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Optimal Operation of Distributed Energy Resources from Multi-Investors in a Distribution Network

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ABSTRACT

Increasing penetration rate of renewable energy in distribution network (DN) require effective measure for self-balancing. Considers the profit of multi-investors with distributed energy resources (DERs) in a district DN, this paper proposed an incentive-based optimal operation method. This is a win-win situation for both the utility grid and the investors of DERs. On the one hand, the demand fluctuation and reverse power flow is reduced to delay the investment of gird expansion; the other part is the multi-investors can benefit from the coordinated response process. The case study demonstrates the effectiveness of the proposed approach.

Keywords: distribution network, distributed energy resources, multi-investors, renewable energy consumption, incentive-based

NONMENCLATURE

Abbreviations

DERs	Distributed Energy Resources
DN	Distribution Network
DG	Distributed Generation
PVG	Photovoltaic Generation
WTG	Wind Turbine Generation
EES	Electrical Energy Storage
ED	Electrical Demand
FL	Flexible Load
SL	Shiftable Load
USO	Unique System Operator
C&D	Charging and Discharging
SDR	Supply to Demand Ratio

Symbols

Υ^{buy}	Time-of-use price of utility grid
Υ^{sell}	Fixed feed-in-tariff for renewable energy
λ_t	Incentive price in DDN at time slot *t*
t	Unit time slot, set to 1 hour in this work
$N^{maxC\&D}$	Maximum C&D times of EES
SOC_t	SOC of EES at time slot *t*
P_t^{EES}	Absolute value of export power of EES at time slot *t*
Cap_N^{EES}	Rated capacity of EES
b_t^C	Binary variable for charging state at time slot *t*, 1 for charging state and 0 for offline state
b_t^D	Binary variable for discharge state at time slot *t*, 1 for discharging state and 0 for offline state
η^{EES}	C&D efficiency of EES
$N^{maxC\&D}$	Maximum allowable C&D times of EES within one day
pr_t^{EES}	Response profit of EES at time slot *t*
pr_t^{FL}	Response profit of FL at time slot *t*
pr_t^{SL}	Response profit of SL at time slot *t*
P_t^{ED}	Total electricity demand at time slot *t*
π_t^{SL}	Proportion of SL at time slot *t*
n^{SL}	Number of available time slot for SL
P_t^{PVG}	Output power of PVG at time slot *t*
P_t^{WTG}	Output power of WTG at time slot *t*

1. INTRODUCTION

In recent years, the awareness of energy shortage and environmental crisis around the world promote the increasing development of renewable energy in distribution network (DN). Although the environment friendly and operation profitable of renewable energy based distributed generation (DG), e.g. photovoltaic generation (PVG) and wind turbine generation (WTG), the inherent output uncertainty and peak-valley mismatching may cause insufficient local consumption, which will further lead to reverse power flow and bring potential disadvantage to utility grid [1]. Moreover, this also supresses the enthusiasm of social capital to join the exploitation of distributed energy resources (DERs) in distribution network.

There is a great number of researchers explored the local consumption of distributed renewable energy in DN, which are mainly carried out from the planning and operation [2]. In planning, the network topological structure and configuration of renewable energy-based DG is the common optimization objective. But thanks to the fluctuation of renewable energy-based DG, it is destined to need real-time balance in operation aspect. Most works used electricity energy storage (EES) and demand response to absorb extra power in a mandatory way [3]. That is increasingly infeasible, because of the improvement of demand side market mechanism and entry of third-party capital in DN. Hence, this paper proposed an incentive-based coordinated operation strategy of DERs from multi-investors in a district DN. Each DER determines their response behaviour based on the internal incentive price and self-operation constraints. The proposed method can not only ensure the local consumption of renewable energy but also can improve the interests of multi-investors of DERs in district DN.

The rest of paper is organized as follows: Section 2 introduces the district DN and provides the detailed model of DERs. Section 3 presents the incentive-based coordinated operation approach and the solving algorithm. Section 4 conducts the case studied and conclusions are given in Section 5.

