

Two-stage Distributed Energy Management for Islanded DC Microgrid with EV Parking Lot

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Abstract—This paper introduces a distributed energy management for islanded DC microgrids with electric vehicles (EVs) penetration. The energy management problem is divided into two stages. The first, named as filtering stage, is controlled through wavelet filter using the ultracapacitor. The second one is modeled as a noncooperative stackelberg game, where the battery energy storage system is designed as a leader and EVs as followers. The preference of the battery energy storage system is designed to extend its cycle life while for each EV's preference is to maximize its charging power. The consensus network is utilised to reach the Nash equilibrium within the followers at each control instant. The simulation results show the power distribution among the system's units throughout one day. Moreover, comparable outcomes with the centralized method have been illustrated under two available power scenarios i.e., two weather profiles.

Index Terms—Islanded microgrid; Renewable energy source; Hybrid energy storage system; Electric vehicle; Wavelet filter; Game theory; Consensus network.

I. INTRODUCTION

The soaring of environmental concerns has motivated the focus on microgrids (MGs) and electric vehicles (EVs). The long term harvesting energy and high energy efficiency have also increased their researches pace. MG is a local controllable power grid with distributed energy generations (DEGs), energy storage systems (ESSs), and loads [1]. Moreover, it can be extended by plugging in electric vehicles [2]. Microgrid can operate either in grid-tied mode, or islanded mode [3]. The importance of islanded microgrids can be considered by its role in the networked microgrids, and applications powering remote areas, islands, and large buildings. Though the former main focus was on AC microgrids, recently, much care goes to DC microgrids especially for commercial and residential applications due to the technological advances in power electronics. Furthermore, DC systems have various advantages over their AC rivals for instance: higher efficiency, larger controllability and entirely decoupled from the grid [4]. Apart from their beauties and benefits, handling and controlling MG's components and EVs aren't trivial or straightforward. More attention and time should be paid in designing a convenient control for higher utilization of MG and drawbacks avoidance [5]. Thus, energy management problem (EMP) in microgrids has been widely studied in recent years. Essentially, EMP can be classified into two classes: the centralized EMP and the decentralized one. For the centralized case, [6] applies the

model predictive control technique for islanded AC MGs. The EMP is decomposed into unit commitment and optimal power flow problems to avoid a mixed-integer non-linear formulation. [7] discusses a rule-based energy management for grid-tied DC distribution with EVs. The proposed method was based on real-time decision making. [8] applies the EMP to maximize the total exchange cost and minimize the cost. A simple search strategy based on Taguchi's orthogonal array is designed for solving the optimization problem. [9] introduces off-line optimization approach to minimize the total energy cost drawn from the main grid over a finite horizon. On the other hand, decentralized EMP has also been applied in MGs. Its advantages are mainly to lower the communication bandwidth and computational capabilities as well as to allow flexibility over reconfigurable system. [10] introduces a decentralized power management for dc MG with multiple renewable DEGs and ESSs. Though the good results, the configuration of the system is fixed. [11] proposes decentralized energy management to control a grid-tied MG with EVs. Since the MG is connected to the grid, the charging of EVs are designed in a simple prefixed way, voltage constant and current constant modes. This method cannot show the case when there is a low available power for charging which can be met in the islanded MG. Optimal allocation of the available charging power of EVs based on consensus algorithm is done [12]. Charging powers of EVs are set to minimize the total charging cost regardless of their characteristics.

To the best knowledge of the authors, non of the papers in the literature discussed the the interaction between the microgrid units themselves and charging EVs. Moreover, this paper focuses on the islanded microgrid thus handles the problem from the energy perspective rather than price. The following features are the contribution of the proposed energy management method in this paper:

- Fully distributed, i.e., no centralized controller is required.
- Robust, i.e., the time of joining or leaving EVs will not affect the system.
- Fast, i.e., the proposed algorithm is fast in execution time to reach the equilibrium among the units.

This paper is organized as follows. In Section II, system structure and model have been presented. Then, distributed energy management method is introduced in section III. While

section IV is devoted for the simulation results. Finally, the conclusion is drawn in Section V.

