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Energy management in multi-microgrids considering point of common coupling constraint

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ABSTRACT

There are different models for Energy Management of Multi-Microgrids (MMGs). Generally, the owners of microgrids are not identical. In this case, due to privacy concerns and overcomes drawbacks of conventional decentralized systems, hybrid energy management system is proposed. Unlike other energy management models, in hybrid model, multi-microgrids are connected to the grid through the common line entitled Point of Common Coupling (PCC). Energy management in hybrid multi-microgrids considering optimal utilization of PCC capacity is a critical issue that has been less taken into account. In this paper, a new bi-level method is proposed for optimal energy management in hybrid MMG systems taking into account the PCC line capacity. In the first level, each microgrid implements its day-ahead scheduling based on different quantities of PCC line capacity and extracts its profit-quantity curve. This novel curve shows the variations of microgrid profits versus different PCC limits. Subsequently, a two-stage optimization problem is presented in the second level, in which in the first stage an introduced microgrid aggregator (MGA) maximizes microgrids aggregated profit and determines optimal quota of each microgrid from PCC line based on corresponding profit-quantity curves while in the second stage, this profit is fairly divided among microgrids via Shapely value. Numerical results demonstrate the efficiency and reliability of the proposed method.

1. Introduction

Energy management is one of the challenges of the microgrid operators. Interconnection of microgrids and hence, energy exchange between them provides a promising potential to decrease microgrid operation cost and could result in the reduction of required load-shedding amount [1–3]. Different models for energy management of MMGs have been presented [4–14]. The comprehensive classification includes four models to manage microgrids, namely: centralized, decentralized, hybrid, and nested energy management systems.

In the centralized EMS, scheduling is performed by a centralized unit and all information of the loads, DERs, and storage units will be gathered by this unit, therefore, the total operation cost of day-ahead scheduling can be reduced. In the centralized EMS, each microgrid sends all its information to a central EMS [4–7]. The central EMS implements a day-ahead scheduling for all MMGs (see Fig. 1a). In [4], energy management problem is decomposed into Unit Commitment (UC) and Optimal Power Flow (OPF) problems. An optimal operation of MMGs considering market operation and network reliability has been discussed in [5]. Ref. [6] proposes an algorithm based on centralized EMS for day-ahead scheduling of MMGs operation in the grid-connected mode. This algorithm is made up of microgrid EMSs and community EMS instead of a big centralized EMS. This model contributes to higher flexibility and distribution of computational burden in comparison to traditional centralized model. Ref. [7] proposes an optimal energy management of MMGs with the sequential operation, the computational burden on the central EMS can be reduced by using hierarchical energy management strategies or sequentially coordinated operations. Centralized EMS can reduce the total operation cost of day-ahead scheduling; however, the microgrid privacy is neglected and we face a heavy computational burden. In this model, since all information of microgrids is sent to a central EMS (which is solely responsible for microgrids scheduling), congestion in PCC does not occur at all.

In the decentralized EMS, each microgrid is an autonomous entity and possesses a local EMS with an objective to maximize its own profit. In decentralized EMS, each microgrid is connected to the grid via a separate PCC and implements its day-ahead scheduling [8–12] (see Fig. 1b). In [8] a bi-level methodology for the self-healing and optimal operation of microgrid is presented. In the lower level, EMS schedules the operation of each MG while the upper level links a number of energy management systems for global optimization for whole set of MGs. Ref. [9] develops a decentralized EMS based on multi-agent system and

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Nomenclature

A. Set and indices

j	index of microgrid
t	index of time
i	index of Distributed Energy Resources (DER)
k	index of energy storage unit
ch, dis	index of energy storage unit charging/discharging mode
M	set of energy storage units
N	set of DERs
T	set of time periods
J	set of microgrids

B. Parameters

λ	day-ahead market price [$/MWh]
MC	minimum charging time [h]
MD	minimum discharging time [h]
α	linear cost coefficient of DERs [$/MWh]
R^{up}, R^{dn}	ramp up/down limit of DER [MW/h]
UP, DN	minimum up-time/down-time of DER [h]
$p^{\min}$, $p^{\max}$	Min/Max power generation of DER [MW]
SU	start-up cost of DER [$]
SD	shutdown cost of DER [$]
f_l	capacity of common line [MW]
$E_s^{\max}$	maximum state of charge [MWh]
$p^{ch,\min}$, $p^{ch,\max}$	Min/Max charge power of storage unit [MW]
$p^{dis,\min}$, $p^{dis,\max}$	Min/Max discharge power of storage unit [MW]
x	number of players in a coalition
b	value of each coalition

C. Variables

P_{ex}	power trading between each microgrid and grid [MW]
F_l	quota of microgrid from common line [MW]
c	total generation cost [$]
p^{ch}, p^{dis}	charge/discharge power of storage unit [MW]
D	contracted demand of each microgrid [MW]
R	revenue that microgrid earns from selling power to consumers [MW]
v	binary variable representing charge of energy storage unit
u	binary variable representing discharge of energy storage unit
P	power generation of DER [MW]
P_s	input/output power of storage unit [MW]
I	binary variable representing ON/OFF status of DER
Y	binary variable representing start-up status of DER
Z	binary variable representing shutdown status of DER
E_s	energy stored in energy storage unit [MWh]
T^{ch}, T^{dis}	number of successive charging/discharging hours [h]
T^{on}, T^{off}	number of successive ON/OFF hours [h]
S	profit of microgrid [$]
λ_1	lagrange multiplier
ℓ	lagrange function
φ	shapely value

