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A Decentralized Model for Coordinated Operation of Distribution Network and EV Aggregators

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***Abstract* – With the rapid growth of electrical vehicles (EVs) in distribution networks (DNs), EV aggregators have been introduced as mediators between these two entities. EV aggregators and DN should be operated coordinately to bring potential benefits to both sides. In this paper, a decentralized model for coordinated operation of EV aggregators and DN is proposed in which the total cost of the system is minimized. An alternating direction method of multipliers (ADMM) is introduced to recast the model to a decentralized one. In ADMM method EV aggregators and DN operation problems are solved separately. Therefore, the computational burden of the problem is reduced while respecting the independency of the EV aggregators. The effectiveness of the proposed model is validated by a modified 33-IEEE bus system.**

***Index Terms* – Aggregator, electrical vehicle, optimal operation, ADMM.**

Nomenclature

Indices and Sets

t	Index of time.
ev	Index of electrical vehicles.
g	Index of conventional DGs.
W	Index of wind turbines.
n,m	Index of distribution network buses.
k	Index of ADMM iteration.
$Agg_{(n)}$	Set of EV aggregators belonging to bus n.
$DG_{(n)}$	Set of conventional DGs belonging to bus n.
$WT_{(n)}$	Set of wind turbines belonging to bus n.
$EV_{(n)}$	Set of EVs belonging to aggregator i.
F	Set of distribution network feeders.

Parameters

α,β,λ	Cost function coefficients of DG g.
η^{chg} / η^{dis}	Charge/discharge efficiency of EV battery.
$\pi^{WS}_{(t)}$	Forecasted price of wholesale market at time t.
μ_{arr} / σ_{arr}	Mean/standard deviation of EVs' arrival time.
μ_{di} / σ_{di}	Mean/standard deviation of EVs' travelling distance.
μ_{dep} / σ_{dep}	Mean/standard deviation belongs to departure time of EVs.
v	Wind speed at time t.
v_r / v_{ci} / v_{co}	Rated/cut-in/cut-out speed of wind turbine.
C_{IC}	EV battery investment cost.
L_{DD}	EV battery maximum depth of discharge
C_L	EV battery cycle life.
Li^{max}	Maximum daily travel distance of EV
SDC	Shut-down cost of DG.
SUC	Start-up cost of DG.
UR/DR	Ramp up/down of DG.
UT/DT	Minimum up/down time of DG.
$b_{(n,m)}$ / $g_{(n,m)}$	Susceptance/conductance of feeder between buses $n-m$.
V_{nom}	Nominal voltage of distribution network.
π^{BD}_{e}	Degradation cost of EV battery.
SOC^{ini}	Initial state of charge for EV battery.
ε	Allowable voltage deviation.
ε_{thr}	Convergence tolerance of ADMM approach
$P^{L}_{(n,t)}$	Load demand of bus n at time t.

Variables

L_i	Daily travel distance of EVs.
t_{arr} / t_{dep}	Arrival/departure time of EVs.
$u/y/z$	Binary variable indicating commitment/ start-up/shut down of DG.
u^{on}/u^{off}	Binary variable indicating on/off status of DG.
$P^{DG}_{(g,t)}$	Power scheduling of DG g at time t.
$u^{chg}_{(ev,t)}$ / $u^{dis}_{(ev,t)}$	Binary variable indicating charge/ discharge status of EV battery at time t.
$P^{W}_{(w,t)}$	Scheduled power of wind turbine at time t.
$P^{Agg}_{(i,t)}$	Scheduled power of aggregator i at time t.
$P^{WS}_{(t)}$	Purchased power from the wholesale market at time t.
$P^{EVchg}_{(ev,t)}$ / $P^{EVdis}_{(ev,t)}$	Charge/discharge power of EV ev at time t.
$SOC^{EV}_{(ev,t)}$	State of charge of EV ev at time t.
υ,η,yp,yw	Auxiliary variables in robust optimization approach.
$P^{flow}_{(m,n,t)}$	Power flow between buses $n-m$ at time t.
$\Delta V_{(n,t)}$	Voltage deviation in bus n at time t.
$\theta_{(n,m,t)}$	Voltage angle difference between buses $n-m$ at time t.
$\lambda_{(i,t)}$	Lagrangian multiplier related to aggregator i at time t in ADMM approach.

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ρ	Penalty factor in ADMM approach.
$P_{(i,t)}^{Agg\_DNO}$	Exchanged power between aggregator i and distribution network at time t in ADMM approach.

Functions

F^{arv}/F^{dep}	Probability distribution function related to arrival/departure time of EVs.
F^{Li}	Probability distribution function related to travel distance of EVs.
L_p	Augmented Lagrangian function.
$\overline{(\bullet)}/\underline{(\bullet)}$	Maximum/minimum bounds of $(\bullet)$.