II. SYSTEM STRUCTURE AND MODEL

The proposed MG consists of renewable energy sources (RESs); wind turbine system (WTS) and photovoltaic System (PVS), hybrid energy storage system (HESS); ultracapacitor and battery energy storage systems (UESS) and (BESS), load, and parking lot to charge a fleet of EVs. Each of this unit is connected to the DC-bus through a compatible converter. Both WTS and PVS are working at the maximum power point tracking (MPPT) algorithm. The system configuration is illustrated in Fig. 1. This paper focuses on a future experimental validation, thus the size of the system has been set to match the existing laboratory testbed.

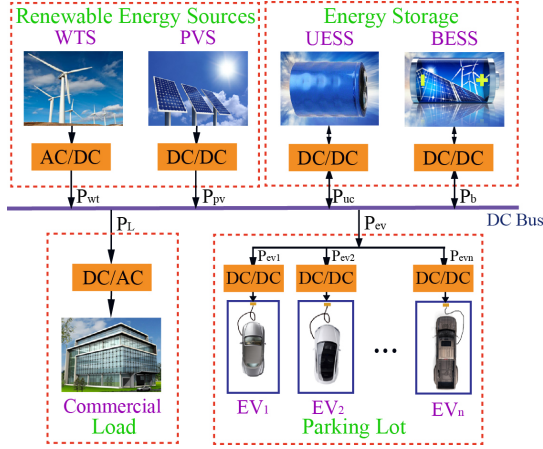


Fig. 1. System Structure

A. RESs, HESS, EVs and load models

The models of WT and PV can be derived as in [13]. While, BESS and UESS are modeled by their equivalent circuit models as shown in Fig. 2 [14]. Open circuit voltage, internal resistance, and resistance-capacitor combination for BESS and the capacitance, internal resistance, and leakage current for UESS. Since this paper focuses on the charging part of EVs, each $EV \in \mathcal{N}$ (number of EVs) can be considered as a battery (on-board battery) with charger (DC/DC converter). The procedure for modeling BESS can also be used here [14]. For the load, it is taken as a real-world commercial building profile (e.g., office) from San Diego city, USA [15]. It should be noted that any type of load profile such as residential, industrial, etc., or any location can be chosen.

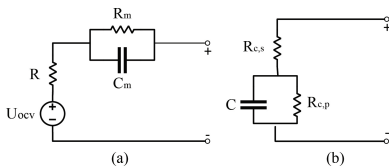


Fig. 2. The equivalent models of (a) BESS cell. (b) UESS cell.

B. Constraints

The system has a plenty of constraints which reflect the existing physical limitations e.g., DC-bus voltage and capacity of each device in MG. Since this paper focuses on the islanded microgrid, it is of interest to highlight the law of energy conservation, equality constraint, expressed in (1).

$$h = P_{wt} + P_{pv} - P_{uc} - P_l - P_b - \sum_{j=1}^{\mathcal{N}} P_{ev,i} = 0, \quad (1)$$

where P_{wt} , P_{pv} , P_{uc} , P_l , P_b , and $\sum_{j=1}^{\mathcal{N}} P_{ev,i}$ are the WTS, PVS, UESS, load, BESS, and summed of EVs powers, respectively.

C. Uncertainties

The more data profile models match the daily life ones, the more stable and efficient system is achieved. To this aim, it is more convenient to introduce the following uncertainty models:

- 1) *Weather data*: Weibull distribution is chosen to model wind speed variations, while Beta distribution is selected for modeling solar irradiance uncertainties [16].
- 2) *Load, EVs' capacities and initial SOC*: load fluctuations, capacities of EVs (i.e., passenger cars, vans, etc.) and initial SOC of EV (i.e., previous trips and incentives of EVs' drivers) can be modeled by Gaussian distribution [17].

D. Sizing

For convenient sizing, i.e., to keep the system working permanently and efficiently, the following guidelines should be borne in mind:

- 1) The number of WT and PV modules is to meet the total load demand i.e., commercial household and EVs loads.
- 2) The ratio between WT and PV modules depends on some criteria such as setup cost, weather data abundance.
- 3) BESS's capacity should hold the cumulative differences between the generated and consumed powers.
- 4) Ultracapacitor should be responsible for the high-frequency power in the system.