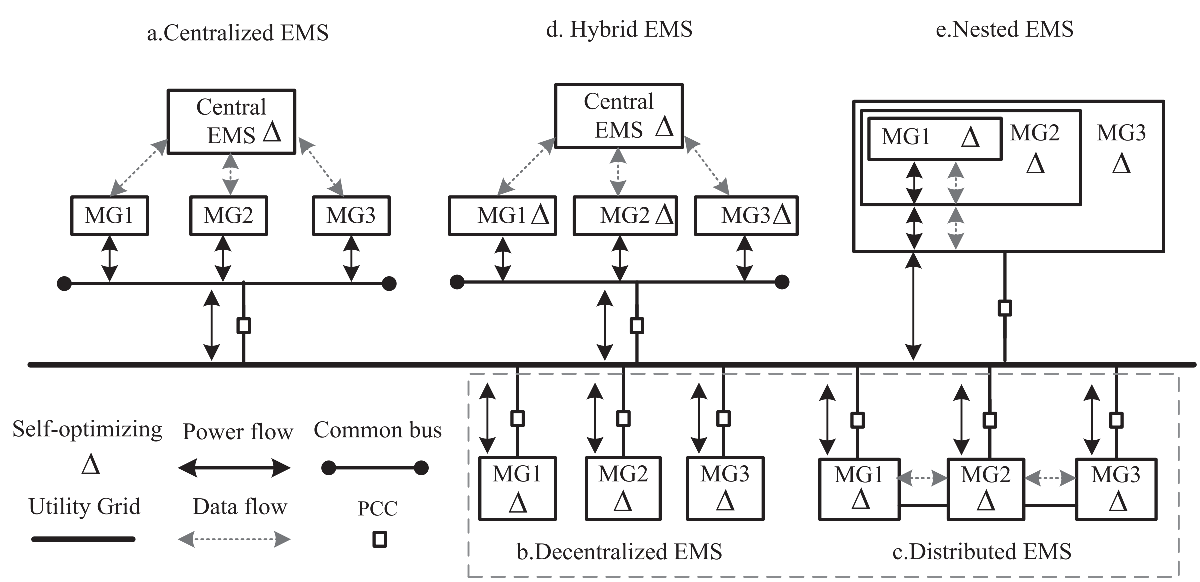

Fig. 1. Types of energy management systems for MMGs.

employs fuzzy logic for its implementation. The most important advantage of using a decentralized architecture is that the managed microgrid has much higher chances of partial operation in cases when malfunctions occur at different parts of it, instead of a complete system breakdown. Decentralized EMS has high reliability, In the case of a controller failure, the rest of the system can still operate in part and not affect the whole system's performance is proposed algorithm in [10]. This algorithm introduced a fair load-shedding algorithm and can help to more insights into the prevention of cascading failures in a microgrid. A bi-level decentralized algorithm to solve EMS problem in grid-connected and islanded modes considering uncertainties of distributed unit outputs and load consumption is introduced in [11]. Ref [12] introduces a control strategy for PV/battery units for decentralized EMS in islanded mode; this strategy can control voltage and frequency. A decentralized strategy for the optimal operation and self-healing in MMGs proposed in [8], in this strategy, two-layer cyber communication is introduced. The lower-layer cyber is controls DER, ESS units and loads in each microgrid. The upper-layer cyber is communicates with its neighboring microgrid. In decentralized EMS each microgrid implements its own scheduling, thus the operation cost of MMGs could be increased. In this model, the privacy of microgrids has been preserved. However, since each microgrid has a separate PCC, therefore congestion in PCC doesn't occur in this model.

Generally, if microgrids could share all information including load data, generation data and grid conditions, the optimal scheduling could be easily implemented (centralized EMS). However, for security considerations, it is not desirable for each MG to do so because the shared information threats the privacy of each MG. Thus, this is the basic motivation for the deployment of distributed EMS [13]. In distributed model, there are communicational (and in some cases electrical) interconnections between microgrids (see Fig. 1c). In distributed/decentralized EMSs each entity optimizes its objective function individually. In this model each microgrid is connected to the grid via its individual PCC (see Fig. 1b), thus no congestion occurs. Additionally, the local controllers in decentralized/distributed EMSs are unaware of the system level parameters and hence are not able to utilize them optimally [2]. For this reason hybrid EMSs have emerged as a trade-off solution (between centralized and decentralized/distributed models) for management of networked microgrids [14–19].

Hybrid EMS is a combination of centralized and decentralized models [19–21]. In this model, each microgrid is responsible for scheduling its local resources and provides plus/deficit amount of its energy to central EMS (see Fig. 1d). Ref [19] introduces a two-level hierarchical optimization method. The first level focuses on an individual MG and the second level is responsible for energy management between MGs. In hybrid EMS, operation costs are lower compared to decentralized EMS. Ref. [20] proposes a three-level model of EMS. In the first level, each microgrid schedules itself and sends the results to the macro-station. In the second level, macro-station determines the amount of power trading among microgrids based on the scheduling of each microgrid, and in the third level, microgrids form coalitions. Ref. [21] proposes a two-stage hierarchical outage management scheme for resilient operations of MMGs. Microgrids are scheduled in the first stage, and Distribution System Operator (DSO) arranges the power transactions among MGs, in the second stage. Furthermore, it has less computational complexity compared to centralized EMS. In this model, the privacy of microgrids has been preserved. Parallel operation of microgrids and unaware of operation point of other microgrids may lead to congestion in PCC.

Hussain et al proposed nested EMS for microgrids [2]. In this model, each lower microgrid optimizes day-ahead scheduling and notifies upper microgrids about corresponding surplus/deficit energy amount. Each lower microgrid is connected to the upper microgrids via a PCC (see Fig. 1e). This model contributes to minimizing operation cost compare to decentralized model. In nested EMS, operation of microgrids is not parallel and scheduling in MMGs hierarchically starts from the lower microgrid, then congestion in PCC does not occur. In [2,22], a complete comparison of the mentioned energy management models is presented.

If microgrid owners are distinct, the decentralized and the hybrid EMS models could be used. Increased operating cost and excessive power trading among microgrids and the grid are disadvantages of the decentralized EMS. The hybrid EMS is evolved to overcome the drawbacks of the decentralized EMS [2]. In the hybrid EMS, microgrids are connected to the grid through a common line. In operation of MMGs, each microgrid tries to maximize its profit by employing maximum utilization of common line while being ignorant of its neighboring microgrids. Lack of information about neighboring microgrids hence may be troublesome and if the share of each microgrid from PCC is not specified, congestion may occur in the common line. This is the critical issue that has been less taken into account.

The necessity of considering PCC capacity limit in multi microgrid studies is important due to the following reasons. First, the design of common line capacity based on annual peak hours (that occurs in 1% hours of the year) is not economical. Therefore, MMGs may face PCC congestion within these hours. Second, existence capacity constraint in the main grid for connecting MMGs that used to operate in islanding mode. The main question is: "What is the best decision of microgrids while facing PCC capacity congestion?". This is the motivation for writing this paper.