I. INTRODUCTION

Recently due to environmental issues and green gas emissions electric vehicles (EVs) have gained great attention. It is expected that the integration of EVs in future distribution networks (DNs) will increase significantly [1]. This high integration of EVs in the future DNs can bring new issues for economic and secure operation of DNs [2]-[3]. A lot of studies have discussed the potential challenges and opportunities of EVs' integration into the DNs [4]-[5]. In [6] a probabilistic method for the optimal charging of EVs in DN is introduced. The object is to minimize the system losses. Authors in [7] introduce an event-triggered scheduling method for vehicle to grid (V2G) operation in smart DNs. A stochastic method is also used to deal with uncertainties. Authors of [8] propose a trip chain stochastic method to study the influence of charge/discharge of EVs on the power grid and charging infrastructures planning. With high integration of EVs in DN, the DN operator may not be able to control the charge/discharge of each EV. Furthermore, a massive communication network is needed to connect EVs and DN. Therefore, aggregators as an intermediary entity are introduced to manage the operational issues between EVs and DN and reduce the burden of the communication system [2].

Many researches have investigated the role of EV aggregators in DN. Authors of [9] propose a two level model for operation of EV parking lots as aggregators in DN. Aggregators manage their revenue risk by gap decision theory. A distributed convex optimization for EV aggregators is presented in [10] with valley filling and cost minimal charging as objectives. Reference [11] presents an optimization model for participating EV aggregators' in energy and reserve market. In [12] a two stage charging scheme for EV aggregators is modeled using game theory in which the charging cost of aggregators are minimized.

The above studies can be divided into two categories. The first category objective is to provide economic benefit for EV aggregators and EVs [9]-[10],[13]. The second category aims at providing technical benefits for the DN [2]-[6]. However, since the DN and EV aggregators are connected through the electrical system, individual operation may affect their technical and economic benefits. Therefore, a model should be introduced to operate EV aggregators and DN in a coordinated manner. In this paper, an ADMM based decentralized model for coordinative operation of EV aggregators and DN is proposed. In the decentralized model, EV aggregators and DN solve their operation model independently and in an iterative manner. Therefore, while EV aggregators and DN both gaining economic benefit, the independency of the aggregators is also respected and the proposed model becomes applicable in systems which the aggregators have private owners. Furthermore, ADMM reduces the communication burden of the system.

The structure of the paper is as follows. Section II describes the formulation of the proposed method. The ADMM method is presented in section III. In section V, modified IEEE 33-bus system is used to verify the proposed method. Finally, section VI concludes the paper.

II. PROBLEM FORMULATION

The general schematic of the proposed model is shown in Fig. 1. As it can be seen EV aggregators and DN exchange data and energy while they are independent entities. In the following of this section the problem formulation including the objective function and constraints are presented.

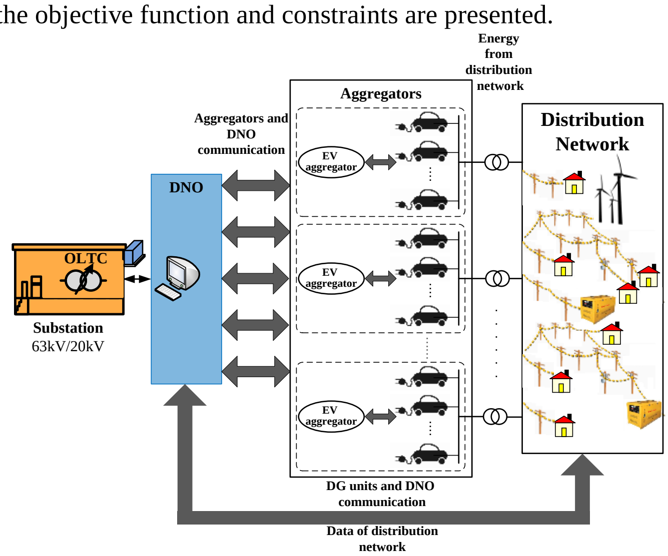

Fig. 1 schematic of the system

A. Objective Function

The objective function is to minimize the total cost of the DN which consists of three terms as follows:

$$\text{Min} \sum_t \pi_{(t)}^{WS} P_{(t)}^{WS} + \left[\begin{array}{l} \sum_t \sum_g SUC_{(g)} u_{(g,t)}^{ON} \\ + \sum_t \sum_g \left\{ c_{(g)} u_{(g,t)} + b_{(g)} P_{(g,t)}^{DG} + a_{(g)} P_{(g,t)}^{DG\,2} \right\} \\ + \sum_t \sum_g SDC_g u_{(g,t)}^{OFF} \end{array} \right] + \sum_t \sum_{ev} D(P_{(ev,t)}^{EVdis}) \tag{1}$$

The first two terms show the cost of purchasing energy from the wholesale market and operation cost of DGs (start-up cost, fuel cost, and shut-down cost), respectively. The third term denotes disutility cost of EVs which should be paid to EV owners for the compensation of battery degradation due to V2G service.

