_{DG\ g,t} + \sum_{e\in E_i^{BDN}} P_{RE\ e,t} - \sum_{j\in N^{BDN}} \frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}} = \sum_{l\in D_i^{BDN}} P_{D\ l,t} + \\ &\sum_{l\in SL_i^{BDN}} P_{S\ l,t} + \sum_{l\in CL_i^{BDN}} P^S_{C\ l,t} + \sum_{b\in B_i^{BDN}} P_{Bt\ b,t} + \sum_{\substack{(m,i)\in K^{BDN}\\ m\in MG}} P^D_{D-M\ (m,i),t} \\ &\forall t\in T,\forall i\in N^{B,BDN}\end{aligned} \tag{26}$$

$$P_{T-D,t} + \sum_{g\in G_1^{BDN}} P_{DG\ g,t} + \sum_{e\in E_1^{BDN}} P_{RE\ e,t} - \sum_{j\in N^{BDN}} \frac{\delta_{1,t}-\delta_{j,t}}{X_{1j}} = \sum_{l\in D_1^{BDN}} P_{D\ l,t} + \sum_{l\in SL_1^{BDN}} P_{S\ l,t} + \sum_{l\in CL_1^{BDN}} P^S_{C\ l,t} + \sum_{b\in B_1^{BDN}} P_{Bt\ b,t} \quad \forall t\in T \tag{27}$$

$$(5)\text{-}(15) \qquad \forall\ BDN \tag{28}$$

In the above formulation, (23) denotes the objective function. The first five terms are cost functions and the last term represents the relaxed consistency constraint. Constraints (24)-(27) model lines power limits and power balance equations. Moreover, (23) is subject to constraints (5)-(15).

MGs Optimization

$$\begin{aligned}\min\ & \sum_{t\in T}\Big(\sum_{g\in G^{MG_m}} \text{Cost}(P_{DG\ g,t}) + \sum_{l\in CL^{MG_m}} \text{Cost}(P^R_{C\ l,t}) + \\ & \sum_{l\in SL^{MG_m}} \text{Cost}(P_{S\ l,t} - P^F_{S\ l,t}) + \sum_{b\in B^{MG_m}} \text{Cost}(P_{Bt\ b,t}) + \\ & \sum_{t} (\lambda_{m,t}(P^M_{D-M\ m,t} - P^{D*}_{D-M\ m,t}) + \\ & \left\| \beta_{m,t} \cdot (P^M_{D-M\ m,t} - P^{D*}_{D-M\ m,t}) \right\|_2^2 \Big)\end{aligned} \tag{29}$$

$$-P_{ij}^{max} \le \frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}} \le P_{ij}^{max} \qquad \forall t\in T, \forall i,j\in N^{MG_m} \tag{30}$$

$$\sum_{g\in G_i^{MG_m}} P_{DG\ g,t} + \sum_{e\in E_i^{MG_m}} P_{RE\ e,t} - \sum_{j\in N^{MG_m}} \frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}} = \sum_{l\in D_i^{MG_m}} P_{D\ l,t} + \sum_{l\in SL_i^{MG_m}} P_{S\ l,t} + \sum_{l\in CL_i^{MG_m}} P^S_{C\ l,t} + \sum_{b\in B_i^{MG_m}} P_{Bt\ b,t} \quad \forall t\in T, \forall i\in N^{In,MG_m} \tag{31}$$

$$P^M_{D-M\ m,t} + \sum_{g\in G_1^{MG_m}} P_{DG\ g,t} + \sum_{e\in E_1^{MG_m}} P_{RE\ e,t} - \sum_{j\in N^{MG_m}} \frac{\delta_{i,t}-\delta_{j,t}}{X_{ij}} = \sum_{l\in D_1^{MG_m}} P_{D\ l,t} + \sum_{l\in SL_1^{MG_m}} P_{S\ l,t} + \sum_{l\in CL_1^{MG_m}} P^S_{C\ l,t} + \sum_{b\in B_1^{MG_m}} P_{Bt\ b,t} \quad \forall t\in T \tag{32}$$

$$(5)\text{-}(15) \qquad \forall\ MG_m \tag{33}$$

The objective function of each MG is represented in (29) . (30)-(32) denote the lines power limits and power balance equations. Furthermore, the MGs optimization problem is subject to constraints (5)-(15).

