Integrated Scheduling of Electric Vehicles and Demand Response Programs in a Smart Microgrid

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Abstract: Microgrids (MGs) usually consist of several types of Distributed Energy Resources (DERs) like renewable and conventional generation units, energy storages and responsive loads. In order to operate the MG with minimum cost and maximum reliably, an integrated scheduling model of DERs should be implemented. In this paper, an operational planning model of a MG which considers Demand Response (DR) and Electric Vehicles (EVs) charge/discharge programs are proposed. The proposed methodology investigates the potential role of EVs and DR in providing reserve capacity for a MG with a high contribution from variable generation such as wind and solar power. The novelty of this paper is the demand side participation in energy and reserve scheduling, simultaneously. The proposed model was tested on a typical MG system in connected mode and the results show that integrated scheduling of EVs and DR programs will reduce total operation cost of MG and cause more efficient use of resources.

Keywords: Demand Response, Electric Vehicle, Microgrids, Renewable Generation, Reserve.

1 Introduction

The Microgrids (MGs) are the systems that integrate Distributed Generation (DG) units, energy storage systems and controllable loads on a low voltage network which can operate in either grid-connected mode or stand-alone mode [1, 2]. A renewable-based MG can be understood as a particular case of a more general concept called a ‘smart grid’. Smart grids are understood to be the key enabling technology for renewable energy development, electric vehicle (EVs) adoption and energy efficiency improvements [3]. Moreover, Energy Management System (EMS) is essential supervisory control tool used to optimally operate and schedule MGs.

On the other hand, with increasing concerns about oil sustainability and the negative environmental impact of petroleum-based transportation worldwide, EVs have often been suggested as an effective technology to reduce gasoline consumption and emissions. The electrification of the transportation sector brings more challenges and offers new opportunities to the power system planning and operation [4, 5].

In [6], a distributed demand response algorithm for EVs charging using the concept of congesting principle in the internet traffic control has been proposed. In [7], a heuristic method has been implemented to minimize the EV charging cost in response to time-of-use price in a regulated market demonstrating that peak demand can be reduced.

EV owners may also make money by using the stored energy in their vehicles; the battery of EV can discharge as well as charge according to the owner convenience. Moreover, Vehicle-to-Grid (V2G) capability provides some valuable power system services such as regulation, spinning reserve, and peaking capacity [8].

An analysis on the six-bus meshed network based on dynamic programming for finding out the optimal size, site has been presented in [9]. The paper also determined the optimal mix of DERs among microturbines (MTs), photovoltaic (PV), and battery storage to meet the electrical and thermal loads. It used minimization of cost as the objective function that the cost included deployment cost, heat compensation cost, and fuel cost. The paper also imposed a reliability constraint on the analysis.

The authors in [10] described a centralized control system for a MG. The controller has been used to optimize the operation of the MG during interconnected operation, i.e., the production of local generators and energy exchanges with the distribution network were

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maximized. Two market policies were assumed to offer options for controllable loads, and this demand-side bidding was incorporated into the centralized control system. However, this work did not considered renewable generation uncertainty and did not allocate reserve in its model. The authors in [11] using particle swarm optimization, reduced the costs of MGs with controllable loads and battery storage by selling stored energy at high prices and shave peak loads of the larger system.

Another investigated concept in this paper deals with demand response (DR). It is used by electric utilities to manage customer electricity consumption in response to supply conditions. Utilities encourage customers to reduce their consumption at critical periods or in response to market prices. Currently, generation and transmission system facilities are oversized to cover peak demand plus a margin for forecasting error and unforeseen events. Smoothing such peak demand could lead to cost and size reduction of the plant. Some systems, such as DR, may encourage energy storage to arbitrage within periods of low and high demand (or low and high prices). In the literature, there are several studies investigating DR concept in MGs for different applications, for instance: demand shifting and peak shaving [12–15], DR exchange in which DR is treated as a public good to be exchanged between buyers and sellers [16], load and generation profiles control [17, 18], incentive based DR regulation considering penalties for customers in case of no load reduction response [19], emergency demand response for real-time voltage control in smart distribution systems [20], and the combination of distributed interruptible load shedding and dispatched micro-sources to manage the network by distribution system operators [21]. A dynamic modeling and control strategy for a sustainable MG primarily powered by wind and solar energy has been presented in [22]. This study has considered both wind energy and solar irradiance changes in combination with load power variations.