Hence, the objective function can be formulated as follows:

B. Constraints

1) *EV aggregator constraints:* The aggregators could exchange energy with DN which equals to the sum of charge/discharge power of EVs which are under their controls as follows:

$$P_{(i,t)}^{Agg} = \sum_{ev \in EV_{(i)}} \left(P_{(ev,t)}^{EVchg} - P_{(ev,t)}^{EVdis} \right); \;\; \forall i,t \tag{2}$$

Since EV aggregators are not the owner of EV batteries, the EV owners should be paid for degradation of their batteries due to the additional cycling of V2G discharge. To account this issue, EVs' disutility is considered in the objective function which could be written as follows:

$$D(P_{(ev,t)}^{EVdis}) = \pi_e^{BD} P_{(ev,t)}^{EVdis}; \;\; \forall e,t \in [t_{arr}, t_{dep}] \tag{3}$$

Battery degradation cost is calculated as follows [13]-[14]:

$$\lambda_e^{BD} = \frac{C_{IC}}{L_c \overline{SOC_{ev}^{EV}} d_{LoL}}; \;\; \forall ev \tag{4}$$

2) *EV constraints:* The technical and trip constraints of EVs can be described as follows:

$$0 \le P_{(ev,t)}^{EVchg} \le \overline{P_{(ev,t)}^{EVchg}} u_{(ev,t)}^{chg}; \;\; \forall ev,t \in [t_{arr}, t_{dep}] \tag{5}$$

$$0 \le P_{(ev,t)}^{EVdis} \le \overline{P_{(ev)}^{EVdis}} u_{(ev,t)}^{dis}; \;\; \forall ev,t \in [t_{arr}, t_{dep}] \tag{6}$$

$$u_{(ev,t)}^{chg} + u_{(ev,t)}^{dis} = 1; \;\; \forall ev,t \in [t_{arr}, t_{dep}] \tag{7}$$

$$u_{(ev,t)}^{chg} + u_{(ev,t)}^{dis} = 0; \;\; \forall ev,t \notin [t_{arr}, t_{dep}] \tag{8}$$

$$\underline{SOC_{(ev)}^{EV}} \le SOC_{(ev,t)}^{EV} \le \overline{SOC_{(ev)}^{EV}}; \;\; \forall ev,t \in [t_{arr}, t_{dep}] \tag{9}$$

$$\begin{aligned} &SOC_{(ev,t)}^{EV} = SOC_{(ev,t-1)}^{EV} + \eta^{chg} P_{(ev,t)}^{EVchg} - P_{(ev,t)}^{EVdis} \big/ \eta^{dis} - Econs_{(ev)}^{EV}; \\ &\forall ev,t \in [t_{arr}, t_{dep}] \end{aligned} \tag{10}$$

The maximum/minimum charge and discharge powers of EVs are shown in (5) and (6), respectively. Constraint (7) indicates that EVs cannot be charged and discharged, at the same time. The charge/discharge power limits of EVs are set to 0 while they are not plugged in by constraint (8). The stored energy in the battery is limited by (9). The energy balance in the battery is expressed by (10).

Arrival time and departure time of EVs are modeled with a normal probability distribution [15]:

$$F_{(t)}^{arr} = \frac{1}{\sigma_{arr}\sqrt{2\pi}} e^{-(t-\mu_{arr}) \big/ 2\sigma_{arr}^2}; \;\; 0 < t \le 24 \tag{11}$$

$$F_{(t)}^{dep} = \frac{1}{\sigma_{dep}\sqrt{2\pi}} e^{-(t-\mu_{dep}) \big/ 2\sigma_{dep}^2}; \;\; 0 < t \le 24 \tag{12}$$

Initial SOC is a stochastic value and can be calculated by EVs travel range before plugging into the DN. The daily travel range is modeled with a lognormal probability distribution as follows:

$$F_{(Li)}^{Li} = \frac{1}{Li\sqrt{2\pi\sigma_{Li}^2}} e^{(Ln(Li)-\mu_{Li})^2 \big/ 2\sigma_{Li}^2}; \;\; Li > 0 \tag{13}$$

The initial SOC of EVs can be calculated by the following equation:

$$SOC^{ini} = (1 - \frac{Li}{Li^{max}}) \times 100 \tag{14}$$

3) *DG unit constraints:* To ensure the safe operation of DGs the following constraints are considered:

$$\underline{P_{(g)}^{DG}} u_{(t,g)} \le P_{(t,g)}^{DG} \le \overline{P_{(g)}^{DG}} u_{(t,g)}; \;\; \forall g,t \tag{15}$$

$$P_{(t,g)}^{DG} - P_{(t-1,g)}^{DG} \le UR_{(g)} \left(1 - u_{(t,g)}^{ON}\right) + \underline{P_{(g)}^{DG}} u_{(t,g)}^{ON}; \;\; \forall g,t \tag{16}$$

