Research Article

Assessing the Impact of Electric Vehicle Fleets on a Multi-Microgrids System Under Different Operating Modes

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Abstract: The Global climate change and the lack of fossil fuels reserves have already had observable effects on the environment. Therefore, an undeniable investment is being made to respond these heavy challenges and to accelerate the momentum towards further embracing the electrification of transportation in smart microgrids, energy efficiency and clean energy production. The paper presents a novel cost-effective management of non-renewable resources of a multi-microgrid system under different operating modes (islanded, connected) with integrating renewable energy sources. Also, we investigate the impact of controlling vehicle-to-grid (V2G) operations on the multi-microgrid system by establishing a coordinated charging control strategy for plug-in electric vehicles (PEVs) with the aim of obtaining the maximum benefit from the grid as well as minimize the overall operating cost of the system. Both, the management of the multi-microgrid system and the EVs charging strategy have been formulated and solved using the Genetic Algorithm (GA), where the obtained results have shown that this method increases the quality, and the efficiency of obtained day-ahead scheduling solutions under any operating mode.

Keywords: Multi-Microgrids, Plug-in Electric Vehicles, Vehicle-to-Grid, Genetic Algorithm, Renewable Energy Sources, Connected, Islanded.

1. Introduction

The global climate change, growing demand for electricity, unsustainable population growth, fast development of industrial sectors and economic growth are representing the most risk factors that will extremely harm all life on earth. According to IEO report, the electricity energy consumption will increase by about 50% in China and 29% in India from 2015 to 2040 [1] which both of these countries have the world's largest population. This insight may give us a good vision about the excessive burden on current energy sources. All these significant long-term challenges that are facing the power grid, force both governments and stakeholders as much as they can to adopt new clean and renewable power generation resources that will further improve dependency on carbon-based fuels and reduce the CO2 emissions. Furthermore, many notable changes have been carried through to an energy economically efficient and environmentally friendly electricity system. It is redefining the overall electrical power systems towards new concepts such as smart grids, smart microgrids, and smart cities that are focusing on increase generating electricity from Renewable Energy Sources (RES) (photovoltaic (PV) systems, small wind farms), using the information and communication technologies (ICTs) [2-4], developing energy storage systems [5-7] and electrifying transportation. Power grids of the near future will control electricity generation by deploying diverse types of distributed generators (DGs), advanced information and communication technologies to ensure the cost reduction, save energy and match the loads at any particular time. Now, unpredictable loads put the capacity of the generation system under some excessive pressure. This pressure is not generally sorted out directly specially in case of insufficient generation at peak periods in the day, but it could be solved through voluntary load curtailment, demand response and peak shaving programs. Most of the systems, power generation control tends to adjust the power output of used generators to follow the changes in the load. This load-following approach gets more difficult by integrating renewable energy sources to the grid. Also, this emission free sources are not unscheduled and unpredicted due to their intermittency. For these reason microgrids are considered as an effective remedy for intermittency in the power grid. These small-scale power systems are controlling several renewable and non-renewable energy sources, loads and flexible storage capacities, not necessarily geographically near to each other. And they can function synchronously and/or isolated (island/stand-alone mode) from the utility grid [8-10]. The Microgrids allow the transition between these two modes following continuous efficient strategy as physical, economic, or other conditions dictate. This transition gives more stability for both central system and local grid, reduces carbon footprint and green gas emissions by enhancing environmentally friendly local energy generation, improves supply security, provides resiliency, efficiency and reliability. More than that, the growing fleet of fully electric cars and plug-in hybrids of electric vehicles (EVs) represents additional stress for the power grid while charging a large number of EVs in peak load which can lead to heavy impact on system aggregated operation cost. Nevertheless, Electric vehicles on the other side could potentially contribute in the load curtailment and peak shaving in the network by using them as flexible storage capacities that can deliver or/and receive energy from power grid.