This paper introduces a hierarchical structure in a hybrid EMS to manage energy in a system composed of multi-microgrids. The proposed method is a bi-level model. In the first level, each microgrid implements its day-ahead scheduling considering different quantities of common line capacity and sends its profit-quantity curve to the second level. In the second level, the introduced agent called microgrid aggregator (which is a set of microgrids representatives) aims to maximize aggregated profit of MMGs considering PCC capacity constraint. The second level is a two-stage problem. In the first stage, employing Lagrange method, aggregated profit is maximized by means of individual profit-quantity curves and quotas of the microgrids from common line capacity are computed. In the second stage, this profit is fairly divided among microgrids via Shapely value. The Shapely value is the average added profit/cost of a user to all coalitions. It emphasizes the fairness of the division of profit/cost between users. The Shapely value has been used to model the allocation of profits/costs between users of a common facility and to measure political power.

The major contributions of this paper are listed as follows:

- Introducing an aggregator unit to override PCC congestion and fair allocation of common line capacity among MGs, aiming at maximizing microgrids profits.
- Introducing a novel profit-quantity curve for each microgrid to find the optimal operating points of microgrids by means of Lagrange method
- Introducing a cooperative game mechanism by proposed aggregator in a competitive environment to fairly divide profit between MGs.

The remaining of this paper is organized as follows: In Section 2 problem formulation is presented. Section 3 provides simulation results. Finally, conclusions are presented in Section 4.

2. Problem formulation

The proposed scheme representing electrical and communication connections between microgrids and grid through PCC and the aggregator is illustrated in Fig. 2. In this figure, $P_{ex,j}$ is sold/bought power to/from the j^{th} microgrid, and $\sum_{j=1}^{J} P_{ex,j}$ represents power trading between MMGs and grid. In Fig. 2, microgrids are connected via a common bus and common line to the grid. Assume that line limitation in PCC equals f_l and three microgrids are connected to the grid through this point. When grid electricity price is cheap/expensive, each microgrid starts to buy/sell from/to grid without knowing about neighboring microgrids. For example, in the peak hours, all three microgrids have scheduled to make use of $0.8 \times f_l$, $0.6 \times f_l$ and f_l of the line capacity respectively. As can be seen, each microgrid by itself meets the line limitation, but as a whole, the purchase of $2.4 \times f_l$ occurs that violates line capacity constraint. For this purpose, in this paper, a new unit to manage congestion called microgrid aggregator is proposed.

This unit is composed of representatives of microgrids and is

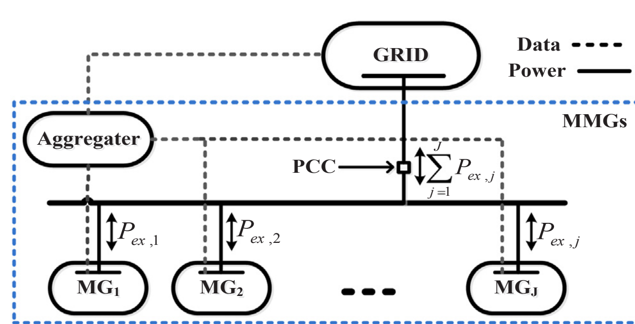

Fig. 2. System model for MMGs and the grid.

responsible for achieving the maximum profit for multi microgrids and fairly allocates it among individual microgrids taking into account PCC capacity.

The proposed bi-level framework is illustrated in Fig. 3 in which first and second levels are carried out by microgrids and aggregator, respectively. In the first level, each microgrid implements its day-ahead scheduling based on the various amounts of its utilization from common line capacity (F_{lj}) and accordingly obtains its profit-quantity curve ($S_j(F_{lj})$). Subsequently, individual curves of microgrids are sent to second level. In the second level, optimal quota of each microgrid from common line capacity (F_{lj}^{opt}) and profit of each microgrid (S_j^{opt}) are obtained and sent back to first level. The detailed mathematical framework of the proposed mechanism is addressed below:

2.1. First level: microgrids day-ahead scheduling

In this level, each microgrid maximizes its profit based on upstream received prices as represented in Eqs. (1)–(17):

$$S_j = \max \sum_{t=1}^{T} \left[\lambda_t(-P_{ex,t}) - \sum_{i=1}^{N} c_{i,t} + R_t \right] \tag{1}$$

Subject to:

$$P_{ex,t} = D_t - \sum_{i=1}^{N} P_{i,t} + \sum_{k=1}^{M} P_{s,k,t} \quad \forall\, k \in M, \forall\, i \in N, \quad \forall\, t \in T \tag{2}$$

$$-f_l \leqslant P_{ex,t} \leqslant f_l \quad \forall\, t \in T \tag{3}$$

$$c_{i,t} = \alpha_i P_{i,t} + Y_{i,t} SU_i + Z_{i,t} SD_i \quad \forall\, i \in N, \quad \forall\, t \in T \tag{4}$$

$$P_i^{min} I_{i,t} \leqslant P_{i,t} \leqslant P_i^{max} I_{i,t} \quad \forall\, i \in N, \quad \forall\, t \in T \tag{5}$$

$$P_{i,t+1} - P_{i,t} \leqslant R_i^{up} I_{i,t} \quad \forall\, i \in N, \quad \forall\, t \in T \tag{6}$$

$$P_{i,t} - P_{i,t+1} \leqslant R_i^{dn} I_{i,t+1} \quad \forall\, i \in N, \quad \forall\, t \in T \tag{7}$$

$$T_{i,t}^{on} \geqslant UP_i(I_{i,t} - I_{i,t-1}) \quad \forall\, i \in N, \quad \forall\, t \in T \tag{8}$$

$$T_{i,t}^{off} \geqslant DN_i(I_{i,t} - I_{i,t-1}) \quad \forall\, i \in N, \quad \forall\, t \in T \tag{9}$$

$$P_{sk,t} \leqslant p_{k,t}^{dis,\max} u_{t,k} - p_{k,t}^{ch,\min} v_{t,k} \quad \forall\, k \in M, \quad \forall\, t \in T \tag{10}$$