$$P_{(t-1,g)}^{DG} - P_{(t,g)}^{DG} \le DR_{(g)} \left(1 - u_{(t,g)}^{OFF}\right) + \underline{P_{(g)}^{DG}} u_{(t,g)}^{OFF}; \;\; \forall g,t \tag{17}$$

$$\sum_{h=t}^{t+UT(g)-1} u_{(t,g)} \ge UT_{(g)} u_{(t,g)}^{ON}; \;\; \forall g,t \tag{18}$$

$$\sum_{h=t}^{t+DT(g)-1} (1 - u_{(t,g)}) \ge DT_{(g)} u_{(t,g)}^{OFF}; \;\; \forall g,t \tag{19}$$

$$u_{(t+1,g)} - u_{(t,g)} \le u_{(t+1,g)}^{ON}; \;\; \forall g,t \tag{20}$$

$$u_{(t,g)} - u_{(t+1,g)} \le u_{(t+1,g)}^{OFF}; \;\; \forall g,t \tag{21}$$

$$u_{(t+1,g)} - u_{(t,g)} = u_{(t+1,g)}^{ON} - u_{(t+1,g)}^{OFF}; \;\; \forall g,t \tag{22}$$

$$u_{(t,g)}^{ON} - u_{(t,g)}^{OFF} = u_{(t,g)} - u_{(t-1,g)}; \;\; \forall g,t \tag{23}$$

$$u_{(t,g)}^{ON} + u_{(t,g)}^{OFF} \le 1; \;\; \forall g,t \tag{24}$$

Constraint (15) expresses the capacity limit of DGs. Ramp up and ramp down capability of DGs are presented by (16) and (17). Minimum up/down time limits of DGs are presented by (18) and (19), respectively. Constraints (20)-(24) avoid conflicted situations in the status of DGs.

4) *Wind turbine constraints:* The wind turbines are non-dispatchable units which their maximum output is a function of wind speed as follows:

$$\overline{P^w}(v) = \begin{cases} P_r \times \dfrac{(v - v_{ci})}{(v_r - v_{ci})} & v_{ci} \le v \le v_r \\ P_r & v_r \le v \le v_{co} \\ 0 & otherwise \end{cases} \tag{25}$$

The power productions of wind turbines are limited to their maximum output as follows:

$$P_{(w,t)}^{W} \le \overline{P^w}\left(v_{(t)}\right); \;\; \forall w,t \tag{26}$$

5) *Load balance constraints:* The load balance at each bus of distribution grid is as follow:

$$\begin{aligned} &P_{(t)}^{WS} + \sum_{g \in DG_{(n)}} P_{(g,t)}^{DG} + \sum_{w \in WT_{(n)}} P_{(w,t)}^{W} + \sum_{i \in Agg_{(n)}} P_{(i,t)}^{Agg} \\ &+ \sum_{(n,m)\in F} P_{(m,n,t)}^{flow} - \sum_{(n,m)\in F} P_{(n,m,t)}^{flow} = P_{(n,t)}^{L}; \;\; \forall n,m,t \end{aligned} \tag{27}$$

6) *Grid constraints:* The linearized power flow model proposed in [16] is adopted in this paper. Since DN active power flow dominates the apparent power only active power flow equation is considered which is represented by (28).

$$P_{(n,m,t)}^{flow} = \begin{Bmatrix} V_{nominal} \left(\Delta V_{(n,t)} - \Delta V_{(m,t)}\right) g_{(n,m)} \\ -V_{nominal}^2 b_{(n,m)} \theta_{(n,m,t)} \end{Bmatrix}; \;\; \forall n,m,t \tag{28}$$

Thermal capacity limits of feeders' flow are presented by (30).

$$-\overline{P_{(n,m)}^{flow}} \le P_{(n,m,t)}^{flow} \le \overline{P_{(n,m)}^{flow}}; \quad \forall n,m,t \tag{29}$$

The voltage magnitude and angle at substation are set to $1.05V_{nominal}$ and 0, respectively. However, the voltage deviations of other buses are limited by:

$$-\varepsilon V_{nominal} \le \Delta V_{(n,t)} \le \varepsilon V_{nominal}; \quad \forall n,t \tag{30}$$

III. DECENTRALIZED MODEL

The optimization problem of (1)-(30) is a mixed integer linear programming which has a global optimal solution. However, since the operation problems of EV aggregators and DNO are related by equation (2), they cannot be optimized separately. Therefore, a fast convergence algorithm based on ADMM is applied, which solves (1)-(30) in a decentralized manner. ADMM solves a convex optimization problem in the following separable format [17]:

$$\begin{aligned} &\underset{x\in X,z\in Z}{Min}\ L_\rho(x,z,\lambda) = f(x) + g(z) + \lambda^T(Ax+Bz-c) \\ &+\left(\rho/2\right)\|Ax+Bz-c\|_2^2 \end{aligned} \tag{31}$$