The widespread attention beyond the community of researchers and major utilities around the world, for the microgrids that are being promoted as an intelligent solution when organizing and facilitating effectively optimization tools and instituting robust and appropriate design methods to manage this kind of novelty systems. While most researches and studies that have been addressed, many of approaches have investigated the optimal management of resources of a Microgrid by considering different time-scheduling horizon. For example, in [11] the authors analyze the optimal decision problem addressed by managing a set of distributed resources (renewable and non-renewable systems, energy storage systems to optimize the buying and selling process of the Distributed Energy Resources (DERs) aggregation in virtual power plants which is similar to Microgrids. In the literature about aggregators used to manage microgrids, most of the research investigations focus on the optimal operation and the best employment of a microgrid's resources, for example, in [12] where the authors propose a risk-constrained scenario-based stochastic framework for the optimal operation of a microgrid, where the aggregator sells electricity, generated by local DERs or procured by pool market to its customers by offering optimal hourly bids in the day-ahead market. In [13] a management framework of a grid-connected microgrid is presented based on agent-based modelling in order to increase the Microgrid stakeholders' revenues from power selling. The developed framework faces the uncertainties relating to the stochasticity nature of renewable power generators, operational and environmental parameters. In [14], investigate the impact of demand response aggregators by proposing an energy and reserve management approach to schedule the resources of small and medium scale in a prosumer microgrid in order of reducing both the microgrid operating cost and the distributed resources utilization. Other interesting contributions, including optimal operation of microgrids can be found in [15] and [16]. Much work has therefore been carried out essentially with grid-connected microgrids as one high priority in the literature, but less strongly investigated and considered in optimal energy dispatch in the stand-alone operating modes. For example, in [17], a system-wide optimal coordinated energy dispatch method is presented for a multi-energy microgrid with various non-renewable generation units, renewable generation units and energy storage devices. For both the grid-connected and islanded operating mode of microgrid with the aim of minimizing the microgrid operating cost and improve the dispatch flexibility, and other contributions on power dispatch of the islanded microgrids [18–23]. The research work in [24] was considered as one of the very rare examples of which proposed a bi-level multi-objective operation model: the first level(upper model) establishes an optimal dispatch of distribution network to reduce power loss and improve the voltage profile and the second level (lower model) attempts to get maximum performance of a grid-connected microgrids at the lowest possible operating cost. The same procedure was applicated in [25], where a robust multi-objective economic dispatch strategy is used for grid-connected microgrids that are under the worst scenario considering simultaneously uncertainties from both EV charging loads and wind power. As many papers have pointed out, the ESS plays significant role in smoothing load, improving the economic efficiency and ameliorating stability, strengthening reliability, and ensuring security of microgrid systems in the presence of intermittency and fluctuation challenges due to vast system integrating several renewable energy resources. [26] is regarded as one example of integrating renewable generation by optimally discharge scheduling of the Energy Storage System (ESS) through reducing the Microgrid's energy consumption from the utility grid and enhancing the generation and load profiles. Similar thing for the integration of EVs into the grid which are expected to reign the roads that will reach 9 million-20 million by 2020[27]. Several researches have been carried out to investigate the impact of controlling EVs charging in coordination with the optimal operation microgrid's resources, in [28], an aggregator model for an EV fleet is introduced to deal with a stochastic formulation of DER-CAM (problem of optimally sizing and scheduling DER [23]), for an optimal DER investment in microgrids considering the impact of freely available EVs and the uncertainty in EV driving schedules. In [30], a coordinated scheduling method is presented for system a grid-connected gas/electricity/heat microgrid in a day-ahead scheduling considering a temporal-spatial EV charging model, where a real-time dispatching is used following the day-ahead exchanged energy with the utility grid

In this paper, we suggest a model for managing multi-microgrids, under different operating modes, which will guarantee the right balance between different power-supply participants and consumers in the power system (microgrids, utility grid …). The objectives of the management strategy are to minimize the overall operating cost of the multi-microgrids system by optimally scheduling micro conventional generators, integrating renewable energy sources, controlling the ESSs charging and discharging and the substantial quantities of power purchased from the central power grid. Therefore, in this sense, the model can manage simultaneously both the charging and discharging of electric vehicles plugged into microgrids on one side, and the microgrids' resources, power exchanged locally or/and power exchanged centrally with the utility grid on the other side, in order to obtain the maximum benefit in the interests of all stakeholders and EVs owners through V2G operations. To assesses the impact of EVs charging strategy, we will design six cases in which the multi-microgrids system will vary depending on both the EVs charging strategy (coordinated, uncoordinated) and microgrids' operating modes. Our contributions are summarized as follows:

- We formulate a global Resource Management problem of multi-microgrids system, which aims to minimize the system operation cost within the day. The optimization problem contains the scheduling of micro-conventional generators, ESSs' scheduling and integrating renewable energy sources. · To obtain the lowest total operating cost, we propose using a genetic algorithm-based optimization approach to solve this convex optimization problem efficiently.
- We formulate a local scheduling optimization problem of each vehicle in the local microgrid using The Genetic Algorithm (GA). The scheduling process is carried out based on an integrated optimizer at the level of each microgrid that will defend the benefits of each EV owner and the microgrid. The EVs optimal scheduling profiles will contribute to reduce minimize the system operation cost by smoothing the load profile, curtailing load peak and using the EVs as extra and small storage capacities.
- The rest of this paper is organized as follows: we focus on the mathematical model of the multi-microgrids system problem in part 2. In part 3, we expose the EV charging strategy investigated in this study. In part 4, we present some numerical simulations and experimental findings to assess the proposed strategies and algorithms. Finally, in part 5, conclusion is presented.

2. Multi-Microgrid System Formulation

2.1. Objective Function Formulation

The main goal of the objective function is to minimize the overall operating cost of all renewable and non-renewable resources, the cost of power exchange among microgrids and with the utility grid under any operation mode (Islanded, integrated, grid-connected modes) in which all operating characteristics of all resources are considered in this paper. The following indices t, (n and m), i, l represent the time slots over the scheduling horizon, the microgrids index, the conventional generators, the plugged in EVs and the ESSs index, respectively. For the micro conventional generators, $\mathrm{u_{t,n,i}}$ represents the binary commitment status (where 0 denotes the generators is OFF and 1 denotes the generators is ON), $\mathrm{P_{i,n}}(\mathrm{t})$ is the amount of generated power, $\mathrm{C}^{G}_{\mathrm{i,n}}$ the generation cost of the i-th generators in the n-th microgrid at time t. For the second term, $P^{Charg}_{ESS/\mathrm{t,n,s}}/P^{Disch}_{ESS/\mathrm{t,n,s}}$ represents the amount of energy charged/discharged from the s-th ESS at the s-th microgrid at the t-the time slot, where $\mathrm{CESS}^{charg}_{\mathrm{t,n,s}}/\mathrm{CESS}^{Disch}_{\mathrm{t,n,s}}$ are the charging/discharging cost of the same ESS. The $\mathrm{P}^{M}_{\mathrm{t,n,m}}$ is the amount of power exchanged in-between integrated microgrids (from microgrid n to microgrid m) at time t. $\mathrm{P}^{M}_{\mathrm{t,n,m}}$ could have both positive value or negative value and calculated twice, where α denotes the ability of exchanging power (α=0 microgrids operate without changing power, α=0 microgrids operate with changing power alongside each other). Finally, $\mathrm{P_{Utility,n}}$ is the power of the n-th microgrid purchased from the utility grid, where its cost is depend on the electricity price on the market $\mathrm{C}^{U}_{\mathrm{t}}$at time t and β determines the operating mode in the objective function, where β = 0 denotes the islanded mode and β = 1 denotes the grid-connected mode. The various cost terms involved in the objective function of the system's operating cost are modelled as follows:

$$min\, \boldsymbol{f} = \sum_{\mathrm{t=1}}^{\mathrm{H}}\sum_{\mathrm{n=1}}^{\mathrm{N}}\sum_{i=1}^{Ng} \mathrm{C}^{G}_{\mathrm{i,n}}.\mathrm{P_{i,n}(t)}.\mathrm{u_{t,n,i}} + \sum_{\mathrm{t=1}}^{\mathrm{H}}\sum_{n=1}^{N}\sum_{\mathrm{s=1}}^{\mathrm{N}_{ESS}} (\mathrm{CESS}^{charg}_{\mathrm{n,s}}.P^{Charg}_{ESS/\mathrm{t,n,s}} + \mathrm{CESS}^{Disch}_{\mathrm{n,s}}.P^{Disch}_{ESS/\mathrm{t,n,s}})$$
$$+ \alpha \sum_{\mathrm{t=1}}^{\mathrm{H}}\sum_{\mathrm{n=1}}^{\mathrm{N}}\sum_{\mathrm{m=1}}^{\mathrm{N}} \mathrm{C}^{M}_{\mathrm{i,n}}.\mathrm{P}^{M}_{\mathrm{t,n,m}}\,(\mathrm{t}) + \beta.\mathrm{C}^{U}_{\mathrm{t}}.\mathrm{P_{Utility,n}}(\mathrm{t})$$
$$\forall\, \mathrm{t}, \forall\, \mathrm{i}, \forall\, \mathrm{n}, \forall\, \mathrm{l} \qquad (1)$$