$$P_{sk,t} \geqslant p_{k,t}^{dis,\min} u_{t,k} - p_{k,t}^{ch,\max} v_{t,k} \quad \forall\, k \in M, \quad \forall\, t \in T \tag{11}$$

$$u_{t,k} + v_{t,k} \leqslant 1 \quad \forall\, k \in M, \quad \forall\, t \in T \tag{12}$$

$$E_{s,k,t} = E_{s,k,t-1} - P_{sk,t} \quad \forall\, k \in M, \quad \forall\, t \in T \tag{13}$$

$$0 \leqslant E_{s,k,t} \leqslant E_{s,k}^{max} \quad \forall\, k \in M, \quad \forall\, t \in T \tag{14}$$

$$E_{s,k,t=initial} = E_{s,k,t=end} \quad \forall\, k \in M \tag{15}$$

$$T_{k,t}^{ch} \geqslant MC_k(u_{k,t} - u_{k,t-1}) \quad \forall\, k \in M, \quad \forall\, t \in T \tag{16}$$

$$T_{k,t}^{dis} \geqslant MD_k(v_{k,t} - v_{k,t-1}) \quad \forall\, k \in M, \quad \forall\, t \in T \tag{17}$$

In Eq. (1), the first term states microgrid revenue based on exchangeable power between microgrid and grid. The second term deals with total generation cost. The third term shows the revenue that microgrid earns from selling power to its consumers. The power balance constraint is represented in (2) to guarantee that the total load minus the sum of microgrid local generation meets the grid power trading. Power flow violation in common line is controlled in (3). Eq. (4) shows DG operation cost in terms of generation, shut-down and start-up costs. The maximum and minimum power limits of generation units are demonstrated in (5). Ramping-up and down limits of thermal units are also represented in (6)–(7). Minimum up time and down time of units are illustrated in (8)–(9). Energy stored in storage unit is subject to minimum and maximum charging and discharging limits depending on Eqs. (10), (11). Eq. (12) guarantees that charging and discharging will not occur at the same time. Energy stored in storage unit and its boundaries are demonstrated in (13), (14). Eq. (15) emphasizes that the amounts of stored energy in opening and closing hours must be same and finally, Eqs (16) and (17) state minimum charging and discharging time of energy storage unit.

In the proposed model, each microgrid implements its day-ahead scheduling based on the variation of its utilization from common line capacity and corresponding profits are stored. In other words, in Eq. (3), the common line capacity (f_l) is varied in the small steps between 0 and maximum PCC capacity, and corresponding day-ahead scheduling is implemented. Accordingly, each microgrid obtains a relevant profit-quantity curve as illustrated in Fig. 4.

This figure illustrates different profits of microgrid versus various utilization amounts of PCC capacity. In Fig. 4, points A and B represent microgrid profits when their quotas of the common line capacity are zero and maximum, respectively.

2.2. Second level: aggregator energy management mechanism

Aggregator aims to maximize profit of MMGs and fairly divide it between microgrids based on received curves taking into account capacity limit of common line. This procedure is implemented in two stages as follows:

(1) Stage 1: Finding Optimal Operation Point for MMGs

Based on microgrids received curves, aggregator employs Eqs. (18) and (19) to maximize benefit of whole set of microgrids considering sum of quotas of MGs should be equal to common line capacity.

$$\max \sum_{j=1}^{J} S_j(F_{l,j}) \tag{18}$$

$$\sum_{j=1}^{J} F_{l,j} = f_l \tag{19}$$

where: quota of MG_j from common line capacity is $F_{l,j}$.

The obtaining profit-quantity curves are concave. For the sake of simplicity, curves are modeled by fitting the data to the polynomial ($\sum_{i=1}^{N} a_i F^i$). Given that Fig. 5 is concave and ascending, Lagrange method results in optimal operating points on the curves that provide the maximum aggregated profit for whole set of microgrids. Therefore, considering Eqs. (18) and (19) Lagrange function can be written as Eq. (20).

$$\ell = \sum_{j=1}^{J} S_j(F_{l,j}) + \lambda_1 \left(\sum_{j=1}^{J} F_{l,j} - f_l \right) \tag{20}$$

The necessary conditions for an extreme value of the objective function are obtained by taking the first derivative of the Lagrange

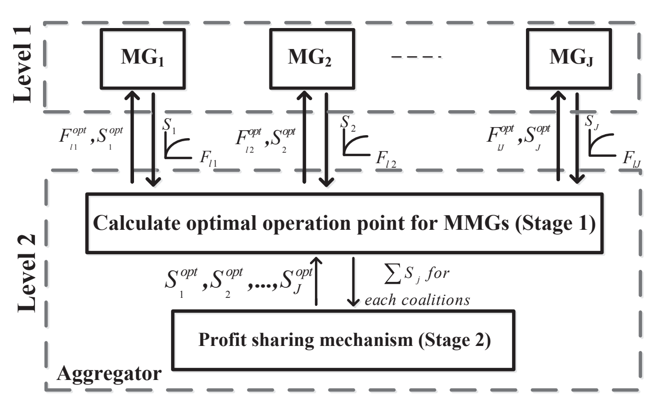

Fig. 3. The proposed architecture to manage common line congestion.

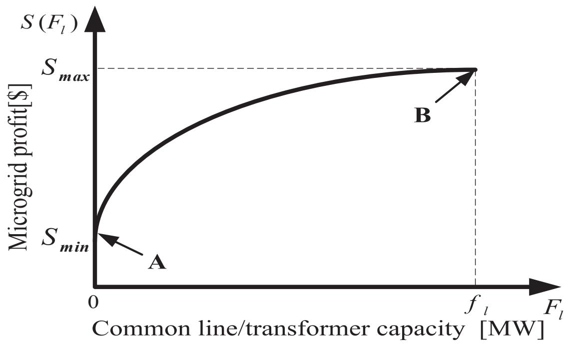

Fig. 4. Microgrid profit variation curve.