2. DISTRIBUTION NETWORK WITH MULTI-INVESTORS AND DERS

2.1 Structure of DN

A district DN is a section of medium-low voltage distribution network, which is geographically neighbour and electrically coupled, and directly connects with high voltage distribution network, as shown in Fig. 1.

It is assumed that there is a unique system operator (USO), which is run by the utility grid corp for the security and stability consideration, to maintain the normal operation of a district DN by coordinating various resources. USO is responsible to purchase electricity from the utility grid (high voltage distribution network) at the price of Υ^{buy} for internal shortage and reverse surplus electricity to the utility grid at the price of Υ^{sell} ($\Upsilon^{sell} < \Upsilon^{buy}$ in normal). On the other hand, USO will provide real-time coordination price to internal users and DERs for certain objective at the price of λ_t at each time slot, which is 1 hour in this paper. Specifically, when USO demands to suppress electricity demand, λ_t will be set higher than Υ^{buy}, all the DERs response to this incentive will pay as their participant power, the action to encourage electricity demand is similar. Furthermore, it needs to be noted that although USO owns the special operating right of district DN, the other capital investment, e.g. large users and third party companies etc., can still participate in the coordinated operation of a district DN to seek profit from both peak-valley price and incentive response with their ownership DERs.

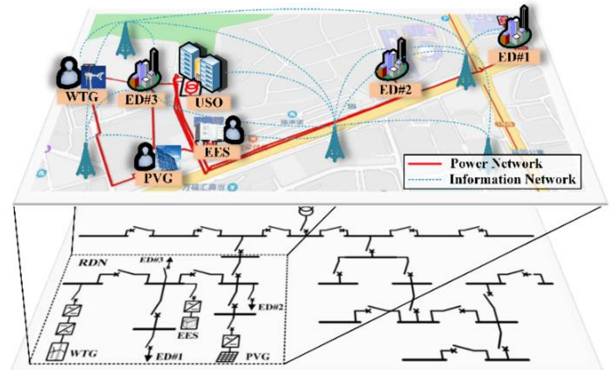

Fig.1 Structure diagram of a district DN

2.2 Modeling of DERs in DN

As can be seen from Fig. 1, there are various DERs own by multi-investors in a district DN, including PVG, WTG, EES, FL and SL. Since renewable energy based DGs are most dependent on the uncertain natural resources, e.g. wind and illumination, etc., EES, FL and SL are the main DERs that could response to the incentive of USO. The detailed model of these three DERs is as follows.

<u>2.2.1 Electrical energy storage</u>

Considering the peculiar state transition flexibility of EES, the charging and discharging state control strategy is essential. This paper assumes the investor of EES would like to charging during valley price slots and discharging during peak price slots to earn the differences. Moreover, in pursuit of maximum profit with maximum C&D times $N^{maxC\&D}$ constraint within one day (24 hours), EES must choose the time slot with the lowest and highest price. Thus, the state of charge (SOC) of EES at each time slot t can be calculated by:

$$SOC_t = SOC_{t-1} + \frac{P_t^{EES}}{Cap_N^{EES}}\left(\eta^{EES} b_t^C - b_t^D / \eta^{EES}\right) \tag{1}$$

$$b_t^C + b_t^D \le 1,\ b_t^C, b_t^D \in \{0,1\} \tag{2}$$

$$\forall t \in \mathbf{T}_t^C, b_t^C = 1;\ \forall t \in \mathbf{T}_t^D, b_t^D = 1 \tag{3}$$

$$\sum_{1\,\mathrm{day}} b_t^C \le N^{\max C\&D}, \sum_{1\,\mathrm{day}} b_t^D \le N^{\max C\&D} \tag{4}$$

$$\sum_{1\,\text{day}}\left(P_t^{\text{EES}}\left(\eta^{\text{EES}}b_t^{\text{C}}-b_t^{\text{D}}/\eta^{\text{EES}}\right)\right)=0 \tag{5}$$

$$\lambda_t^{\max\text{C}}=\max\Upsilon^{\text{buy}}\left(t>\mathbf{T}_t^{\text{C}}\right),\ \lambda_t^{\min\text{D}}=\min\Upsilon^{\text{buy}}\left(t>\mathbf{T}_t^{\text{D}}\right) \tag{6}$$