2.2. Micro-Generation Units' Constraints

Constraint in (2) guarantee that each conventional generator operates on a specific bound, where $\mathrm{P^{min}_{n,i}}, \mathrm{P^{max}_{n,i}}$ are the minimum and maximum generation limits, respectively. Eq (3), limits each generator of remaining operational or switched off for not more than a maximum or less than a number of hours, constraints (4) and (5) specify the ramp up and ramp down limits of generators. Constraints (6) et (7) enforce line capacity limits of both existing lines, the first line in-between microgrids is limited in $\mathrm{P}^{M}_{\mathrm{Max,n,m}}$ and the second line between microgrids and utility grid is limited in $\mathrm{P}^{Max}_{\mathrm{Utility,n}}$.

$$\mathrm{P^{min}_{n,i}}.\mathrm{u_{t,n,i}} \leq \mathrm{P_{n,i}(t)} \leq \mathrm{P^{max}_{n,i}}.\mathrm{u_{t,n,i}},\ \mathrm{u_{t,n,i}} \in \{0;\ 1\}\ \forall\, \mathrm{t}, \forall\, \mathrm{n}, \forall\, \mathrm{i} \qquad (2)$$

$$\begin{cases} \text{if } u_{t,n,i} = 1 \text{ then } MU_{n,i} \times (1 - u_{t,n,i}) \leq XU_{n,i} \\ \text{if } u_{t,n,i} = 0 \text{ then } MD_{i,n} \times u_{t,n,i} \leq XD_{i,n} \end{cases} \forall t, \forall n, \forall i \quad (3)$$

$$P_{i,n}(t+1) - P_{i,n}(t) \leq RU_{i,n} \ \forall n, \forall i \quad (4)$$

$$P_{i,n}(t) - P_{i,n}(t+1) \leq RD_{i,n} \ \forall n, \forall i \quad (5)$$

$$0 \leq P_{Utility,n}(t) \leq P_{Utility,n}^{Max} \ \forall n \quad (6)$$

$$0 \leq P_{t,n,m}^{M}(t) \leq P_{Max,n,m}^{M} \ \forall n, \forall m \quad (7)$$

2.3. Integrated Multi-Microgrids System Power Balance Constraint

In the multi-microgrids system, the conventional generators along with the wind, solar power, ESSs must meet the load demand at each microgrid and at any hour t, where the system load balance equation is given as:

$$P_{PV}(t) + P_{WT}(t) + \beta.P_{Utility}(t) + \alpha \sum_{t=1}^{H}\sum_{n=1}^{N}\sum_{i=1}^{Ng} P_{i,n}(t).u_{t,n,i} + \sum_{t=1}^{H}\sum_{n=1}^{N}\sum_{l=1}^{N_{PEV}} P_{EV/t,n,i}^{Disch} + \sum_{t=1}^{H}\sum_{n=1}^{N}\sum_{s=1}^{N_{ESS}} P_{ESS/t,n,i}^{Disch}$$
$$= D(t) + \sum_{t=1}^{H}\sum_{n=1}^{N}\sum_{m=1}^{N} P_{t,n,m}^{M}(t) + \sum_{t=1}^{H}\sum_{n=1}^{N}\sum_{s=1}^{N_{ESS}} P_{ESS/t,n,i}^{Charg} + \sum_{t=1}^{H}\sum_{n=1}^{N}\sum_{l=1}^{N_{PEV}} P_{EV/t,n,i}^{Char}$$
$$\forall t, \forall n, \forall i, \forall l, \forall s \quad (8)$$

2.4. ESS Charging Strategy

For each microgrid's ESS, the state of charge must be limited range within of less than a maximum value $LB_{l,n}$ but above maximum value $UB_{l,n}$ at each time slots t (10). Equation (11) imposes the systems to not exceed the ramp up/down limits by more than $RU_{l,n}$ or less than $RD_{l,n}$. The initial SOC of ESS at the beginning of the scheduling horizon can critically affects on the results of operation, benefits and costs. We consider that scheduling strategy will give priority to charge ESSs from renewable energy sources PV and WT.