Accordingly, the size of the system can be designed successfully. The system size in this paper is listed in table I.

TABLE I
SIZE OF THE SYSTEM

Component	WTS	PVS	UESS	load	BESS	EV _{1,2,3}
Rated Capacity	90 kWp	84.4 kWp	3.36 kWh	25 kW	175 kWh	12/24/12 kWh

III. DISTRIBUTED ENERGY MANAGEMENT METHOD

This paper divides the energy management problem into two stages. This conceptual division highlights the relations between the units inside the system. Each stage is discussed as follows,

A. First Stage Control

Its purpose is filtering (smoothing) of the generated power. Here, UESS tries to take the responsibilities of the short-term power (high-frequency). In such a way, elimination of fluctuations and smoothing procedure of the generated power will be gained besides protecting and prolonging cycle lives of the remaining units in the system. To this intent, three-level Haar wavelet filter is used to control UESS. Here, the level of wavelet decomposition is set by the desired cut-off frequency. Fig. 3 shows the procedure along with the working principle structure of the wavelet filter.

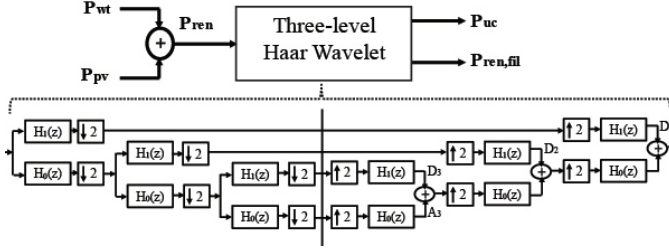


Fig. 3. Block diagram of the first stage control.

Where H_0 and H_1 are the low and high pass filters with eight-sample window. In fact, the reason behind choosing the Haar based filter is due to the straightforward procedure and simplicity in determining the high and low pass filters coefficients [18]. The sum of the high components (D_1, D_2 and D_3) will go to the UESS while the low component (A_3) will be considered as the filtered generated power which goes to the second stage control as follows:

$$P_{ren} = P_{wt} + P_{pv}, \quad (2)$$

$$P_{uc} = D_3 + D_2 + D_1, \quad (3)$$

$$P_{ren,fil} = A_3, \quad (4)$$

with P_{ren} is the generated power from WTS and PVS, and $P_{ren,fil}$ is the filtered generated power. It is noteworthy to mention that maintaining the DC-bus voltage relies on UESS also, so the UESS's DC/DC converter is in fact a regulator.

B. Second Stage Control

It is worth to remind the competition behaviour of the charging EVs and the physical access ability of the BESS along with the probable change number of EVs and their SOC and BESS's SOC at each stage i.e., independent stages. Thus, the energy management problem is modeled as a multistage noncooperative generalized stackelberg game i.e., distribution of the filtered power among the remaining units. In this game, BESS is set as the leader, while EVs are designed to be the followers. Thus, the formulation of this game can be written in its strategic form, $G = [\mathcal{N} \cup B, (P_{ev,i})_{i \in \mathcal{N}} \cup P_b, (u_{ev,i})_{i \in \mathcal{N}} \cup u_b]$ with \mathcal{N} is the number of the followers, B indicates to BESS, $P_{ev,i}$ and P_{sum} are the strategy sets for the followers and the leader, and $u_{ev,i}$, u_b are the utility functions for them, respectively.

C. Utility Functions

In this paper, the quadratic form is selected to describe the preferences of players [14], [19]. The key points behind this selection are: 1) commonly and successfully applied in smart grids and EVs to form players' preferences [19], [20]; 2) concavity feature which guarantees the existence and uniqueness of Nash equilibrium.