$$0\le SOC_{\min}\le SOC_t\le SOC_{\max}\le 1,\ 0\le P_t^{\text{EES}}\le P_{\max}^{\text{EES}} \tag{7}$$

where $\mathbf{T}_t^{\text{C}}$ and $\mathbf{T}_t^{\text{D}}$ are the time slot set of EES for charging and discharging behaviour within one day from time slot t, λ_t^{maxC} and λ_t^{minD} are, respectively, the maximum and minimum Υ^{buy} at the time slot in $\mathbf{T}_t^{\text{C}}$ and $\mathbf{T}_t^{\text{D}}$, which is refreshed at each time slot t.

Since the investor of EES determines C&D plan for their profit, that can either smooth or deteriorate the daily demand profile. Therefore, at each time slot, USO will send coordinated response information with the price λ_t to optimize the operation state of district DN with a certain objective. Then, EES needs to identify self-participant situation with (1)-(7). For instance, USO increases internal incentive price λ_t to reduce electricity demand. When EES is in discharging state, investors consider (7) to decide whether there is available power, if so and $\lambda_t > \lambda_t^{\text{minD}}$, the part of remain discharging plan will be advanced. And when EES is in offline state and $\lambda_t > \lambda_t^{\text{minD}}$, investor will advance the remain discharging plan to get higher profit; when EES is in charging state, investor will delay this charging plan to the time slot with the lowest Υ^{buy} in the subsequent offline time slot within one day and execute the process of offline state as well [4]. So, once the response of electricity power is determined, the response profit of EES can be calculated by using the following formulas:

$$pr_t^{\text{EES}}=\begin{cases}\Delta P_t^{\text{C}}\left|\lambda_t-\lambda_t^{\max\text{C}}\right|b_t^{\text{C}}+\Delta P_t^{\text{D}}\left|\lambda_t-\lambda_t^{\min\text{D}}\right| & ,\lambda_t^{\text{EES}}>\Upsilon^{\text{buy}}\\ \Delta P_t^{\text{C}}\left|\lambda_t-\lambda_t^{\max\text{C}}\right|+\Delta P_t^{\text{D}}\left|\lambda_t-\lambda_t^{\min\text{D}}\right|b_t^{\text{D}} & ,\lambda_t^{\text{EES}}<\Upsilon^{\text{buy}}\end{cases} \tag{8}$$

where ΔP_t^{C} and ΔP_t^{D} are the response power of EES at time slot t.

2.2.2 Electricity demand response

Generally, the demand of electricity users can be divided into four part: fixed basic load P^{FBL}, fluctuating daily load P_t^{FDL}, flexible load (FL) P_t^{FL} and shiftable load (SL) P_t^{SL}, as shown in Fig. 2. The first part is essential for users and must be met, e.g., lightings and monitoring cameras, which can regard as fixed power. Fluctuating daily load is the main source of uncertainty, it is strongly associated with user behaviour, e.g. televisions, elevators, and computers. FL is a kind of demand which is controllable within a certain range, e.g., thermostatically controlled air condition. SL is temporally adjustable but fixed in total demand within one day, e.g., smart dishwashers, washing machines and electric vehicles [5]. This paper assumes each aggregated electricity demand is owned by an investor and consisted with at least three part, i.e., the first three parts, SL is only available in few users at the specific time slot. It is feasible and profitable to participate in the coordinated operation with FL and SL for investors. The electricity demand at each time slot is formulated as:

$$P_t^{\text{ED}}=P^{\text{FBL}}+P_t^{\text{FDL}}+P_t^{\text{FL}}+P_t^{\text{SL}} \tag{9}$$

$$P_t^{\text{FL}}=P_t^{\text{planFL}}\left(\lambda_t/\Upsilon^{\text{buy}}\right)^{-\varepsilon},\ P_t^{\text{minFL}}\le P_t^{\text{FL}}\le P_t^{\text{maxFL}} \tag{10}$$