In this paper, the MG is operated by a Microgrid Energy Management System (MEMS) that manages the technical features of generation and consumption as well as economical aspect of operation. The MEMS is responsible for optimal scheduling of MG generation units as well as making possible demand side participation in energy and reserve scheduling.

The main focus of this paper is on proposing an integrated scheduling method in a MG and considering demand side participation, renewable generation uncertainty and EVs in energy and reserve operational planning.

The rest of this paper is organized as following. In section 2 the concept of the proposed model is described. The model formulation is detailed in Section 3. Simulation results are given in Section 4 and the paper is concluded in Section 5.

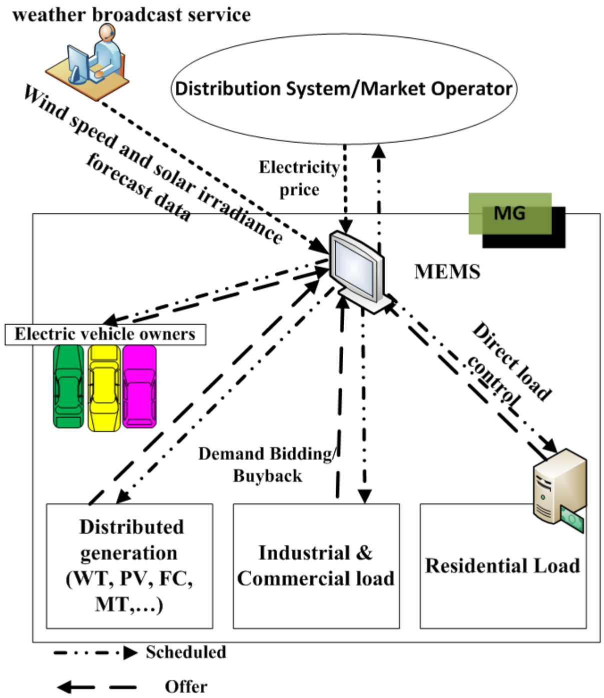

Fig. 1 MG operational scheduling data flow.

2 Microgrid Energy Management System (MEMS)

The MEMS manages and schedules all distributed energy resources such as DGs, EVs and DR in its grid in order to optimally operate the MG with minimum cost. The MG operational planning data flow is shown in Fig. 1. The assumptions used in proposed model are elaborated next.

Assumptions

- The MEMS is allowed to access day-ahead electricity prices of the open market for following 24-hour scheduling.
- The wind speed and solar radiation forecasts and their forecast errors are received form nearest weather broadcast service. The forecast error is considered as a percentage of wind and PV predicted output power.
- Electric vehicle owners submit their parked time period and required stored energy for departure time for next 24-hour to MEMS by cell phone or internet portal.

In the proposed model, the load can participate in both of energy and reserve scheduling and earn benefit from reducing or shifting their consumption [23]. In real world, it is hard to expect every residential load to take part in demand response programs, and have interaction with power market and system operator. In the daytime, people may not be at home or all the residents are not familiar with energy management procedures. So, it is logical to use an automatic system to help residential consumers in order to participate in energy management programs. While it is usually difficult and confusing for the residential consumers to manually respond to prices that are changing every hour, MEMS can help them to manage their consumption with objectives of cutting expenses and increasing welfare. In the proposed model, every load type such as industrial, commercial and residential loads can participate in demand response programs.

In this paper, an incentive payment oriented demand response scheme is presented for MG operational planning. Incentive-based demand response programs provide a more active tool for load-serving entities, electric utilities, or grid operators to manage their costs and maintain reliability. Incentive payment oriented demand resources can be used as reserves in the day-ahead scheduling and dispatch, or as capacity resources in system planning. In this paper, three types of incentive-based demand response programs are considered for load management program that are listed below [24, 25]:

- Demand bidding/buyback programs
- Ancillary services market programs
- Direct load control

3 Model Formulation

The DERs scheduling program is run for 24-hour day-ahead scheduling to calculate the hourly energy requirement form the main grid for the next 24 hours. Also, this scheduling will determine the generation output of DGs and demand side participation as well as EVs charge/discharge program. Moreover, it is determined that which resources should provide the reserve requirement for each hour.