1) *Battery energy storage*: the preference is to extend its cycle life through making the charging/discharging power equals to the optimal one (i.e., reflecting its physical dynamic behaviour). Thus the utility function of BESS is to maximize (5).

$$u_b = -(P_b - P_b^{opt})^2, \quad (5)$$

with,

$$P_b^{opt} = -1[SOC_b - (SOC_b^{min})^\psi (SOC_b^{max})^{1-\psi}]P_b^{ref} \quad (6)$$

$$= \begin{cases} (SOC_b^{max} - SOC_b)P_b^{ref} & \mathcal{N} = 0 \\ -(SOC_b - SOC_b^{min})P_b^{ref} & \mathcal{N} > 0, \end{cases}$$

$$\psi = \text{sgn}(\mathcal{N}),$$

where P_b^{opt} is the optimal instant power of BESS, SOC_b is the state of charge of BESS, SOC_b^{min} and SOC_b^{max} are the minimum and maximum allowed SOC of BESS, P_b^{ref} is the optimal reference charging/discharging power at the minimum allowed SOC and sgn is the sign function.

In fact, BESS tends to have charge in the absence of EVs, and discharge meanwhile their existence. In such a way, BESS can help to buffer the power and utilize it during the intermittent or lack of renewable energy generation.

2) *Electric vehicles*: each EV is willing to enlarge its own charging power, thus the aim is to maximize (7).

$$u_{ev,i} = -\frac{1}{2}SOC_{ev,i}P_{ev,i}^2 + P_{ev,i}^{ref}P_{ev,i} \quad (7)$$

Likewise, $SOC_{ev,i}$ is the state of charge of EV's battery, $P_{ev,i}^{ref}$ is the unit reference charging power of the on-board battery which can be set by multiplying the minimum allowed SOC by the optimal charging power of it, and $P_{ev,i}$ is the charging power of EV.

D. Generalized Stackelberg Nash Equilibrium

Here, the solution of the stackelberg game will be shown. For the leader, the solution is straightforward and can be written as,

$$P_b^* = P_b^{opt} + \Delta P, \quad (8)$$

where, ΔP is the feedback power from the system due to the common constraint and local EVs' constraints e.g., the available power to charge EVs exceeds their demands. Whereas, under an available power (P_{ava}) for charging EVs,

there exists another game between the followers who share the following inequality constraint,

$$\sum_{i=1}^{\mathcal{N}} P_{ev,i} \leq P_{ava}, \quad (9)$$

$$P_{ava} = P_{ren,fil} - P_l - P_b \quad (10)$$

Actually, this noncooperative power distribution game is a generalized Nash equilibrium problem (GNEP) with all players need to reach so-called Nash equilibrium to define the power distribution at each stage. In this paper, the distributed charging algorithm to find GNE is based on Karush–Kuhn–Tucker (KKT) conditions of optimality and Lagrange multipliers method. Where, the general optimization problem for each player as well as KKT conditions with the common inequality constrain are shown as follows,

$$\begin{aligned} & \text{Min } \{-u_{ev,i}\} \\ & \text{s.t. } g = \sum_{i=1}^{\mathcal{N}} P_{ev,i} - P_{ava} \leq 0 \end{aligned} \quad (11)$$

$$L_{ev,i}(P_{ev,i}, \lambda_{ev,i}) = -u_{ev,i} + \lambda_{ev,i}g \quad (12)$$

$$\frac{dL_{ev,i}}{dP_{ev,i}} = -\nabla_{P_{ev,i}} u_{ev,i} + \lambda_{ev,i} \nabla_{P_{ev,i}} g = 0, \quad (13)$$

where $\lambda_{ev,i}$ is the Lagrange multiplier of each player. The distributed method tries to reach the most socially stable equilibrium by making all $\lambda_{ev,i}$'s have the same value [19].

This decentralized method relies on communications between players, so it is more convenient to show the whole envisioned conceptual structure of the system as in Fig. 4. Here, two layers are shown, the physical layer, and the cyber layer besides the in-between control mapping. The first one represents the physical system dynamics, while the second depicts such communications between the nodes i.e., leader and followers.