$$P_t^{\text{SL}}=P^{\text{totalSL}}\pi_t^{\text{SL}},\ \sum_{1\,\text{day}}\pi_t^{\text{SL}}=1 \tag{11}$$

$$\pi_t^{\text{SL}}=1/n^{\text{SL}},\ t\in\mathbf{T}_t^{\text{SL}} \tag{12}$$

where P_t^{planFL} is the planned demand of FL at time slot t, $\varepsilon > 0$ is the elastic factor, the greater the ε, the greater the flexibility, P_t^{minFL}, and P_t^{maxFL} are the maximum response range of FL at the time slot t, P^{totalSL} is the total demand of SL within one day, $\mathbf{T}_t^{\text{SL}}$ is the available time slot set of SL.

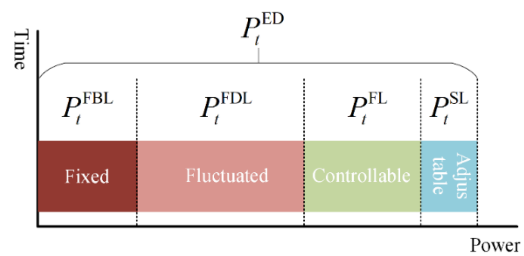

Fig. 2 Diagram for the composition of electricity demand

After receiving the incentive price λ_t from USO, the investors of FL and SL will also to identify self-participant situation with (9)-(11). The actual demand of FL can be obtained by (10); the response profit of FL is defined as:

$$pr_t^{\text{FL}}=P_t^{\text{planFL}}\left(1-\left(\lambda_t/\Upsilon^{\text{buy}}\right)^{-\varepsilon}\right)\left(\lambda_t-\Upsilon^{\text{buy}}\right) \tag{13}$$

The response behaviour of SL is similar to EES. Considering (11), increased λ_t will delay the planned demand to the time slot with the lowest $P_t^{\text{ED,plan}}$ in the subsequently available time slot within one day, decreased λ_t will advance the planned demand at the time slot with highest $P_t^{\text{ED,plan}}$ in the subsequently available time slot within one day. After that, the response profit of SL is formulated as:

$$pr_t^{\text{SL}}=\Delta P_t^{\text{SL}}\left|\lambda_t-\Upsilon^{\text{buy}}\left(t^{\text{shifted}}\right)\right| \tag{14}$$

where t^{shifted} is the target time slot of the load shift.

3. INCENTIVE-BASED OPTIMAL OPERATION OF DERS FROM MULTI-INVESTORS IN A DISTRIBUTION NETWORK

3.1 Problem formulation

The utilization of renewable energy within a district DN is mainly implemented by PVG and WTG. However, from both the perspective of energy utilization and system security, it is indeed to maximize local consumption of renewable energy generation and minimize reverse power flow. The relatively low feed-in-tariff for renewable energy also make investors of renewable energy-based DG more willing to trade within a district DN rather than sell to the utility grid. Based on the above, this paper proposed an incentive-based coordinated operation approach to ensure local consumption of renewable energy and improving the interests of multi-investors of DERs in a district DN. Thus, the determination of incentive price λ_t for DERs is vital. Since the relationship between internal price and supply to demand ratio (SDR) is inverse proportional [1], we presented the following piecewise function to calculate λ_t at each time slot:

$$\lambda_t = (1+\mu_t)\Upsilon^{buy} \tag{15}$$

$$\mu_t = \begin{cases} -\dfrac{P_t^{\text{supply}}}{P_t^{\text{demand}}} + \min\left(1, \dfrac{P_t^{\text{supply}} + \Delta P_t^{\max\text{supply}}}{P_t^{\text{demand}} - \Delta P_t^{\max\text{demand}}}\right) & , \dfrac{P_t^{\text{supply}}}{P_t^{\text{demand}}} < 1 \\ \dfrac{P_t^{\text{demand}}}{P_t^{\text{supply}}} - \min\left(1, \dfrac{P_t^{\text{demand}} + \Delta P_t^{\max\text{demand}}}{P_t^{\text{supply}} - \Delta P_t^{\max\text{supply}}}\right) & , \dfrac{P_t^{\text{supply}}}{P_t^{\text{demand}}} > 1 \end{cases} \tag{16}$$