The proposed model aims at minimizing the total operation cost of MG. The objective cost function of this model (OF) is sum of overall hourly operation cost of MG which is given by (1):

$$\begin{aligned} &Minimize,\\ &OF = \sum_{t=1}^{T}\sum_{i=1}^{I}[C(i,t) + SU(i,t)]\\ &\qquad + \sum_{t=1}^{T}[CG(t) - RG(t)]\\ &\qquad + \sum_{v=1}^{N_v} P_{EV}^{Dch}(v,t) \times C_{Dch}^{v,t}\\ &\qquad + \sum_{t=1}^{T}\sum_{l=1}^{L} IDE(l,t) \times IO_E(l,t)\\ &\qquad + \sum_{t=1}^{T}\sum_{h=1}^{H} HDE(h,t) \times HO_E(t)\\ &\qquad + RC \end{aligned} \tag{1}$$

where $C(i,t)$ is the bid form ith DG at tth period that covers all fuel and maintenance costs as well as capital cost. $SU(i,t)$ is start-up cost of DG, $CG(t)$ and $RG(t)$ are the purchased energy cost and sold energy revenue from/to the main grid, respectively; N_v is the total number of EVs; $P_{EV}^{Dch}(v,t)$ and $C_{Dch}^{v,t}$ are power discharge and discharge price of EV v in period t; In this study, the period t duration is considered 1 hour. As a result, the charge/discharge scheduling period length is same as one in generation scheduling. $IDE(l,t)$ and $IO_E(l,t)$ are the energy reduction amount in kWh and price offer in $\$/kWh$ by lth industrial or commercial loads, respectively. The residential (home) energy reduction by hth home is indicated with $HDE(h,t)$, the incentive payment for reduction is shown by $HO_E(t)$, and the reserve commitment cost is indicated by RC.

The bid function of each DG should contain the fuel and maintenance cost (a_i) as well as a percentage of investment cost (b_i). The cost function of DG is given by Eq. (2):

$$C(i,t) = a_i.PG(i,t) + b_i \tag{2}$$

where $PG(i,t)$ is the active power output of ith DG at tth period of scheduling.

The MG in interconnected mode can exchange power with the main grid. The cost and revenue of purchasing and buying power from the upstream network is calculated as follows:

$$CG(t) = Ta_{PP}(t) \times Pg_{pp}(t) \tag{3}$$

$$RG(t) = Ta_{SP}(t) \times Pg_{SP}(t) \tag{4}$$

where $Ta_{PP}(t)$ and $Pg_{pp}(t)$ are the purchased electricity tariff and imported power from the main grid at tth period, respectively. On the other hand, $Ta_{SP}(t)$ and $Pg_{SP}(t)$ are the sold electricity tariff and exported power to the main grid at tth period, respectively. The electricity tariffs which are used for power exchange cost calculation are equal to hourly electricity price of the main grid.

The reserve cost in the objective function is calculated by Eq. (5):

$$\begin{aligned} RC = &\sum_{t=1}^{T}\sum_{l=1}^{L} IDR(l,t) \times IO_R(l,t)\\ &+ \sum_{t=1}^{T}\sum_{v=1}^{N_v} R_{EV}(v,t) \times \Psi_{EV}(t)\\ &+ \sum_{t=1}^{T}\sum_{h=1}^{H} HDR(h,t) \times HO_R(t)\\ &+ \sum_{t=1}^{T}\sum_{h=1}^{H} R_{DG}(i,t) \times PR_{DG}(t) \end{aligned} \tag{5}$$

where $IDR(l,t)$ and $IO_R(l,t)$ are the reserve amount and offer from lth load, respectively; $R_{EV}(v,t)$ and $\Psi_{EV}(t)$ represent, respectively, the reserve provided by EV v in period t and the price for reserve; $HDR(h,t)$ and $HO_R(t)$ are the residential load amount and price offer for participation in reserve scheduling, respectively. The other source of offering reserves is

DGs with $R_{DG}(i,t)$ and $PR_{DG}(t)$ that indicate reserve amount and bid.

The start up cost of DG units is calculated as follows:

$$SU(i,t) \geq Scost(i) \times (u(i,t) - u(i,t-1)) \quad (6)$$

$$SU(i,t) \geq 0 \quad (7)$$

where $Scost(i)$ is the start up cost of ith DG, and $u(i,t)$ is a binary variable that shows the on-off state of DGs.