$$x(k+1) = \underset{x\in X}{\arg\min} L_\rho(x, z(k), \lambda(k)) \tag{32}$$

$$z(k+1) = \underset{z\in z}{\arg\min} L_\rho(x(k+1), z, \lambda(k)) \tag{33}$$

$$\lambda(k+1) = \lambda(k) + \rho(Ax(k+1) + Bz(k+1) - c) \tag{34}$$

where, λ represent the Lagrangian multiplier vector, $\rho > 0$ is a penalty parameter, and $\|.\|_2$ is l_2-norm of vector. ADMM includes the iteration process among (31)-(34), where k is the ADMM iteration index [17]. Therefore, the variables x and z are separately optimized in (32) and (33), respectively. The convergence criteria of ADMM is determined based on the primal residual as follow [17]:

$$\|\lambda(k+1) - \lambda(k)\|_2 \le \varepsilon_{thr} \tag{35}$$

The iterative ADMM based operation problems of DN and aggregators can be written as follows:

Step 1) Set the initial values for $\rho, \varepsilon_{thr}, P_{(i,t)}^{Agg}(k), \lambda_{(i,t)}$.

Step 2) DNO solves the following operation problem:

$$\begin{aligned} x(k+1) = \arg\min_x &\sum_t \pi_{(t)}^{WS} P_{(t)}^{WS} + \sum_t\sum_j SUC_{(j)} u_{(j,t)}^{ON} \\ &+\sum_t\sum_j \{c_{(j)}u_{(j,t)} + b_{(j)}P_{(j,t)}^{DG} + a_{(j)}P_{(j,t)}^{DG\,2}\} + \sum_t\sum_j SDC_{(j)}u_{(j,t)}^{OFF} \\ &+\sum_t\sum_i \lambda_{(i,t)}P_{(i,t)}^{Agg\_DNO} + \frac{\rho}{2}\sum_t\sum_i \left(P_{(i,t)}^{Agg\_DNO} - P_{(i,t)}^{Agg}(k)\right)^2 \end{aligned} \tag{36}$$

Subject to: (15)-(30).

Step 3) Receiving $P_{(i,t)}^{Agg\_DNO}(k+1)$ from DNO, each aggregator schedules EVs which are under its control with solving the following problem:

$$\begin{aligned} z(k+1) = \arg\min_z &\sum_t\sum_i D_{(i,t)}^{Agg} - \sum_t\sum_i \lambda_{(i,t)} \sum_{e\in EV_{(i)}} (P_{(e,t)}^{EVchg} - P_{(e,t)}^{EVdis}) \\ &+\frac{\rho}{2}\sum_t\sum_i \left(\sum_{e\in EV_{(i)}} (P_{(e,t)}^{EVchg} - P_{(e,t)}^{EVdis}) - P_{(i,t)}^{Agg\_DNO}(k+1)\right)^2 \end{aligned} \tag{37}$$

Subject to: (2)-(14).

Step 4) Compute the primal residual and check the following criteria. If it is not met, go to step 5; else, the iterations stop and the optimal solutions are obtained.

$$\left[\sum_t\sum_i \left(P_{(i,t)}^{Agg\_DNO} - \sum_{e\in EV_{(i)}} (P_{(e,t)}^{EVchg} - P_{(e,t)}^{EVdis})\right)^2\right]^{\frac{1}{2}} \le \varepsilon_{thr} \tag{38}$$

Step 5) Update $\lambda_{(i,t)}$ using (39). Then, modify $P_{(i,t)}^{Agg}(k)$, and go to Step 2.

$$\begin{aligned} &\lambda_{(i,t)}(k+1) = \lambda_{(i,t)}(k) \\ &+\rho\left(P_{(i,t)}^{Agg}(k+1) - \sum_{e\in EV_{(i)}} (P_{(e,t)}^{EVchg}(k+1) - P_{(e,t)}^{EVdis}(k+1))\right) \end{aligned} \tag{39}$$

IV. SIMULATION RESULTS

The proposed method is applied to a modified IEEE 33-bus DN. Fig. 2 shows the simulated DN which is 12.66 DN with four EV aggregators. System data is extracted from [18]. The voltage limits are assumed to be ±5% of the nominal value and the thermal limits of lines are taken to be 7 MW. In this network, there are seven DGs including four diesel generators and three wind turbines of the same type whose parameters are obtained from [19] and presented in Tables 1 and 2, respectively. Candidate buses for DGs' installations are selected according to the results of expansion planning study which is carried out in [20].It is assumed that all DGs produce active power at unity power factor. The network demand, wholesale market prices, wind speed, and share of each bus from hourly demand are shown in Fig. 3. It should be mentioned that scaled down demand and market prices are associated with a typical day in the NYISOs PJM [21].