$$P_t^{\text{supply}} = P_t^{\text{PVG}} + P_t^{\text{WTG}} + P_t^{\text{ESS}} b_t^{\text{D}} \tag{17}$$

$$P_t^{\text{demand}} = P_t^{\text{ED}} + P_t^{\text{ESS}} b_t^{\text{C}} \tag{18}$$

$$\Delta P_t^{\max\text{supply}} = \Delta P_t^{\max\text{ESS}} b_t^{\text{D}} \tag{19}$$

$$\Delta P_t^{\max\text{demand}} = \Delta P_t^{\max\text{ED}} + \Delta P_t^{\max\text{ESS}} b_t^{\text{C}} \tag{20}$$

Thus, the optimal problem can be formulated as: $\min\left|P_t^{\text{EES}} + P_t^{\text{ED}} - P_t^{\text{PVG}} - P_t^{\text{WTG}}\right|$ for each time slot and $\max\left(\sum_{1\,\text{day}} pr_t^{\text{EES}} + \sum_{1\,\text{day}} pr_t^{\text{FL}} + \sum_{1\,\text{day}} pr_t^{\text{SL}}\right)$ for each day, subject to (1)-(20).

3.2 *Practical solving algorithm*

Since the proposed optimal model is a bilevel nonlinear mixed integer programming problem, it is time-consuming and unnecessary to find the global optimal solution in practical application. Thus, this paper presents a simplified solving algorithm, which using practical profit prioritization criteria (PPC) [6], to find a near optimal solution. In short, the most profitable DER is responded firstly until all the surplus renewable energy is consumed or all the available DERs are run out. However, as will be seen in Case Study, the near optimal solution has improved the performance of the district DN significantly. The detailed solving process is described in Algorithm 1.

Algorithm 1

Initialize P^{FBL}, P_t^{FDL}, P_t^{FL}, P_t^{SL}, P_t^{EES}, P_t^{PVG}, P_t^{WTG}

for t = 1 to T **do**

Calculate the SDR to identify the power imbalance;

Calculate the maximum available $\Delta P_t^{\text{maxdemand}}$ and $\Delta P_t^{\text{maxsupply}}$ using (1)-(7), (9)-(12), (19)-(20);

Calculate λ_t for DERs using (15)-(20);

Calculate response profit of each DER using (8), (13), (14), compare the expect profit and get the priority order;

Accept the response of DER in order until SDR=1 and update overall information of a district DN.