$$E_{t,n}^{ESS} = E_{t-1,n}^{ESS} + \boldsymbol{\eta}_{Char} X_{t,l,n}^{Char} + \frac{X_{t,l,n}^{Disch}}{\eta_{Disch}} \quad (9)$$

$$LB_{l,n} \leq E_{t,n}^{ESS} \leq UB_{l,n} \quad (10)$$

$$RD_{l,n} \leq E_{t,n}^{ESS} - E_{t-1,n}^{ESS} \leq RU_{l,n} \quad (11)$$

2.5. Modeling of Wind Turbines

The wind turbine output depends essentially on the stochastic behavior of wind speed during the day. Eq (12) represents the function that describes the generated power of wind turbine which can be defined as the following:

$$P_{WT} = \begin{cases} 0 \ 0 \leq V \leq V_{cut-in} \\ a + b \times V + a \times V^2 \ V_{cut-in} \leq V \leq V_{rated} \\ P_{W_{rated}} \ V_{rated} \leq V \leq V_{cut-out} \\ 0 \ V_{cut-out} \leq V \end{cases} \quad (12)$$

Table 1. The Characteristics of Wind Turbines

		$P_{min}(kw)$	$P_{max}(kw)$	V_{cut-in} (m/s)	$Vcut-out$ (m/s)	V_{rated} (m/s)	$P_{W_{rated}}$ (kw)	a	b	c
MG1	WT1	0	500	3	25	10	500	0.2	-0.005	0.019
MG2	WT1	0	500	3	25	10	500	0.2	-0.005	0.019
MG2	WT2	0	500	3	25	10	500	0.2	-0.005	0.019

2.6. Modeling of Solar Cells

The output power model of PV, which depends on cells temperature, solar irradiance and the ambient temperature, is expressed in Eq. (13) as follows:

$$P_{PV} = P_{STC}\frac{G_{ING}}{G_{STC}}\left[1 + k\left(T_c - T_{ref}\right)\right] \quad (13)$$

The temperature of cells can also be obtained from Eq (14).

$$T_c = T_a + \frac{(N_{OT}-20)}{0.8} \times G \quad (14)$$

3. The Charging Control Strategy

As shown in Figure1, the microgrids are considered which includes developed charging infrastructure and equipment needed at the charging stations to ensure the bidirectional power flows. A smart measurement tool is installed on each charger which measures following PEV data at the charger node and transfers them to the central optimizer. In this section, the charging control strategy is applied based on the GA optimizer concept used in [33]. The optimizer generates the optimal charging strategy at each sampling step to make every EV battery fully-charged and ready for next trip with the ability of feeding back its stored energy to the microgrid. To reach that objective, in n-th microgrid, at t_k-th step, the charging of l-th PEV is controlled by minimizing its total charging