The constraints of the proposed model are:

- *power balance equation*

$$\left(\sum_{i=1}^{I} PG(i,t)\right) + Pg_{pp} - Pg_{sp} + \sum_{v=1}^{N_v} P_{EV}^{Dch}(v,t) \geq D(t) + \sum_{v=1}^{N_v} P_{EV}^{Ch}(v,t) - \sum_{l=1}^{L} IDE(l,t) - \sum_{h=1}^{H} HDE(h,t) \quad (8)$$

where $D(t)$ is the predicted demand of whole MG at tth period;$P_{EV}^{Dch}(v,t)$ and $P_{EV}^{Ch}(v,t)$ are, respectively, power discharge and charge of vehicle v in period t; Power balance equation is the most important constraint in operation planning. If the total generation be less than consumption, system frequency drop occurs which is undesirable.

- *EVs constraints*

In each period of scheduling, the EV charge and discharge are not simultaneous:

$$X(v,t) + Y(v,t) \leq 1 \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\};\ X,Y \in \{0,1\} \quad (9)$$

where $X(v,t)$ and $Y(v,t)$ are, respectively, the binary variables of EV v related to power discharge and charge states in period t.

The battery energy balance for each vehicle should be considered. The state of charge variable ($E_s(v,t)$) represents the stored energy in the battery of vehicle v at the end of period t. The energy consumption for traveling in period t ($E_{trip}^{v,t}$) has to be considered jointly with the energy remained from the previous period and the charge/discharge in the period [26].

$$E_s(v,t) = E_s(v,t-1) + \eta_v^C \times P_{EV}^{Ch}(v,t) - E_{trip}^{v,t} - \frac{1}{\eta_v^D} \times P_{EV}^{Dch}(v,t) \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\} \quad (10)$$

where η_v^C and η_v^D represent, respectively, the grid-to-vehicle charging and vehicle-to-grid discharging efficiency coefficients of EV v.

The discharge and charge limit for each EV considering the battery discharge rate is given as follows [27]:

$$P_{EV}^{Dch}(v,t) + R_{EV}(v,t) \leq P_{Dch,v}^{Max} \times X(v,t) \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\} \quad (11)$$

$$P_{EV}^{Ch}(v,t) \leq P_{Ch,v}^{Max} \times Y(v,t) \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\} \quad (12)$$

where $P_{Dch,v}^{Max}$ and $P_{Ch,v}^{Max}$ are the maximum power discharge and charge of EV v.

Depletion of EV battery up to a certain minimum level (Ψ_v^{min}) and charging up to a maximum level (Ψ_v^{max}) are ensured by Eqs. (13) and (14) to prevent loss of battery life [28].

$$E_s(v,t) \leq \Psi_v^{max} \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\} \quad (13)$$

$$E_s(v,t) \geq \Psi_v^{min} \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\} \quad (14)$$

where Ψ_v^{min} and Ψ_v^{max} is defined based on the battery capacity limit for each EV that are calculated as follows:

$$\Psi_v^{max} = \phi_v^{max} \times E_{Bat,v}^{max} \quad \forall v \in \{1,\dots,N_v\} \quad (15)$$

$$\Psi_v^{min} = \phi_v^{min} \times E_{Bat,v}^{max} \quad \forall v \in \{1,\dots,N_v\} \quad (16)$$

where $E_{Bat,v}^{max}$ represents the maximum capacity of battery of EV v; ϕ_v^{max} and ϕ_v^{min} are, respectively, the maximum and minimum percentage of battery capacity considering battery life.

The vehicle battery discharge and charge limits considering, respectively, the battery state of charge and the battery capacity and the previous period stored energy are given as follows [29]:

$$\frac{1}{\eta_v^D} \times \left(P_{EV}^{Dch}(v,t) + R_{EV}(v,t)\right) \leq E_s(v,t-1) \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\} \quad (17)$$

$$\eta_v^C \times P_{EV}^{Ch}(v,t) \leq \Psi_v^{max} - E_s(v,t-1) \quad \forall t \in \{1,\dots,T\};\ \forall v \in \{1,\dots,N_v\} \quad (18)$$

- *DG unit output constraint*

$$PG(i,t) \geq PG_i^{min}.u(i,t) \quad (19)$$

$$PG(i,t) + R_{DG}(i,t) \leq PG_i^{max}.u(i,t) \quad (20)$$

where $PG_i^{min}$and PG_i^{max} are the minimum and maximum limitation of ith DG output and $u(i,t)$ shows the on/off state of DG. The spinning reserve provided by ith DG is shown by $R_{DG}(i,t)$. The conventional DG like micro turbine, diesel generator and fuel cell may prepare spinning reserve, and WT and PV do not offer reserve.