end for

4. CASE STUDY

4.1 *Case description*

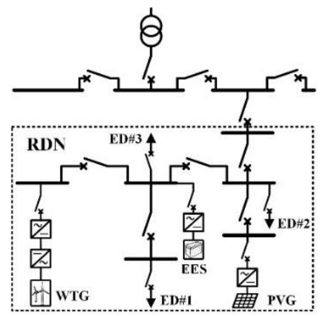

Fig. 3 Case study network of a district DN

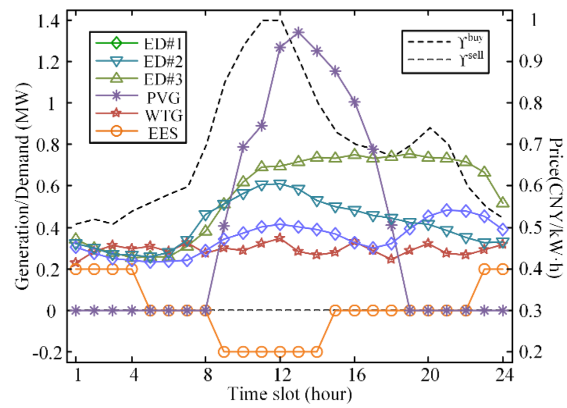

Fig. 4 Power and price information of the typical day

The proposed approach is applied to a district DN in Fig. 3. There are one aggregated WTG, PVG, EES, and three aggregated EDs, which are owned by different investors. The generation curves and load curves of the typical day are given in Fig. 4. η^{EES}, $N^{\text{maxC\&D}}$, P_t^{minFL}, P_t^{maxFL}, ε_1, ε_2, and ε_3 are separately set as 10%, 6, $0.5P_t^{\text{FL}}$, $1.5P_t^{\text{FL}}$, 0.5, 1, 1.5. Υ^{buy} and Υ^{sell} are shown in Fig, 4. For each ED, the minimum demand within one day is assumed as P^{FBL}, the ratio of P_t^{FDL} and P_t^{FL} for ED#1 and ED#2 is set to 6:4. ED#3 is assumed to consist of P_t^{FDL}, P_t^{FL} and P_t^{SL} at the ratio of 5:3:2 during 11 am-2 pm and 6-9 pm, the rest time slot is same with ED#1 and ED#2.

4.2 *Results and discussion*

By solving the optimization problem in Section 3 using Algorithm 1, the total net power of district DN and incentive price λ_t is drawn as Fig. 5 and the total profit of utility grid and each DER are given in Tab. 1.

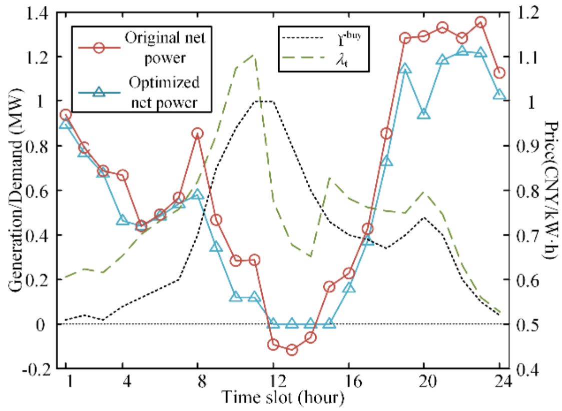

Fig. 5 Total net power of the district DN and incentive price

Tab. 1 Total profit of utility grid and each DER within one day

	Original (CNY)	Optimized (CNY)	Profits (CNY)
UG	9890.74	9178.8	Lost 711.94
ED#1	5910	5861.7	Save 48.3
ED#2	7327.2	7238.2	Save 89
ED#3	9720.4	9550.8	Save 169.6
EES	468	771.4	Earn 303.4
WTG	4850.3	4887.2	Earn 36.9
PVG	7748.56	7813.3	Earn 64.74

Tab. 2 Results of different scale-up factor

Scale-up factor	1	1.5	1.57	1.58	2	2.5
Total reverse power/MW	0	0	0	0.25	5.28	10.76

As can be seen from Fig. 5, the incentive price λ_t follows the Υ^{buy} well and smooth net power to a certain extent. It is noticeable that during time slot of 12 to 14, λ_t is decreased a lot to encourage electricity use, which help consume all the surplus power. Meanwhile, the results in Tab. 1 show the proposed incentive-based coordinated operation approach can efficiently improve the profit of multi-investors of DERs. Since the EES is the most flexible resources, it gets the highest profits. It needs to be noted that although the revenue of utility grid is obviously reduced, but the reduced peak-valley difference of demand and reverse power could help saving investment in grid expansion.

Moreover, to explore the maximum consumption ability of the district DN in current configuration of DERs, the scale-up factor (change from 1 to 2.5 at interval of 0.5) is multiple with the generation curve of WTG and PVG. By applying the proposed approach, the total reverse power of the district DN within one day at different renewable energy penetration rate is given in Tab. 2. Results show the district DN can completely consume up to 1.57 times renewable energy without additional configuration of resources, which will further reduce the related investment of utility gird.

5. CONCLUSIONS

This paper proposed an incentive-based coordinated operation method to improve the profits of multi-investors of DERs and shelf-balance of a district DN. The simulation results conducted in test system within the typical day indicate the method can smoothing net power curve and reduce the reverse power of the district DN. It is also delightedly to find both the profit of the multi-investors and the expansion investment of utility grid are improved by using the proposed method.

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