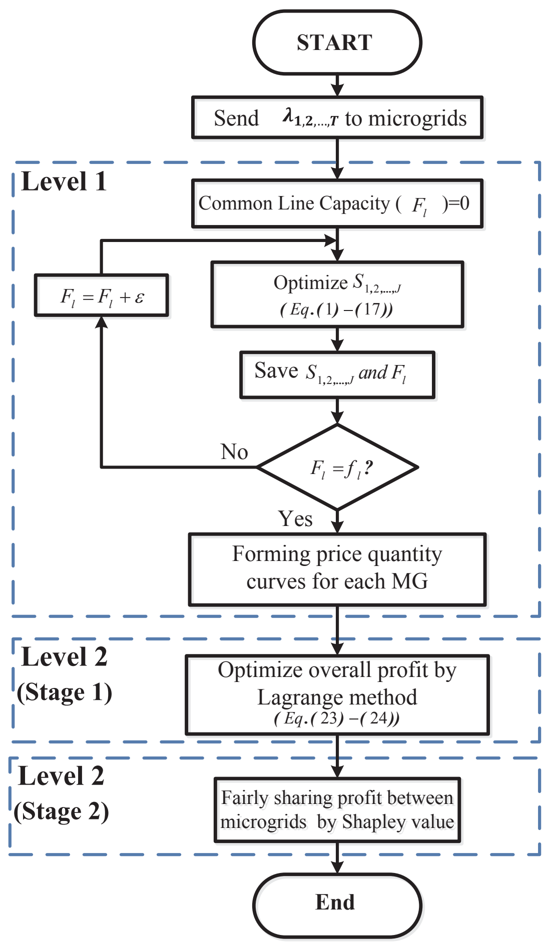

Fig. 5. Flowchart of the proposed method to override the PCC congestion.

function with respect to independent variables and Lagrange multiplier.

$$\frac{\partial \ell}{\partial F_{l,j}} = \frac{dS_j(F_{l,j})}{dF_{l,j}} - \lambda_1 \tag{21}$$

$$\frac{\partial \ell}{\partial \lambda_1} = 0 \tag{22}$$

Set the derivatives equal to zero, profits of microgrids that result in maximum aggregated profit for MMGs are determined.

$$\frac{dS_j(F_{l,j})}{dF_{l,j}} - \lambda_1 = 0 \tag{23}$$

$$\sum_{j=1}^{J} F_{l,j} = f_l \tag{24}$$

Finding individual profits, optimal quota of each microgrid from PCC capacity is obtained. In this case, there are $j + 1$ variables. This problem is a non-linear optimization problem with constraints, which is solvable by numerical methods such as the Gradient method and Newton method [23,24].

(2) Stage 2: Aggregator Profit Sharing Mechanism

This stage deals with the problem of how to divide the total profit of collaboration among different microgrids. Since microgrids compete and cooperate as coalition in unstructured interactions, we are facing a cooperative game theory. There are many ways for profit sharing in cooperative game theory entitled, Shapely value, Nucleolus, Min/Max core, Least Core and τ-value, among which Shapely is the most common in literatures [25].

In Shapely value, profit is calculated for each coalition. Then, considering benefits of all coalitions, the fair profit of each microgrid is determined. The idea of Shapely value has been employed widely in the fair distribution of coalitional [25–28]. For our coalitional game $(\varphi,\ b,\ J)$, the Shapely value of each MGj is denoted as $\varphi_j(b)$ and can be represented as (25):

$$\varphi_j(b) = \sum_{j \in \Theta x} \frac{(|x|-1)!(|J|-|x|)!}{|J|!}[b(x) - b(x-j)] \tag{25}$$

where Shapely value for j^{th} microgrid is φ_j, $|x|$ is the number of players in a coalition, $|J|$ is the number of microgrids, $b(x)$ is the value of coalition, and $b(x-j)$ is the value of coalition when player j is removed from the coalition considering above mentioned issues.

The total number of coalitions will be equal to 2^{J-1}. Proposed method is solved for each coalition, and corresponding profits are saved. Finally, using Shapely, the share of each MG is determined.

Flowchart of the proposed method is demonstrated in Fig. 5. In this flowchart for calculating profit-quantity curve of each microgrid in level 1, the common line capacity is in the small steps ($\varepsilon = 0.005 \times f_l$) between 0 and f_l, and corresponding day-ahead scheduling is implemented.

3. Simulation results

In this paper optimization problem is implemented in GAMS 23.8.2 software using CPLEX solver and MATLAB. The input and output data are transferred using GAMS/MATLAB interface. For energy management in a set of microgrids, three different scenarios are introduced. In this case study, three distinct microgrids are connected to grid through a common line. The capacity of common line is 4.5 MW.

If the capacity of common line is not sufficient, congestion happens in common line. There are two scenarios for line congestion management. In the first scenario, each microgrid is authorized to use $1/J$ of common line capacity. In the second scenario, the proposed model for energy management of MMGs considering common line congestion is presented and the quota of each microgrid from PCC point is calculated. The third scenario is similar to the second scenario except that one of the microgrids has expensive units. It should be mentioned that the proposed method can be generalized for any number of microgrids.

Individual loads for three microgrids in terms of industrial, residential and commercial loads are illustrated in Fig. 6.

Specifications of microgrid units are provided in Tables 1 and 2. In Table 1, D and ND stand for dispatchable and non-dispatchable units. The forecasted values for hourly market prices and non-dispatchable unit outputs are represented in Tables 3 and 4, respectively [30]. For the sake of simplicity here, it is assumed that non-dispatchable unit outputs are specified.

Figs. 7 and 8 represent microgrid individual and aggregated scheduling in case no control is implemented by microgrid aggregator. Fig. 7 deals with power exchanged between each microgrid and the

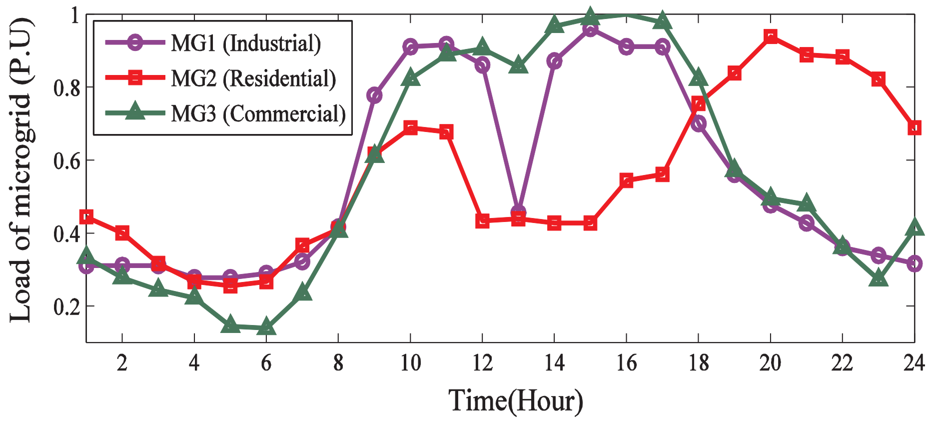

Fig. 6. Daily load profit at each microgrid [29].