- *Reserve requirement*

The reserve requirement is determined based on renewable generation forecast error as given by Eq. (21):

$$\sum_{l=1}^{L} IDR(l,t) + \sum_{h=1}^{H} HDR(h,t) + \sum_{i=1}^{I} R_{DG}(i,t) + \sum_{v=1}^{N_v} R_{EV}(v,t) \geq R(t) \quad (21)$$

where $R(t)$ is the minimum reserve requirement at period t that is calculated by (22):

$$R(t) = \alpha . PG(w,t) + \beta . PG(pv,t) \quad (22)$$

where $PG(w,t)$ and $PG(pv,t)$ are output power from wind turbine w and photovoltaic unit pv, α and β are the forecast error coefficients which are used to determine the uncertainty of output power of wind and solar units which may unexpectedly increase or decrease from their predicted values. These coefficients are calculated based on historical data and the geographical condition of MG.

- *Load constraint*

The load reduction should be constrained to maximum amount of their offers. Also the scheduling program should consider demands energy and reserve participation, simultaneously. Constraints in Eqs. (23) and (24) show that sum of energy reduction and reserve commitment of each individual load at every hour should be lower or equal to maximum amount of their offers.

$$IDE(l,t) + IDR(l,t) \leq ID^{Max}(t) \quad (23)$$

$$HDE(h,t) + HDR(h,t) \leq HD^{Max}(t) \quad (24)$$

where $ID^{Max}(t)$ and $HD^{Max}(t)$ are the maximum amount of reduction that are offered by industrial and residential loads at period t, respectively.

The shiftable loads constraint which shows the time limitation of their performance is given as follows:

$$\sum_{t=\tau s}^{\tau e} d(t,H,ty) = \tau w \quad (25)$$

$$HDA(t,H,ty) = \sum_{\tau w} d(t,H,ty) . HDA^{Max}(H,ty) \quad (26)$$

where indices H and ty show the home number and shiftable appliance, respectively. For shiftable load scheduling, we define a binary variable $d(t,H,ty)$ that indicate on/off state of some home appliances ty that can set their on/off time. τs and τe are the allowable start and end time of these shiftable appliances working period, and τw is the required time that they need to perform their applications. $HDA(t,H,ty)$ is the power consumption of shiftable appliances ty at home H that turn on at time t ($\tau s \leq t \leq \tau e$) where the nominal power of these appliances is shown by $HDA^{Max}(H,ty)$.

4 Case Study

The proposed operational planning model was tested on a typical MG in low voltage distribution network. This test system is depicted in Fig. 2. Two types of loads are considered in MG: three residential and two medium industrial workshops loads. A variety of DERs, such as a proton-exchange membrane Fuelcell (FC), a Microturbine (MT), a directly coupled wind turbine (WT), and five Photovoltaic (PV) arrays are installed in MG. It is assumed that all DGs produce active power at a unity power factor. The technical aspects of MT and FC are obtained from [30-31] and their cost function calculation are described in [10].

The minimum and maximum operating limits of DERs as well as their cost function coefficients are presented in Table 1. Data of actual wind and PV production are taken from [10]. Table 2 provides the hourly energy price of a real electricity market [10]. The total hourly load demand of the MG on a weekday is presented in Table 3. The industrial loads price and amount offers for load reduction is presented in Table 4. The residential loads reduction offers for each house can be found in Table 5. The WT and PV generation forecast errors are taken as 20% of their hourly forecasted outputs.

The case study considers 50 EVs, for which the technical information has been obtained from vehicle manufacturers. A Typical 10 kWh battery capacity for most of EVs is selected [32]. Also, two other vehicle types that are used in this case study are Nissan Leaf with a battery capacity of 24 kWh and Citroen C-Zero with a battery with 16 kWh [33, 34]. Typical battery charge and discharge efficiency are assumed 90% and 95%, respectively [35]. In order to optimize EV battery life, depletion of EV battery up to 85% of the rated battery capacity is assumed.

A standard single-phase 220 V, 15 A socket is assumed for charging point in home or work place. For this analysis, a fixed charging power of 4 kW is selected because this is commonly available in most single-phase residential households without having to reinforce wiring [32, 36].