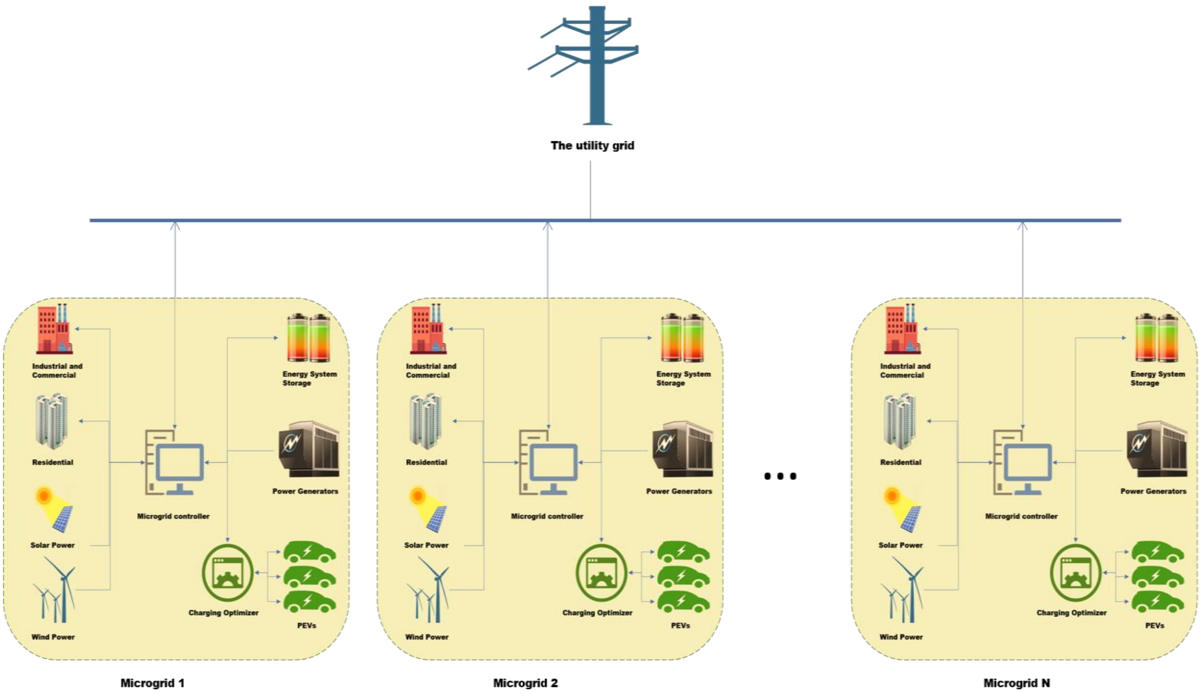


Figure 1. The Configuration of a Multi-Microgrid System with Plug-in Electric Vehicles

cost in order to always put EV owners' interests first. The optimization problem f(x) is defined in the following expression:

$$Minimize\ f = \sum_{n=1}^{N} \sum_{t_k=1}^{T} \left[\sum_{w_n^t \geq 0} \eta_{Char} . E_n . w_n^{t_k} . Price(t_k) - \sum_{w_n^t \leq 0} \eta_{Disch} . E_n . \left| w_n^{t_k} \right| . Price(t_k) \right] \quad (15)$$

The objective function f is formed by two terms that describes the cost of the power delivered/received from the grid. Where $P_{EV,l,n}\ (t_k)$ determines the EV mode from the given three states:

- $P_{EV,l,n}\ (t_k)\ = 0$: The Idle mode (not charging or discharging).
- $P_{EV,l,n}\ (t_k)\ \geq 0$: The Charging mode.
- $P_{EV,l,n}\ (t_k)\ \leq 0$: The Discharging mode.

It must be underlined that the scheduling process is carried out for every PEVs of a given microgrid in day-ahead planning horizon. In order to obtain a high scheduling accuracy, we define a small-time step (with 15min time steps (t_k)):

1. The continuous listening in the connectors' output ports in the charger attached to EVs to determine the online vehicles for each microgrid at k-th time period.

2. The optimizer receives the online EVs' operational data (including battery charging state and unplug time) measured and acquired at the connectors.
   - Initial state of charge (current SOC at time steps (t_k)) of each PEV.
   - Plug-in time of PEV to the grid ($t_{in.l}$).
   - Rower rates of each PEV
   - Full battery capacity.
   - Real-time SOC in the next time steps.
   - Predefined departure time for each PEV ($t_{off.l}$).
   - Needed SOC for each PEV at its departure time ($\mathrm{SoC}_{\mathrm{l,n}}^{\mathrm{need}}$).
3. Forecasting electricity price ($\mathbf{Price}_{t_k}$) at t_k till the departure time and expecting future profits of each PEV.
4. The optimizer affects the optimal charging schedules which can maximize PEV owners' profits using Genetic algorithm.

3.1. Constraints

Constraint (17) ensures that the optimizer satisfies each single PEV's energy demand ($\mathrm{SoC}_{\mathrm{n}}^{\mathrm{need}}$) at departure time at each microgrid. Constraints (18) and (19) limit the variations of the SOC at each time slot t within a predefined range not more than a maximum level $\mathrm{SoC}_{\mathrm{l,n}}^{\mathrm{max}}$and not less than a minimum level $\mathrm{SoC}_{\mathrm{l,n}}^{\mathrm{min}}$.

$$\mathrm{SoC}_{\mathrm{n}}^{\mathrm{t}} = \mathrm{SoC}_{\mathrm{n}}^{\mathrm{t-1}} + \boldsymbol{\eta}_{\mathrm{Char}}\, P_{EV,l,n}\,(t_k) + \boldsymbol{\eta}_{\mathrm{Disch}}\, P_{EV,l,n}\,(t_k) \tag{16}$$