III. NUMERICAL RESULTS

The proposed method is applied to a test distribution grid including four MGs. Fig. 2 demonstrates the test distribution network, it is consist of several sections, which are adopted from [6]. Network components data are taken from [3]. All simulation results are performed using a 4.00 GB and 2.6 GHz personal computer, with GAMS software. $\lambda=1$, $\beta=1$, $\alpha=1$, and $\varepsilon=0.0001$ are chosen as the initial values of algorithm parameters.

Fig.3 illustrates the optimal schedule of 2nd MG. As its total load is more than sum of its DG's maximum power generation, exchanging power between base distribution network and 2nd MG is always positive (power flow direction is from the base distribution network to 2nd MG).

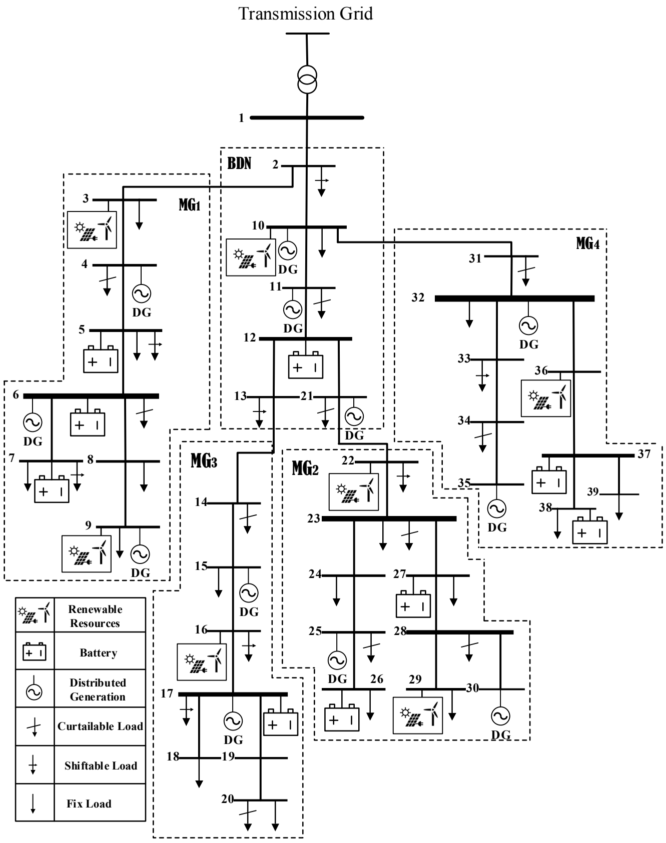

Fig. 2. 39-bus test distribution network

Curtailable loads of 2nd MG are completely served between hours 0-10 and as the MG load increases most parts of curtailable loads are curtailed.

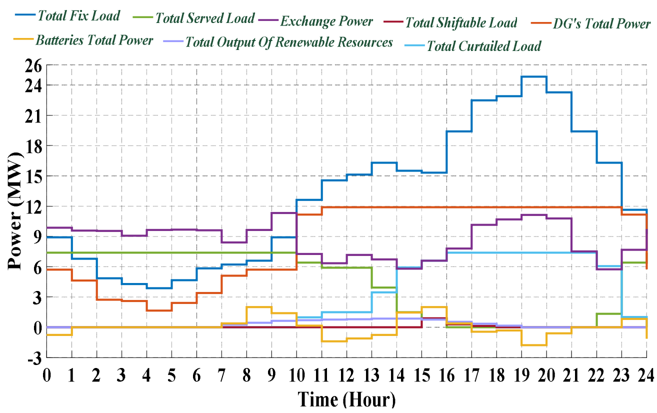

Fig. 3. Optimal schedule of 2nd MG

The energy storage systems of this MG are always charged before load peak periods and discharged during these intervals.

Fig.4 demonstrates the optimal schedule of BDN. Due to the low price of power at low load periods, the amount of power purchased from the transmission network is at the maximum rate, between hours 1-10.