TABLE I
Data of diesel generators

DG unit	DG1	DG2	DG3	DG4
$\overline{P^{DG}}$	3.5	3	3	4.1
$\underline{P_{DG}}$	1	0.75	0.75	1
a ($\$/MW^2$)	0.002	0.003	0.003	0.18
b ($\$/MW$)	87	87	92	81
c ($)	27	25	28	26
SUC ($)	15	10	10	15
SDC ($)	10	10	10	15
MUT (h)	2	1	1	2
MDT (h)	2	1	1	2
DR (MW/h)	1.8	1.5	1.5	1.8
UR (MW/h)	1.8	1.5	1.5	1.8

TABLE II
Data of wind turbines

$P_r(MW)$	$v_{ci}(m/s)$	$v_r(m/s)$	$v_{co}(m/s)$
6	3	13	25

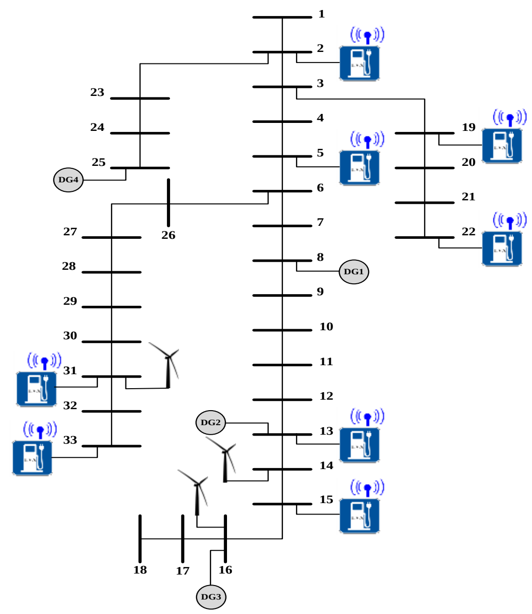

Fig. 2 Test system

Meanwhile, the hourly wind speed is retrieved from **Error! Reference source not found.**. It is assumed that there are 1200 EVs in the DN. The share of each aggregator from EVs and the EV parameters are borrowed from [22] and are presented in Table 3. The power exchange of aggregators with distribution network is limited to 1 MW. In the case studies, the Monte Carlo simulation method is employed to generate arrival time, departure time, and travel range of EVs by sampling from the related PDFs. The data of PDFs are retrieved from [15] and shown in Table 3.

TABLE III
EVs model data

Share of each aggregator from EVs							
Bus 2	Bus 5	Bus 13	Bus 15	Bus 19	Bus 22	Bus 31	Bus 33
150	150	200	150	150	100	100	200
Parameters of EVs							
Capacity	$\overline{P}^{EVchg,dis}$		η^{chg}, η^{dis}			$\underline{SOC}$	
40 kWh	6.4 kW		90%			5%	
$\overline{SOC}$	L_c		C_{BI}			d_{DOD}	
95%	1000		125 $/kWh			0.8	
Parameters of PDFs							
$\mu_{dep}(h)$	$\sigma_{dep}(h)$	$\mu_{arr}(h)$	$\sigma_{arr}(h)$		$\mu_d(km)$	$\sigma_d(km)$	
9.97	2.2	17.01	3.2		3.2	0.9	

It is supposed that EVs are fully charged when they plug out from the DN. Likewise, the typical energy required for a EV to drive a mile is set to be 0.25 kWh.

Battery degradation cost has the major impact on the results of the proposed model. Thus, two case studies are studied. Case 1 is a comparison benchmark. In Case 2, the battery investment cost is reduced. Fig. 4 illustrates the convergence of the proposed model in Case 1. The penalty factor and primal residual tolerance of ADMM are set to 20 and 0.001, respectively. As can be seen both DNO objective function and primal residual converge rapidly within 14 iterations.

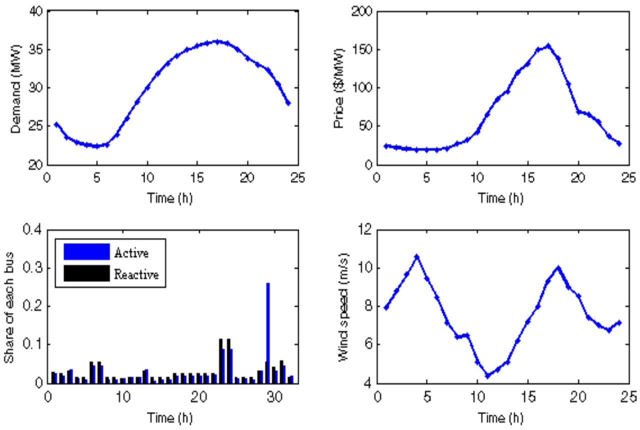

Fig. 3 Forecasted network demand, market prices, wind speed and share of each bus from hourly demand