Table 1
Installed DG units in microgrids.

	unit	Type	Cost Coefficient ($/MWh)	Min.-Max. Capacity (MW)	Min. Up/ Down Time (h)	Ramp UP/ Down Rate (MW/h)
MG1	DG 1	D	27.7	1–5	3	2.5
	DG 2	D	151.3	0.8–3	1	3
	DG 3	ND1	0	0–1.5	–	–
MG 2	DG 1	D	39.1	1–5	3	2.5
	DG 2	ND1	0	0–1.5	–	–
	DG 3	ND2	0	0–1	–	–
MG 3	DG 1	D	39.1	1–5	3	2.5
	DG 2	D	61.3	0.8–3	1	3
	DG 3	D	95.6	0.8–3	1	3
	DG 4	ND1	0	0–1.5	–	–

Table 2
Installed storage units in microgrids.

	Capacity (MWh)	Min.-Max. Charging/ Discharging Power (MW)	Min. Charging/ Discharging Time (h)
MG 1	4	0.4–2	5
MG 2	4	0.4–2	5
MG 3	4	0.4–2	5

Table 3
Hourly market price.

Time (h)	1	2	3	4	5	6
Price ($/MWh)	15.03	10.97	13.51	15.36	18.51	21.8
Time (h)	7	8	9	10	11	12
Price ($/MWh)	17.3	22.83	21.84	27.09	37.06	68.95
Time (h)	13	14	15	16	17	18
Price ($/MWh)	65.79	66.57	65.44	79.79	115.45	110.28
Time (h)	19	20	21	22	23	24
Price ($/MWh)	96.05	90.53	77.38	70.95	59.42	56.68

grid. As it is evident, each microgrid schedules its day-ahead activities based on common line limitation aiming to maximize its profit. Thus at any time amounts of exchanged powers do not exceed 4.5 MW.

Fig. 8 shows the sum of power exchanged between the microgrids and the grid. As shown, at hours 1–5, 7–11 and 15 market prices enforce MMGs to buy power from the grid. However, at hours 17–20 and 22 market prices will persuade MMGs to sell power. Also, it is observed that in most of the time total exchanged power violates PCC capacity. The space enclosed by two dashed lines in Fig. 8 demonstrates the acceptable line while taking congestion into account.

Table 4
Generation of non-dispatchable units.

Time (h)	1	2	3	4	5	6
ND1	0	0	0	0	0	0
ND2	0	0	0	0	0.63	0.8
Time (h)	7	8	9	10	11	12
ND1	0	0	0	0	0	0.75
ND2	0.62	0.71	0.68	0.35	0.62	0.36
Time (h)	13	14	15	16	17	18
ND1	0.81	1.2	1.23	1.28	1	0.78
ND2	0.4	0.37	0	0	0.05	0.04
Time (h)	19	20	21	22	23	24
ND1	0.71	0.92	0	0	0	0
ND2	0	0	0.57	0.6	0	0

3.1. First scenario

In this scenario, each microgrid is authorized to use 1/3 of common line capacity, hence there will be no congestion in common line and each microgrid can ultimately exchange up to 1.5 kW with upstream grid. In this scenario, the introduced aggregator provides the microgrids with day-ahead market prices. Subsequently, microgrids do their self-scheduling considering authorized common line capacity and report the corresponding power exchanges (with the grid) to the aggregator. In this scenario, the profit of MG1, MG2, and MG3 are 2319 $, 2128 $ and 2558 $, respectively and profit of MMGs would be 7005$ which equals the sum of profits made by each microgrid.

3.2. Second scenario

In this scenario, the introduced aggregator provides the microgrids with day-ahead market prices. Subsequently, microgrids do their self-scheduling based on various capacities of common line and report the corresponding profit-quantity curves to the aggregator.

Obviously, if the authorized capacities vary from 0 to 4.5 MW, the amounts of microgrid profits are increased. Fig. 9 illustrates profit-quantity curves corresponding to three microgrids.

Fitting the equations of these three curves (Fig. 9) by quadratic functions microgrids' profit equations will be derived as presented in Eqs. (26)–(28):

$$S(F_{l,1}) = -154.2F_{l,1}^2 + 1365F_{l,1} + 704.3 \tag{26}$$

$$S(F_{l,2}) = -104.6F_{l,2}^2 + 887.1F_{l,2} + 1040 \tag{27}$$

$$S(F_{l,3}) = -86.33F_{l,3}^2 + 810.3F_{l,3} + 1661 \tag{28}$$

By derivating above equations with respect to common line capacity and Lagrange multiplier we have:

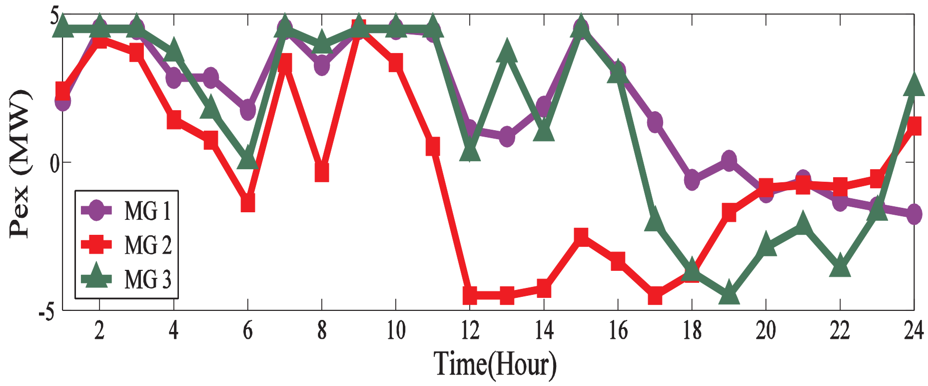

Fig. 7. Power exchanged between each microgrid and the grid.