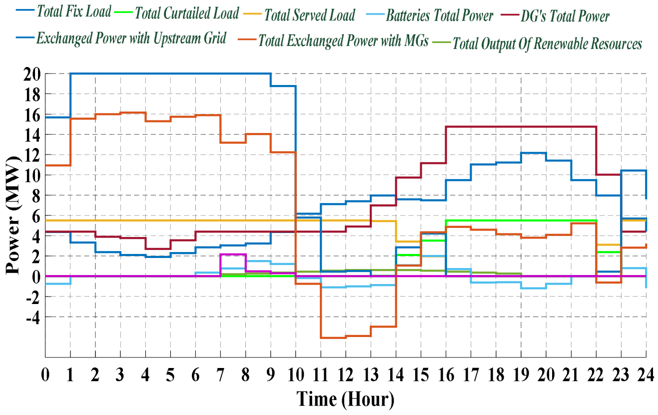

Fig. 4. Optimal schedule of BDN

With increasing the load, the price of power on the transmission bus increases and the base distribution network operator seeks to supply network's load by increasing DG's generation and curtailing its curtailable loads. Shiftable loads of BDN that should be scheduled between hours 7-10, are mostly shifted to hour 7. The reason is that the BDN's load and price of transmission bus are less than other hours at 7 am. Fig.5 demonstrates the purchased power from the transmission grid during the scheduling horizon, compared to the total fix load of the distribution network.

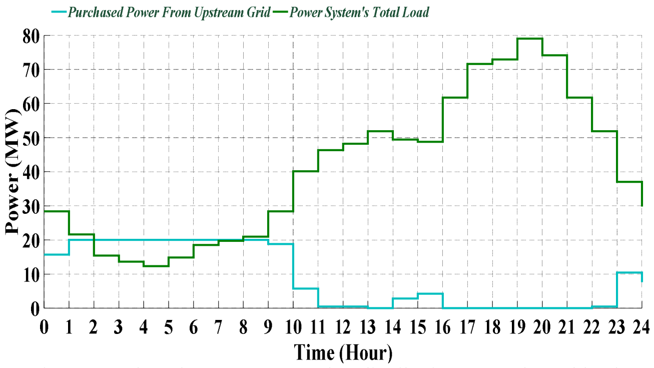

Fig. 5. Purchased power compared to distribution network total load

Total load of the distribution network and the marginal price of transmission bus are at their minimum during hours 1-10. Therefore the BDNO tries to buy the maximum possible power from the upstream grid (it should be noticed that the maximum rate of purchasing power is set to 20MW). It can be seen that, as we approach the load peak hours, the amount of purchasing power is reduced. Fig.6 illustrates the willingness of BDNO for purchasing power from the transmission network. As an example, for prices more than 42$ the operator would not buy any power from the transmission grid.

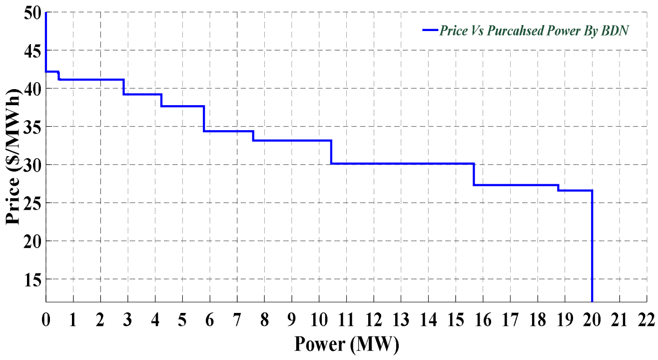

Fig. 6. The willingness of BDNO for purchasing power

Fig.7 demonstrates the convergence of exchanging power between 1st MG and BDN at hour 5. It is obvious that at first iterations, the optimal value is different from the perspective of each side. After 20 iterations, both sides reach an agreement on the amount of exchanging power.

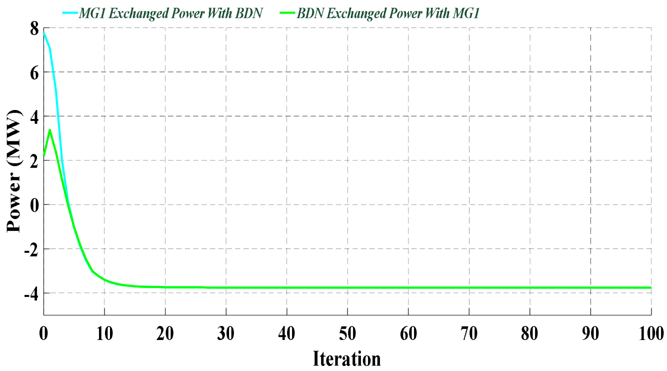

Fig. 7. Convergence of exchanging power between 1st MG and BDN

Fig.8 shows the convergence of exchanging power between 2nd MG and BDN at hour 20. As it can be seen after about 15 iterations, both entities get converge to a specific exchanging power.