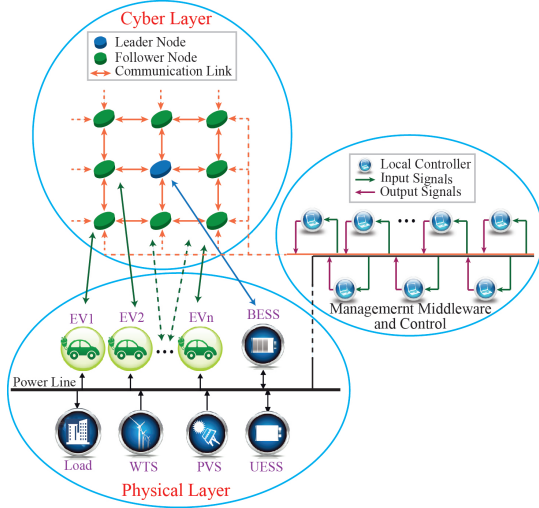


Fig. 4. The distributed energy management scheme within the system layers

The aim in this decentralized method is to let each player updates its demand repetitively until a uniform value of all $\lambda_{ev,i}$ s is obtained. To this end, the concept of the consensus network is utilised [20]. Here, each player is represented by a node and the nodes are connected by links i.e., communications between neighbours are allowed, to form the entire network. Intuitively, because of the distributed energy management nature, there is an individual controller for each player who can share only its own control variable ($\lambda_{ev,i}$) rather than sharing all its parameters to others, and utilize the previous two layers.

In the proposed algorithm, one of the system nodes will: i) check the validity of the inequality constraint; ii) assist in reaching the power equilibrium state by tuning its parameters corresponding to the power mismatch i.e., violating (9). Without the loss of generality, this node will be indexed “1”.

The attempt to attain the equilibrium can be accomplished through iterative manner. The proposed consensus-based distributed power management (CDPM) algorithm for a single stage of the whole procedure is shown below. Where each local controller at a node can execute its belonging part. At the first step, an initialization of all $\lambda_{ev,i}$ s has been done with zero values i.e., giving maximum charging powers to EVs. Then, the consensus phase takes place which pursues to converge all the values of $\lambda_{ev,i}$ s to a single one. This can be achieved by updating each node's $\lambda_{ev,i}$ utilizing the sum of weighted differences between this node's $\lambda_{ev,i}$ and its neighbored nodes' $\lambda_{ev,i}$ s as in line 3. Where N_i is the set of neighbours of node i , and $w_{i,j}$ is the connectivity strength between node i and j and should be chosen within $[0 \ 1/n]$ to insure the intended convergence. When the convergence is achieved, the power distribution among the players will be assigned accordingly. Afterwards, the validity of the common constraint will be checked. The algorithm will reach the Nash equilibrium the time the constraint is satisfied. Otherwise, it will be repeated again carrying a modification on the $\lambda_{ev,1}$ as a translation of the power difference.

Fig. 5 shows the convergence of $\lambda_{ev,i}$ s in such a stage, where three EVs exist. The convergence manner just follows the mechanism described before by mentioning the red color is the $\lambda_{ev,1}$ which takes care of the convergence. All the values begin with zero then increase according to the power mismatch until they reach the final value i.e., the equilibrium. As it can be seen, the convergence is fast enough to be implemented in real applications.

IV. SIMULATION RESULTS

The simulation platform is Matlab with 64-bit, 2 core processor (2 GHz), and 6 GB RAM. First, the power and SOC distribution responses within the units throughout whole day for the proposed control algorithm are presented. It is supposed that the coming time interval between EVs is 30 (min). Moreover, three cases have been chosen for the coming time of EVs, i.e., C1:morning, C2:afternoon and C3:evening. As it can be seen from Fig. 6, the dynamic generated power by WTS and PVS or consumed power by load follow the

Algorithm CDPM

I. Initialization

1: $\lambda_{ev,i}(0) = 0$; $\forall i \in \mathcal{N}$
II. Consensus Phase

2: **while** $\delta\lambda_{ev,i} > \varepsilon_0$ **do** ; $\forall i \in \mathcal{N}$

3: $\lambda_{ev,i}(k+1) = \lambda_{ev,i}(k) + \sum_{j \in \mathcal{N}_i} w_{i,j}(\lambda_{ev,j}(k) - \lambda_{ev,i}(k))$