$$\sum_{t=1,\, \mathrm{x}_{\mathrm{n}}^{\mathrm{t}} \geq 0}^{T} \boldsymbol{\eta}_{\mathrm{Char}}\, P_{EV,l,n}\,(t_k) + \sum_{t=1,\, \mathrm{x}_{\mathrm{n}}^{\mathrm{t}} \leq 0}^{T} \boldsymbol{\eta}_{\mathrm{Disch}}\, P_{EV,l,n}\,(t_k) = \mathrm{SoC}_{\mathrm{l,n}}^{\mathrm{need}} \tag{17}$$

$$\boldsymbol{\eta}_{\mathrm{Char}}\, P_{EV,l,n}\,(t_k) \leq \mathrm{SoC}_{\mathrm{l,n}}^{\mathrm{max}} \tag{18}$$

$$-\boldsymbol{\eta}_{\mathrm{Disch}}\, P_{EV,l,n}\,(t_k) \leq -\mathrm{SoC}_{\mathrm{l,n}}^{\mathrm{min}} \tag{19}$$

Therefore, the cost of charging and discharging of EV fleet is obtained by using Eq. (20).

$$\mathrm{C}_{\mathrm{PEV}} = \sum_{n=1}^{N} \sum_{\mathrm{i=1}}^{\mathrm{N}_{PEV}} \sum_{\mathrm{t=1}}^{\mathrm{H}} \mathrm{Cost}_{\mathrm{Char}}.P_{EV/\mathrm{t,n,i}}^{Char} + \mathrm{Cost}_{\mathrm{Disch}}.P_{EV/\mathrm{t,n,i}}^{Disch} \tag{20}$$

4. Simulation Results

4.1. Description of the System

The test system contains two microgrids in six cases in different operating modes (islanded, Connected, integrated), to assess the impact of EV charging and the ability of reinjecting the energy stored in EV batteries pack into these microgrids, on the economic aspect of the generation system. The first microgrid is consisting of 4 conventional generators, one 500 kW wind Turbine, 500 kW PV system and 1 MW ESS system. The second microgrid is formed by 5 conventional generators, one 1 MW wind Turbine, 500 kW PV system and 2 MW ESS system. All configuration and operation parameters of micro conventional generators and ESSs are summarized in Tables2-3. Hourly forecasted electricity market prices in Figure 2 [31]. Both microgrids are connected and exchange power with the utility grid by a dedicated line with 10 MW capacity limit. Same thing for the local power exchange, microgrids are related to each other using a dedicated line (capacity limit of 4 MW). Table 4 shows the output of wind power and solar power that have been estimated based on wind speed solar and insolation data over 24 hours at a location in the western USA [32] along with the hourly microgrids' load demand. Let us consider two fleets of 2,000 and 4,000 EVs are assumed to be plugged-in respectively into microgrid 1 and 2 via an adequate equipment that generates the optimal charging/discharging strategy in a period of 24 hours using a genetic algorithm-based optimization technique [33]. The deterministic and probabilistic uncertainties (initial SOC, arrival and departure times …) are similarly generated using [33]. To perform the simulation of the economic dispatch for all studied cases, we used C++ in a personal computer with 3.00 GHz core i5 processor and 8 GB RAM. The program is run with 70 population and 500 iterations, it is required a couple of repeated trials with different parameter combinations for the optimization technique used to set the right parameters. Where the crossover probability (Pc) and mutation probability (Pm) 0.95, 0.1 are respectively selected to perform the GA. Table 3 reports the characteristics for each storage system [34], including its lower and upper bound for storage level, its maximum capacity, its initial energy level and charging/discharging efficiency.