The above formulation has been implemented in GAMS [37] using Mixed-Integer Linear Programming (MILP) solver CPLEX on a VAIO computer with a 2.27 GHz core i5 processor and 4 GB of RAM. The computation time for the proposed multi-objective method is 3 sec.

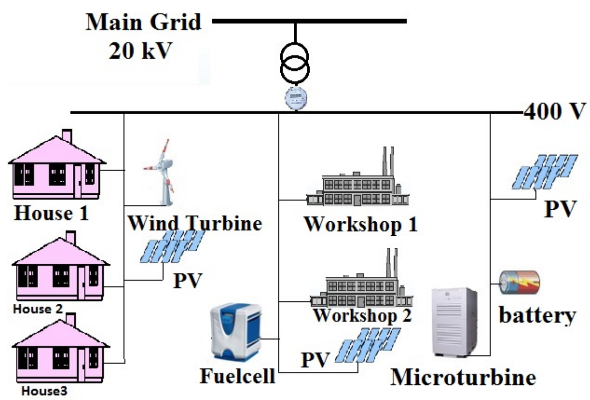

Fig. 2 Typical MG test system.

Table 1 The technical and economical features of DERs.

units	Min power (kW)	Max power (kW)	Start-Up cost (Ect)	b_i (Ect/kWh)	c_i (Ect/h)
MT	1.5	100	0.14	4.37	85.06
FC	10	100	0.24	2.84	255.18
WT	0	30	-	-	-
PV1	0	5	-	-	-
PV2	0	5	-	-	-
PV3	0	5	-	-	-
PV4	0	5	-	-	-
PV5	0	5	-	-	-

Table 2 Hourly price of open market.

t	1	2	3	4	5	6
$\$/MWh$	22.6	19	13.9	12	11.5	19.9
t	7	8	9	10	11	12
$\$/MWh$	23	38.3	149.8	400	400	400
t	13	14	15	16	17	18
$\$/MWh$	149	400	201	194.9	60	41.3
t	19	20	21	22	23	24
$\$/MWh$	35.1	43.9	117.1	54	30	25.5

Table 3 Typical load data of the study case network.

Hour	Demand (kW)	hour	Demand (kW)
1	52	13	72
2	50	14	72
3	50	15	76
4	51	16	80
5	56	17	85
6	63	18	88
7	70	19	90
8	75	20	87
9	76	21	78
10	80	22	71
11	78	23	65
12	74	24	56

Table 4 The industrial load offer.

Hour	Workshop 1		Workshop 2	
	Maximum Reduction (kW)	Price (Cent/ kWh)	Maximum Reduction (kW)	Price (Cent/ kWh)
8	15	12	15	14
9	9	14	24	13
10	5	15	5	12
13	7	9	-	-
14	7	10	-	-
15	21	11	16	12
16	7	8.5	19	10
17	10	10.5	25	12
18	4	12	18	10.5
19	15	10	10	10
20	28	11	18	13
21	10	10	21	10
22	3	12	8	20
23	6	18	-	-

Table 5 Residential load reduction offers (W).

Hour	House 1	House 2	House 3
7	300	200	-
8	500	0	200
9	500	200	200
10	500	0	300
11	1000	1000	0
12	200	200	150
13	200	200	200
14	1000	0	1200
15	900	850	-
16	200	200	200
17	1000	900	850
18	1000	750	1000
19	200	150	200
20	1000	950	0
21	1000	750	800
22	950	-	-
23	1000	500	1000
24	200	200	150

In order two evaluate the robustness of the proposed method, the case study has been carried on in two cases:

- Case 1: Energy and reserve scheduling without considering DR and EV charge/discharge programs
- Case 2: Energy and reserve scheduling with considering DR and EV charge/discharge programs

In the first case, all reserve requirements should be provided by MT and FC. Also, The EVs are considered as load that should be charged enough in order to be ready for scheduled driving pattern. The result of energy resources scheduling in the first case has been shown in Fig. 3. Also, the scheduled reserve capacity has been illustrated in Fig. 4. In this case, all required reserves have been provided by MT. So, a part of the MT capacity should be kept for covering renewable generation uncertainty. Also, for arranging spinning reserve during hours 1-8, 23 and 24, the MT is forced to be turned on in its minimum power output to be ready (stand-by) to deliver spinning reserve.