4: $P_{ev,i} = \frac{P_{ev,i}^{ref} - \lambda_{ev,i}(k+1)}{SOC_{ev,i}}$

5: **end while**
III. Checking Constraint

6:

$$\left\| \sum_{i=1}^{\mathcal{N}} P_{ev,i} - P_{ava} \right\| \leq \varepsilon_1 : \begin{cases} \text{Yes} \rightarrow \text{Terminate} \\ \text{No} \rightarrow \text{Continue} \end{cases}$$

IV. Tuning I's Parameters

7: $P_{ev,1}(k+1) = P_{ev,1}(k) + k_p \left(\sum_{i=1}^{\mathcal{N}} P_{ev,i} - P_{ava} \right)$

8: $\lambda_{ev,1}(k+1) = P_{ev,1}^{ref} - SOC_{ev,1} P_{ev,1}$
V. Go back Step II

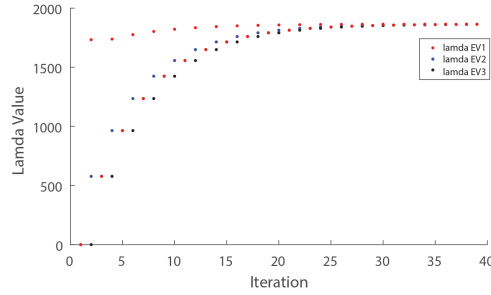


Fig. 5. Number of iterations for convergence of $\lambda_{ev,i}$ s.

aforementioned functions. Since UESS is at the first control stage and has only relation with the generated power, its power will be the same in the three cases. As set, UESS's power is highly dynamic and vanishes at zero value in the absence of renewable powers. The BESS's power in the three cases shares the same dynamic in the absence of EVs i.e., before coming of EVs and after their leaves. Meanwhile their presences, the dynamic follows the BESS-EVs interaction. In either case, BESS's power dynamics are done in low-frequency comparing with that of UESS. For EVs' powers and as it determined by their preferences, each EV is charged by its maximum power for a period of time then drops slightly as to the increment in SOC. The three cases are only shifted to each other, thus, the coming time of EVs will not effect the system performance.

On the other hand, the SOC distribution response is shown in Fig. 7. Since its task is a filter, UESS's SOC should change between a specific range and end, ideally, at its initial value (here, 0.5). BESS's SOC reflects its mission by supporting the load demand and charging EVs with power. The only difference of its SOC in the three cases is in the existence

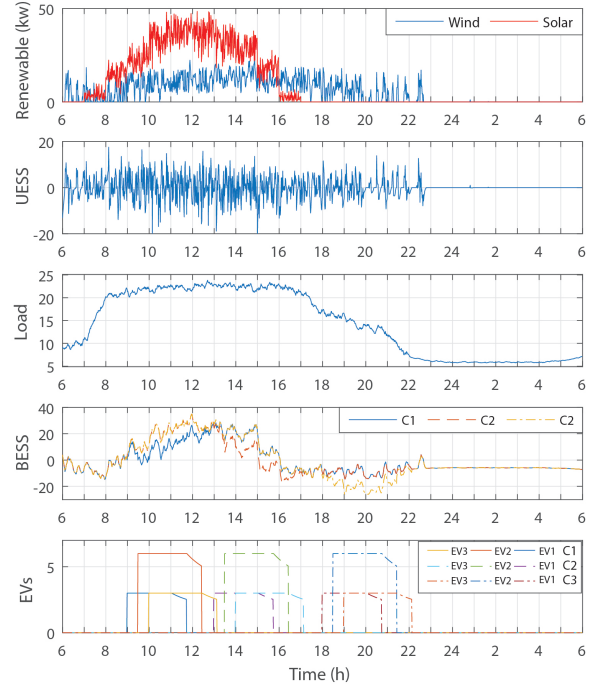


Fig. 6. Power distribution response.

of EVs. Moreover, the final value of SOC matches the initial value, which indicates the proper size of the system. EVs' SOC's show their initial values and increments until the final values i.e., fully charged, with similarity in the three cases.