$$\frac{\delta S(F_{l,1})}{\delta F_{l,1}} = \lambda_1 \tag{29}$$

$$\frac{\delta S(F_{l,2})}{\delta F_{l,2}} = \lambda_1 \tag{30}$$

$$\frac{\delta S(F_{l,3})}{\delta F_{l,3}} = \lambda_1 \tag{31}$$

$$F_{l,1} + F_{l,2} + F_{l,3} = f_l \tag{32}$$

By solving these four equations, quotas of common line for each microgrid are computed. Accordingly, quota of MG1, MG2 and MG3 from common line are 2.154 MW, 1.708 MW, 0.636 MW, and profit of MG1, MG2, and MG3 are 2910 $, 2273 $ and 2132 $, respectively. In this case, the aggregated profit will be 7315$. Thus the proposed method has been able to increase profit by 4.4% in comparison to the first scenario. Here, the aggregator allows MG1, MG2, and MG3 to use 47%, 37% and 16% of common line capacity, respectively. In this scenario, the microgrid quota of PCC line depends directly on the slope of its profit-quantity curve. In other words the more the slope of the curve the more quota of PCC line is assigned to the microgrid. It should be noted that slope of the curve depends on several factors such as DER costs, loads and storage unit characteristics, customer contracts and market prices that necessarily does not show microgrid competence to use more quota of the line. For example in our study microgrid 1 utilizes the maximum PCC capacity (and hence achieves the maximum profit) to avoid using its another (expensive) DG unit. It looks that is not the fair decision and provides market power for more expensive microgrids. For this purpose in case of occurring congestion, Shapely value mechanism is proposed for fairly splitting the aggregated profit among microgrids. Therefore, part of the benefits gained by MG1 and MG2 are transferred to MG3. It should also be noted that in all coalition problems a profit sharing mechanism in terms of Shapely, Core, and Nucleolus is employed to share the aggregated profit among existing stakeholders. Applying Shapely corresponding profits would become 2863$, 2168$ and 2284$. It is observed that part of the benefits gained by MG1 and MG2 are transferred to MG3. Fig. 10 shows the sum of power exchanged between the microgrids and the grid after applying the proposed method. As can be seen, congestion is removed in whole period of time.

In this scenario, at hours 12–19 some microgrids are sellers while the others are buyers, simultaneously, thus some exchanging powers are provided among them. In other hours, all of microgrids are either buyers or the sellers. Table 5 shows the amount of sold or purchased power by microgrids at hours 12–19.

For example at hour 12, MG1 and MG3 need to buy 2.154 MW and 0.636 MW from the grid, while MG2 has 1.708 MW surplus power that should sell it to the grid. Therefore, MMGs need to buy 2.79 MW and sell 1.708 MW from/to the grid. Part of this power imbalance in MMGs is compensated by exchanging power between MG2 with MG1 and MG3, and the remaining part is supplied from the grid as shown in last rows in Table 5.

Please no that, if the capacity of common line is high enough, congestion does not occur in the common line. Subsequently, aggregator implements energy management based on microgrids' profit-quantity curves. Here, the obtained results are the optimal ones that provide the maximum profits for all microgrids, while no congestion occurs in PCC line. In other words, there is no need to determine the microgrids optimal sharing. In this case, profits of MG1, MG2, and MG3 would be 3730 $, 2931 $ and 3556 $, respectively that are drastically higher than former results.

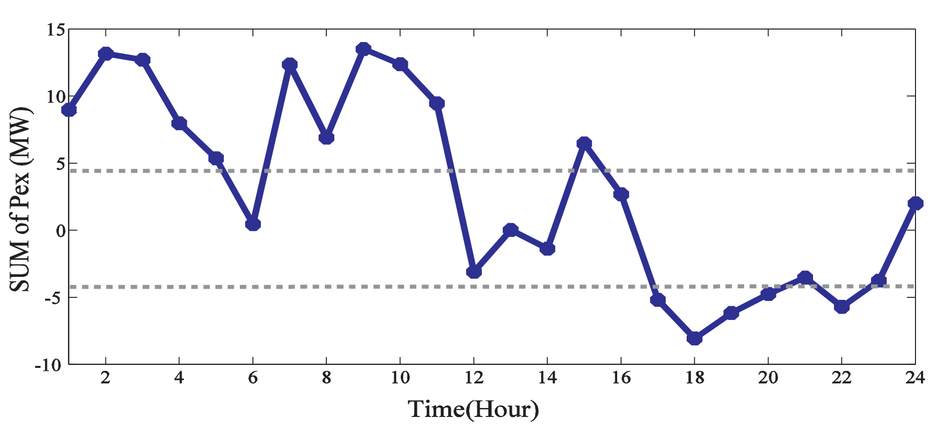

Fig. 8. Sum of power exchanged between the microgrids and the grid.

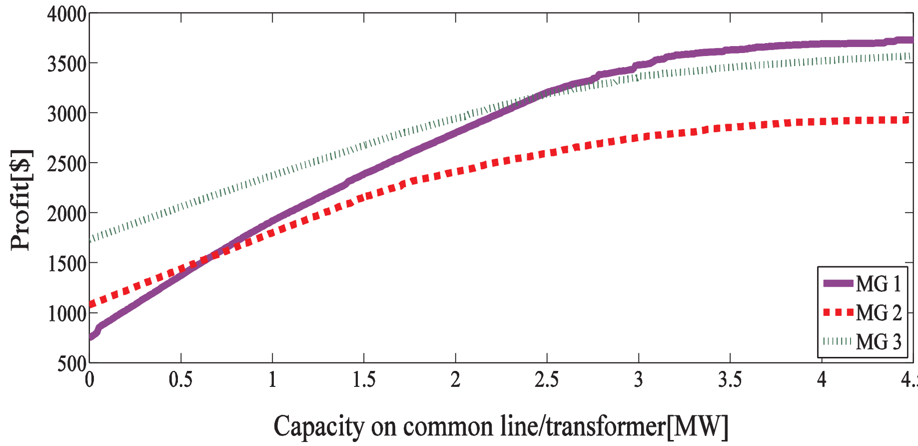

Fig. 9. Profits of microgrids versus different common line capacities.