The results of energy and reserve scheduling in the second case has been shown in Figs. 5-8. As shown in Fig. 5, due to high electricity prices, the imported power from the main gird has been reduced during hours 9-16. As shown in Figs. 6 and 7, during hours 9-16 load reductions and EVs discharging have been scheduled in order to reduce the imported power from the main grid. EVs have been scheduled to be charged during hours 2-7, 18-20, 23 and 24 in which the electricity prices are relatively low. The scheduled reserve capacity in the second case has been illustrated in Fig. 8. Comparing with Fig. 4, the MT capacity has been released to provide energy instead of reserve. Also, EVs and loads have provided the most reserve capacity in the second case.

Moreover, the results emphasize that the demand response during the hours with high energy price is higher than during low energy price hours. That means the MEMS intends to purchase load curtailment when the hourly electricity price is high; in some hours that the electricity prices are higher than DGs offer price, MEMS prefers to use all capacity of DGs for delivering energy.

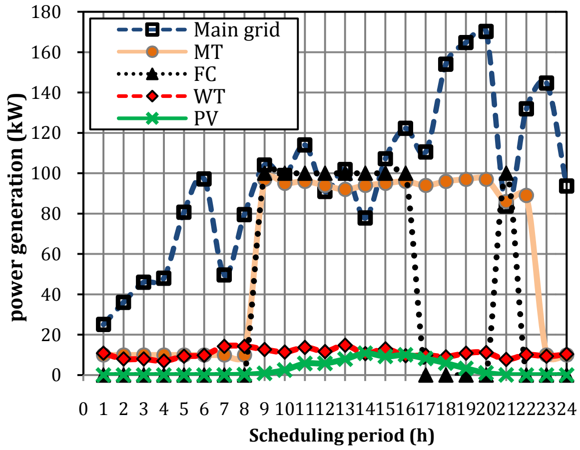

Fig. 3 Scheduled energy in case 1.

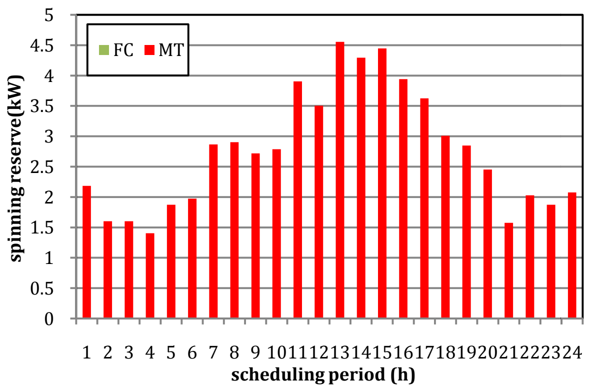

Fig. 4 scheduled reserve in case 1.

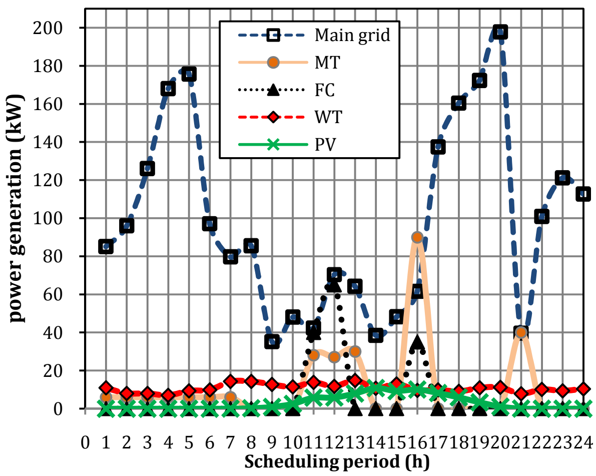

Fig. 5 Scheduled energy in case 2.

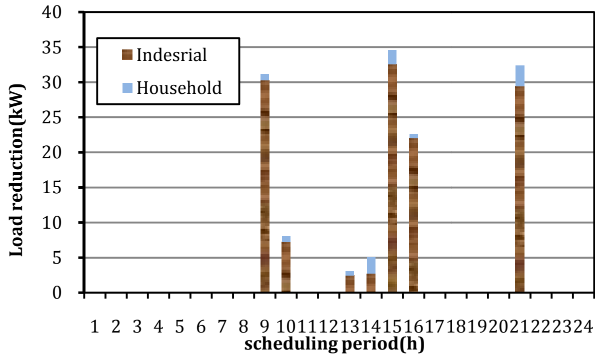

Fig. 6 Scheduled load reduction in case 2.