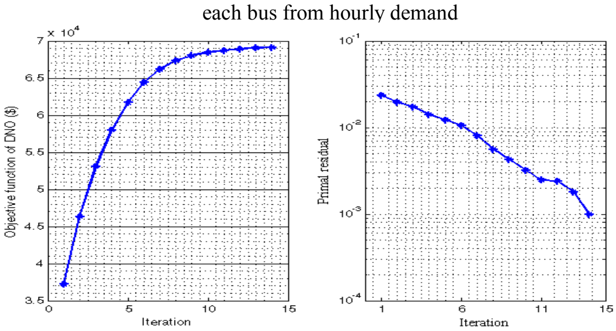

Fig. 4 Convergence of DNO objective function and primal residual

The hourly energy scheduling of DGs and EV aggregators are shown in Figs. 5, and 6, respectively. In Case 1, the DGs are mainly scheduled from 9h to 24h, as the demand and wholesale market price are increased. Meanwhile, all the aggregators charge the EVs at low-price hours namely, 1h to 9h and 20h to 24h, and discharge at high price hours namely, 13h to 19h. With these strategies, DNO purchases less energy from the wholesale market prices during high price hours as presented in Fig. 7. From Fig. 5, it can be concluded that reduction of battery investment cost in Case 2, increases the energy exchanges between the aggregators and distribution network. This means that compared with Case 1, the aggregators charge the EVs more at low price hours and sell the exceeded energy back to the distribution network by discharging the EVs at high price hours. Therefore, as shown in Fig. 6, the energy productions of DGs are reduced. Moreover, it can be seen in Fig. 7 that DNO purchases more energy from the wholesale market during low price hours and less energy during high price.

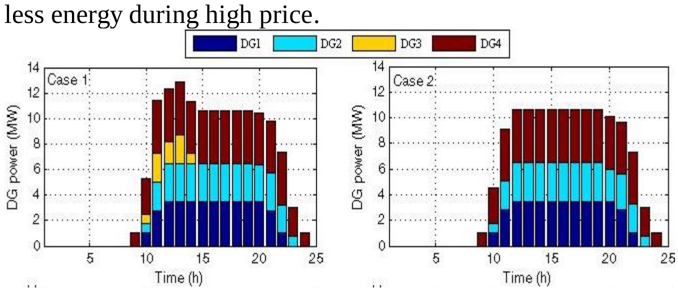

Fig. 5 Hourly energy scheduling of conventional DGs

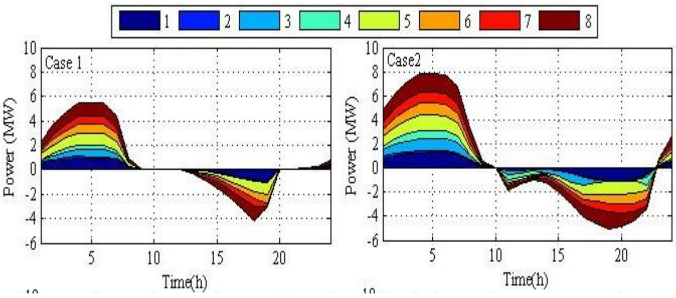

Fig. 6 Hourly energy scheduling of EV aggregators

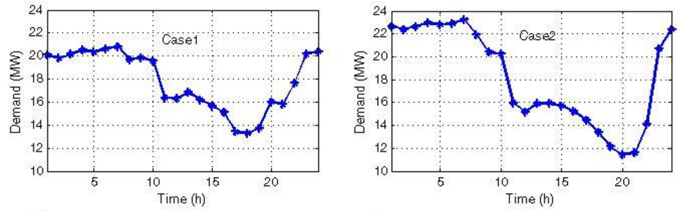

Fig. 7 Hourly energy purchasing from the wholesale market

The operation cost of DN and benefit of aggregators are presented in Table 4. As can be seen, with decrement of battery investment cost in Case 2 the benefit of aggregators is increased and therefore, the operation cost is reduced.

Table IV
Operation results

	Case 1	Case 2
Operation cost ($)	69160	64231
Benefit of aggregators	1687	6299

V.CONCLUSION

This paper proposed a decentralized model to operate EV aggregators and DN in a coordinative manner. In the proposed model an ADMM based solution method was applied in which the EV aggregators and DN minimize their cost as independent entities. The results showed that the proposed method converges rapidly while providing economic benefit for both EV aggregators and DN. Furthermore, they confirmed that participation of EV aggregators in energy scheduling of smart distribution network provides a higher efficiency for the whole system. This fact is more evident with decrement of battery investment cost.

REFERENCES

[1] J. A. P. Lopes, F. J. Soares, P. M. R. Almeida, and A. M. M. da Silva, “Smart charging strategies for electric vehicles: Enhancing grid performance and maximizing the use of variable renewable energy resources," inProc. 24th Int. Battery Hybrid Fuel Cell Electr.Vehicle Symp.Exhib., Stavanger, Norway,pp. 1–11, May 2000

[2] L. Jian, Y. Zheng, X. Xiao, and C. C. Chan, "Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid," Applied Energy, vol. 146, pp. 150-161, 2015.