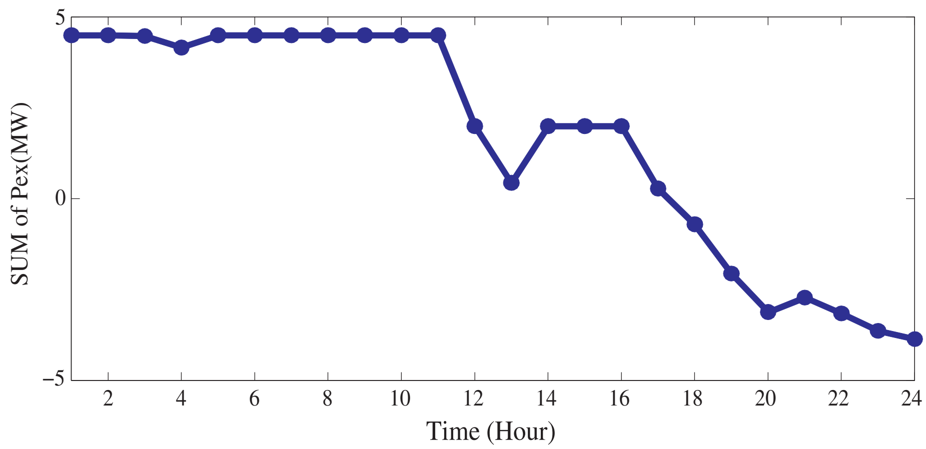

Fig. 10. Sum of power exchanged between the microgrids and the grid after applying proposed model.

3.3. Third scenario

The main goal of presenting this scenario is to show the necessity of the Shapely value in the second stage. For this purpose, microgrid characteristics should be considered slightly distinct from each other. The values of coefficients in Eqs. (26)–(28) depend on the microgrid DERs costs, load, and storage unit characteristics, customer contracts and market prices. If each of these parameters changes, the coefficients of the Eqs. (26)–(28) will change as well. In this scenario, microgrid DG operation cost is selected. Accordingly, it is assumed that cost coefficient of the DG1 in MG1 (Table 1) varies from 27.7 $/MWh to 83.1 $/MWh. If the second scenario is resolved, Eq. (26) changes as Eq. (33) while equations (27), (28) are unchanged:

$$S(F_{l,1}) = -141.6F_{l,1}^2 + 1785F_{l,1} - 5107 \tag{33}$$

In this case, shares of MG1, MG2 and MG3 from common line will be 3.51 MW, 0.88 MW, and 0.11 MW. Accordingly profits of MG1, MG2 and MG3 are −518 $, 1716 $ and 1787 $ and total profit will be 2985 $ that are drastically different from the second scenario (In this case, profit of each player is dependent on profit of other players. In our study in order to clearly show this interrelation, the cost of MG1 is highly increased. Consequently, MGA assigns more PCC capacity to MG1 in order not to turn on its expensive units. This results in more aggregated profit gained by whole microgrids (2985 $, Table 6). Increasing use of MG1 from common line will result in a smaller share for MG2 and MG3 and hence leading to reductions in their profits. However, since the initial profit allocation is not fair, Shapely value is employed to fairly allocate the profit among all microgrids. Therefore, profits of MG2, MG3 are increased. Actually, the aggregator allows MG1, MG2, and MG3 to use78%, 20% and 2% of common line capacity, respectively. In comparison to the second scenario, it is observed that MG1 quota of PCC capacity is increased while MG3 quota is drastically decreased. This could be interpreted that expensive microgrids will exercise market power to access much more capacity of common line. To avoid this issue Shapely values is employed to fairly split the aggregated profit among MGs. Applying Shapely method, the profits of

Table 5
Amount of sold or purchased power by microgrids at hours 12–19.

	12th hour	13th hour	14th hour	15th hour	16th hour	17th hour	18th hour	19th hour
$P_{ex,MG1}$ (MW)	2.154	0.864	2.154	2.154	2.154	2.154	1.402	0.047
$P_{ex,MG2}$ (MW)	−1.708	−1.708	−1.708	−1.708	−1.708	−1.708	−1.708	−1.708
$P_{ex,MG3}$ (MW)	0.636	0.636	0.636	0.636	0.636	−0.636	−0.636	−0.636
$\sum_{j=1}^{3} P_{ex,MGj}$ (MW)	1.082	−0.208	1.082	1.082	1.082	−0.19	−0.942	−2.297

Table 6
Profit of microgrids in different scenario.

	Microgrid	MG1	MG2	MG3	MMGs
First Scenario	Profit [$]	2319	2128	2558	7005
	Percent use of PCC capacity	33%	33%	33%	100%
Second Scenario	Profit without using Shapely [$]	2910	2273	2132	7315
	Profit using Shapely [$]	2863	2168	2284	7315
	Percent use of PCC capacity	47%	37%	16%	100%
Third Scenario	Profit without using Shapely [$]	−518	1716	1787	2985
	Profit using Shapely [$]	−1733	2066	2652	2985
	Percent use of PCC capacity	78%	20%	2%	100%

MG1, MG2, and MG3 are −1733 $, 2066 $ and 2652 $, respectively. In fact, a major part of MG1profit is transferred to other two microgrids. In other words, despite the second level (first stage) allocated the most PCC capacity for the most expensive microgrid (MG1), nevertheless, it is not the case and aggregated profit must be fairly divided among all microgrids. This clearly shows the necessity of existence of Shapely value in the second stage. The detailed results of all three scenarios are reported in Table 6.

4. Conclusion

This paper proposes a method for energy management in multi-microgrids while taking congestion of common line into account. The proposed method examines energy management in systems composed of multi-microgrids in two levels. In the first level, individual microgrids implement their day ahead scheduling based on variable common line capacities and make corresponding profit-quantity curves. In the second level, an agency called microgrid aggregator is introduced that aims to maximize the profit of the whole set of microgrids considering PCC constraint. For this purpose, a novel mathematical method based on Lagrange function is employed to find optimal operating points of microgrids and determine the share of each microgrid from common line capacity. The Shapely value is employed to fairly allocate the payoffs among corresponding microgrids. The simulation results indicate that proposed method is able to increase the profit of the microgrids and fairly share common line capacity among microgrids while removing congestion in the whole period of time.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijepes.2019.105465.

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