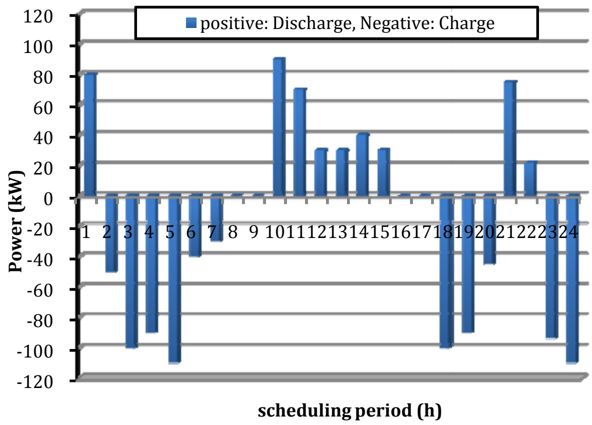

Fig. 7 Charge/discharge program of EVs in case 2.

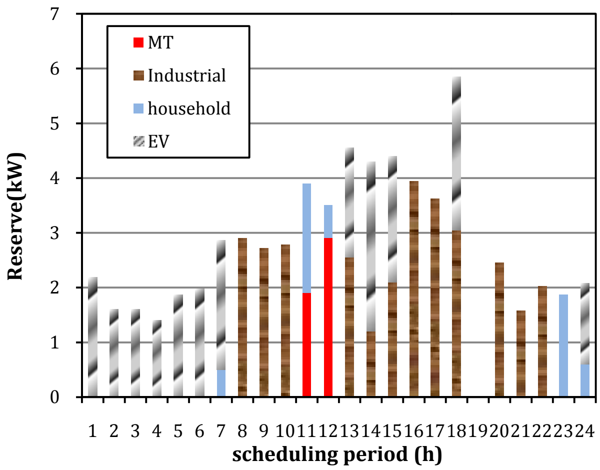

Fig. 8 Scheduled reserve in case 2.

Table 6 compares the operational cost of MG in the cases 1 and 2. The result evidenced that EVs charge/discharge program as well as demand side participation in energy and reserve has been reduced the total operation cost of MG.

Table 6 Cost comparison between two cases.

Cost ($)	Main grid	DGs		DR		EV		Total
		Energy	Reserve	Energy	Reserve	Discharge	reserve	
Case 1	43,972	17,819	342	-	-	-	-	62,133
Case 2	39,298	8,879	58	1,477	103	1,854	115	51,784

Table 7 Cost of scheduling with an without participation of loads and EVs in providing reserve.

Cost ($)	Main grid	DGs		DR		EV		Total
		Energy	Reserve	Energy	Reserve	Discharge	reserve	
Without providing reserve	39,162	9,619	342	1,498	-	1,941	-	52,562
with providing reserve	39,298	8,879	58	1,477	103	1,854	115	51,784

In order to evaluate the effect of loads and EVs participation in providing the reserve capacity, the energy and reserve scheduling has been carried out with and without considering DR and EVs participation in reserve scheduling. The result of the comparison has been shown in Table 7. As shown in Table 7, while the loads and EVs have not been allowed to participate in reserve scheduling, all reserve requirement have been provided by DGs. In this case, a part of DGs capacity should be allocated to reserve and, as a result, they lose the opportunity to provide energy in during the hours when the electricity prices are high. Moreover, due to providing reserve capacity, the MT should be keep turn-on in all hours in order to be in stand-by to provide reserve. It has also increased the total operation cost. The results evidenced that the participation of demand side and EVs in providing reserve reduced the total operation cost of MG. On the other hand, while the EVs and loads are taken into account in reserve scheduling, the DGs capacity will be released in order to provide energy. So, the total operation cost reduced.

5 Conclusion

A novel integrated DERs scheduling approach for a MG was proposed in this paper. This approach allows responsive loads and EVs owners to participate in both energy and reserve operational scheduling. Demand bidding/buyback programs, ancillary service market program and direct load control are considered as demand response programs. The results evidenced that participating of loads and EVs in energy and reserve operational planning reduced total operational cost of MG. In addition, the renewable uncertainty will also be covered by reserve scheduling through the operational planning program.

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