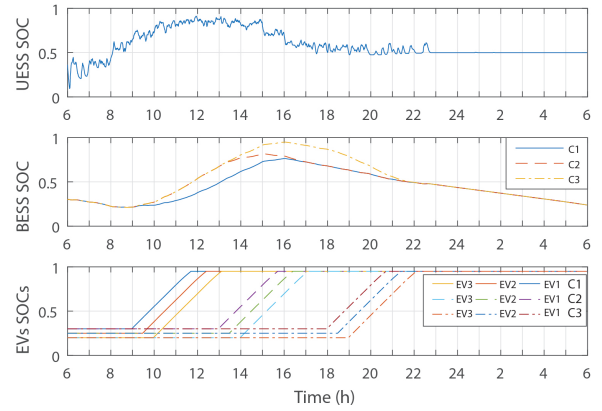


Fig. 7. SOC distribution response.

Second, to validate the performance of the proposed distributed algorithm, a comparison with the centralized control has been done. The centralized control method used here is the sequential quadratic programming (SQP). Three quantitative criteria have been chosen for evaluation named as execution time (ET) i.e., for the algorithm code, charging time (CT) i.e., elapsed time to fully charge EV, and mean square fluctuation

(MSF) i.e., reflects the smoothness in charging.

$$MSF = \frac{1}{N} \sum (P_{ev,i}^t - P_{ev,i}^{t-1})^2, \quad (14)$$

with $P_{ev,i}^t$ and $P_{ev,i}^{t-1}$ are the charging powers of EV_i at time t and $t-1$, and N is the number of charging power samples in the whole charging time for each EV. Here, two scenarios are chosen, the first is a normal day where a plenty of power exists, the second is under lack of power i.e., partially non windy or cloudy day. Since the results are the same in the first scenario for both control methods and match the ones in Fig 6, only the second scenario is shown in Fig. 8. While, the results under comparison criteria for both scenarios are listed in table II. It is clear that the results in the first scenario in terms of MSF and CT are the same. While for the second scenario, though the centralized method has advantages over the distributed one in MSF (i.e, smoother charging) and charging time (i.e., faster charging) but the results are comparable. However, in terms of ET it is obvious that the proposed algorithm is faster by 70.39 % in the worst case (i.e., in second scenario when the three EVs exist).

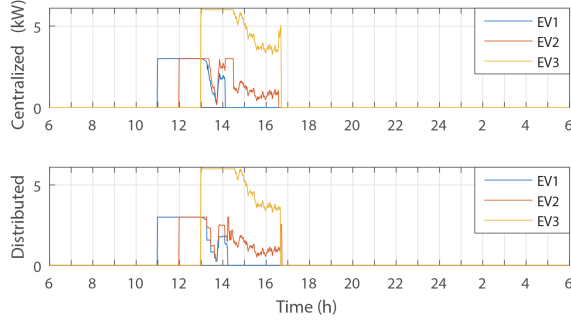


Fig. 8. EVs Power Response under the second scenario by the centralized and distributed control methods.

TABLE II
EVALUATION CRITERIA

Method	Evaluated Element	Senario 1		Senario 2	
		Cen.	Dis.	Cen.	Dis.
MSF (kW ²)	EV_1	.019e-3	.019e-3	.0048	.0115
	EV_2	.107e-3	.107e-3	.0260	.0428
	EV_3	.019e-3	.019e-3	.0070	.0124
CT (Min)	EV_1	165	165	188	195
	EV_2	177	177	276	285
	EV_3	189	189	221	223
ET (Sec)	EV_1	.0581	.0136	.0615	.0138
	$EV_{1,2}$.0621	.0154	.0682	.0155
	$EV_{1,2,3}$.0707	.0173	.0743	.0220

V. CONCLUSION

This paper proposed a two-stage distributed energy management for islanded DC microgrid with EVs penetration. The first stage was considered as a filtering stage for the generated powers, and controlled by wavelet filter through UESS. The second stage, introduced a noncooperative stackelberg game

to distribute the power between BESS and EVs. BESS was chosen as a leader while EVs as followers. Moreover, The convergence algorithm to Nash equilibrium among the EVs had been shown. In the simulation section, power and SOC responses for one day had been illustrated. The results showed how the EVs are satisfied according to their preferences by the charging powers. Then, quantitative comparisons with the centralized optimization method had been presented under two weather scenarios. The results showed comparable outcomes with the proposed distributed method along with leading advantage in the execution time, at least 70.39 % faster.

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