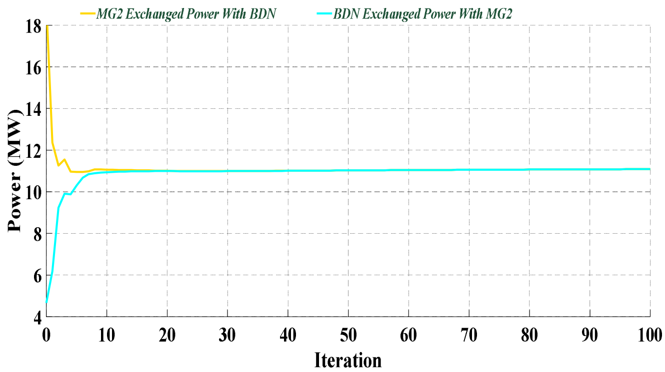

Fig. 8. Convergence of exchanging power between 2nd MG and BDN

Fig.9 shows the optimal exchanging power between 1st MG and BDN from the BDNO's point of view at hour 5. By increasing the parameter α from 1.0 to 1.5, although the number of iterations and computation time will be reduced, but the answers' accuracy will be lost.

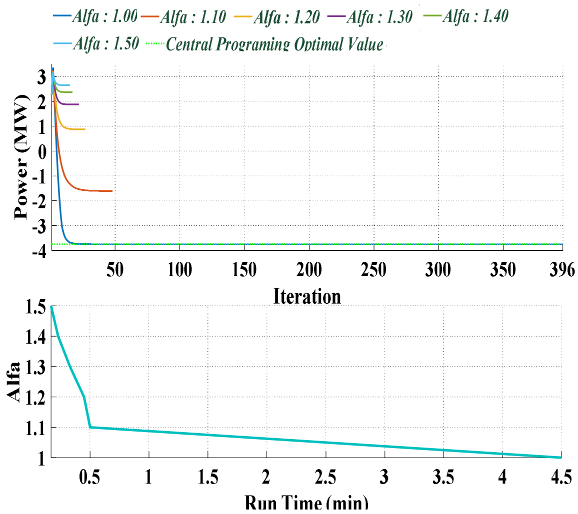

Fig. 9. Effect of the parameter α on the convergence of the problem

Effect of stopping criterion on the number of iterations, computation time (run time) and error in exchanging power between BDN and 1st MG at hour 5, are discussed in table.I. The error is defined as the difference between answers of the centralized problem and those of decentralized one. It can be seen, by increasing the stopping criterion, the number of iterations and optimization run time decrease, but the error value increases. A trade-off between error value, the number of iterations and run time can lead to choosing $\varepsilon = 0.01$ as the appropriate stopping criterion.

IV. CONCLUSION

In this paper, we proposed a daily decentralized scheduling for smart distribution networks and grid-connected MGs. Compared with the existing decentralized scheduling articles, LMP of transmission bus is not considered as a fixed price. At each hour it is estimated by the BDNO, using price conjecture curves. All types of responsive loads are studied, and the effect of energy storage systems and renewable resources are taken into account. The proposed method is applied to a 39-bus test distribution network and simulation results show the effectiveness of the method. Answers of the decentralized problem are the same as a centralized one, up to three decimal places. Moreover, the proposed algorithm preserves the privacy of MGs. Future works include considering the uncertainty of fix loads and renewable resources, investigating the MGs connection, their interactions and the way power is exchanged between them, and making a better estimation of transmission bus LMP by investigating the data histories.

TABLE I. EFFECT OF STOPPING CRITERION

ε	Error (MW)	Iteration	Run Time (min)
0.00001	0	615	7.58
0.0001	0	397	4.50
0.001	0	187	2.3
0.01	0.0006	35	0.42
0.1	0.0440	16	0.18

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