[3] M. Vahedipour-Dahraie, H. Rashidizaheh-Kermani, H.R. Najafi, A. Anvari-Moghaddam, and J.M. Guerrero, “Coordination of EVs Participation for Load Frequency Control in Isolated Microgrids”, *Appl. Sci*., vol.7, no.6-539, pp.1-16, 2017.

[4] M. Kinter-Meyer, K. Schneider, and R. Pratt, “Impacts assessment of plug-in hybrid electric vehicles on electric utilities and regional U.S. power grids. Part IV Technical analysis" Pacific North West NationalLab., Richland, WA,PNNL-SA-61669,Jan. 2007.

[5] H. Rashidizaheh-Kermani, M. Vahedipour-Dahraie, H.R. Najafi, A. Anvari-Moghaddam, and J.M. Guerrero, “A Stochastic Bi-level Scheduling Approach for Participation of EV Aggregators in Competitive Electricity Markets”, *Appl. Sci*., vol.7, no.10-1100, pp.1-16, 2017.

[6] A. Arias, M. Granada and C. A. Castro, "Optimal probabilistic charging of electric vehicles in distribution systems," in *IET Electrical Systems in Transportation*, vol. 7, no. 3, pp. 246-251, 2017.

[7] Linni Jian, Yanchong Zheng, Xinping Xiao, C.C. Chan,"Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid",*Applied Engy*,Vol 146, pp.150-161, 2015.

[8] T. Shun, L. Kunyu, X. Xiangning, W. Jianfeng, Y. Yang and Z. Jian, "Charging demand for electric vehicle based on stochastic analysis of trip chain," in *IET Generation, Transmission & Distribution*, vol. 10, no. 11, pp. 2689-2698, 2016.

[9] M. Shafie-khah, P. Siano, D. Z. Fitiwi, N. Mahmoudi and J. P. S. Catalão, "An Innovative Two-Level Model for Electric Vehicle Parking Lots in Distribution Systems with Renewable Energy," in *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1-1,2017.

[10] J. Rivera, C. Goebel and H. A. Jacobsen, "Distributed Convex Optimization for Electric Vehicle Aggregators," in *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1852-1863, 2017.

[11] R. J. Bessa and M. A. Matos, "Optimization Models for EV Aggregator Participation in a Manual Reserve Market," in *IEEE Trans. Power Systems*, vol. 28, no. 3, pp. 3085-3095, 2013.

[12] W. Wei, F. Liu and S. Mei, "Charging Strategies of EV Aggregator Under Renewable Generation and Congestion: A Normalized Nash Equilibrium Approach," in *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1630-1641, 2016.

[13] C. Ju, P. Wang, L. Goel, and Y. Xu, "A Two-layer Energy Management System for Microgrids with Hybrid Energy Storage considering Degradation Costs," *IEEE Trans. Smart Grid*, vol. PP, pp. 1-1, 2017.

[14] A. Anvari-Moghaddam, T. Dragicevic, J.C. Vasquez, and J.M. Guerrero, “Optimal Utilization of Microgrids Supplemented with Battery Energy Storage Systems in Grid Support Applications”, 2015 IEEE First International Conference on DC Microgrids (ICDCM), Atlanta, GA, 2015, pp. 57-61.

[15] A. Santos, N. McGuckin, H. Y. Nakamoto, D. Gray, and S. Liss, "Summary of travel trends: 2009 national household travel survey," 2011

[16] S. F. Santos, D. Z. Fitiwi, A. W. Bizuayehu, M. Shafie-khah, M. Asensio, J. Contreras, et al., "Impacts of Operational Variability and Uncertainty on Distributed Generation Investment Planning: A Comprehensive Sensitivity Analysis," *IEEE Trans. Sustainable Energy*, vol. 8, pp. 855-869, 2017.

[17] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Foundations and Trends® in Machine Learning*, vol. 3, pp. 1-122, 2011.

[18] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Trans. Power Delivery*, vol. 4, pp. 1401-1407, 1989.

[19] Mohammadreza Mazidi, Hassan Monsef, Pierluigi Siano,"Design of a risk-averse decision making tool for smart distribution network operators under severe uncertainties: An IGDT-inspired augment ε-constraint based multi-objective approach", Energy, vol. 116, Part 1,2016,pp. 214-235

[20] S. Wong, K. Bhattacharya, and J. D. Fuller, "Electric power distribution system design and planning in a deregulated environment," IET Generation, Transmission & Distribution, vol. 3, pp. 1061-1078, 2009.

[21] J. New York Independent System Operator’, http://www.nyiso.com/public/markets_operations/index.jsp, accessed 18 April 2017.

[22] Willy Online Pty Ltd. <http://wind.willyweather.com.au/> .

[23] W. Yao, J. Zhao, F. Wen, Y. Xue, and G. Ledwich, "A Hierarchical Decomposition Approach for Coordinated Dispatch of Plug-in Electric Vehicles," *IEEE Trans. Power Systems*, vol. 28, pp. 2768-2778, 2013.