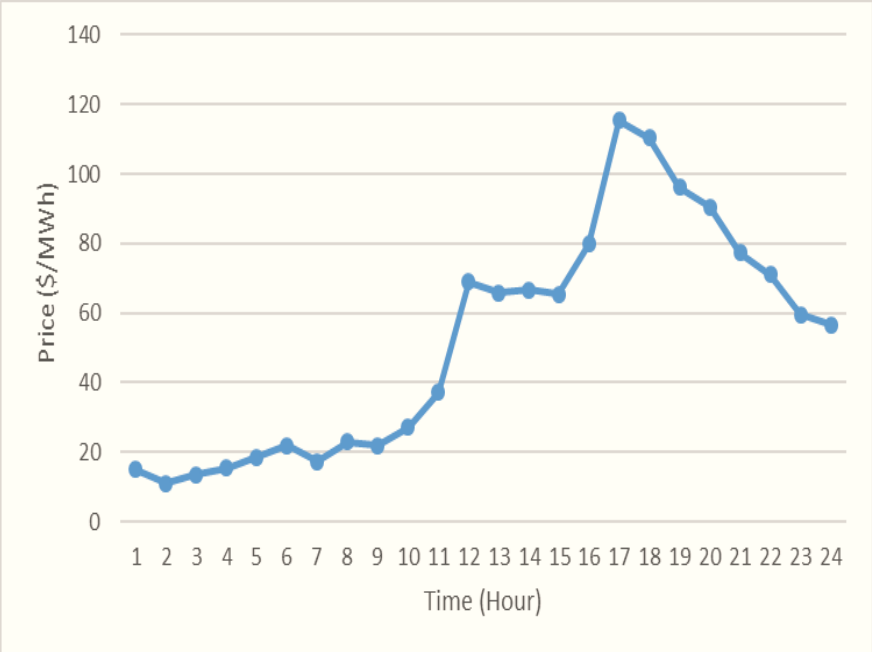


Figure 2. Hourly Electricity Price Values for the Scheduling Day

Table 2. Characteristics of Generators in Microgrid 1 and 2.

	Microgrid 1				Microgrid 2					
	G1	G2	G3	G4	G1	G2	G3	G4	G5	G6
Max capacity (MW)	5	5	5	3	6	6	5	3	3	3
Minimum production level (MW)	1	1	5	0.8	1	1	1	0.8	0.8	1
Ramp-up limit (MW)	2.5	2.5	2.5	3	3	3	2.5	3	3	3
Ramp-down limit (MW)	2.5	2.5	2.5	3	3	3	2.5	3	3	3
Initial status	1	1	0	0	1	1	1	0	0	0
Minimum up-time (h)	3	3	1	1	3	3	3	1	1	1
Minimum down-time (h)	3	3	1	1	3	3	3	1	1	1
Number of periods online (h)	8	8	-4	-4	8	8	8	-4	-4	-4
Cost coefficient ($/MWh)	27.7	39.1	50.5	61.3	26.8	35.5	39.1	64.1	72.3	85.6

Table 3. Characteristics of ESS in Microgrid 1 and 2.

	ESS Microgrid 1	ESS Microgrid 2	
	B1	B1	B2
Capacity [MW]	1	1	2
Initial storage level [MW]	0.1	0.2	0.1
Unit storage cost [e/MW*h]	0.3	0.3	0.3
η_{Char}[%]	98	97	96
η_{Disch} [%]	97	96	95
LB [%]	5	10	15
UB [%]	75	80	85
RD/RU [%]	50	60	70

Table 4. Forecast Demand, Wind and Solar Generation Outputs for Both Microgrids

Hour	Hourly load MG1 (MW)	Solar output (KW)	Wind output (KW)	Hourly load MG2 (MW)	Solar output (KW)	Wind output (KW)
1	7	0.00	390.32	13.05	0.00	780.64

2	6.8	0.00	431.07	12.6	0.00	862.14
3	6.73	0.00	500.00	11.62	0.00	1000.00
4	7.31	0.00	475.51	13.35	0.00	951.03
5	7.06	0.00	500.00	14.07	0.00	1000.00
6	7.08	37.03	500.00	15.12	37.03	1000.00
7	8.43	121.55	500.00	14.51	121.55	1000.00
8	9.27	216.53	436.09	13.31	216.53	872.18
9	9.54	272.55	449.80	12.49	272.55	899.60
10	10.14	373.02	361.85	14.16	373.02	723.69
11	10.45	424.34	500.00	14.43	424.34	1000.00
12	10.5	447.53	500.00	16.46	447.53	1000.00
13	12.35	445.88	420.05	17.33	445.88	840.09
14	13.74	392.04	246.14	18.69	392.04	492.27
15	13.83	296.83	266.01	19.91	296.83	532.01
16	14.18	287.84	216.46	20.21	287.84	432.92
17	14.63	164.92	152.87	20.76	164.92	305.74
18	14.64	37.39	179.87	20.59	37.39	359.73
19	14.04	0.00	209.23	18.11	0.00	418.47
20	13.99	0.00	270.61	17.93	0.00	541.22
21	12.43	0.00	249.65	15.62	0.00	499.31
22	11.43	0.00	347.55	13.39	0.00	695.10
23	8.12	0.00	405.60	13.09	0.00	811.21
24	7.74	0.00	500.00	12.69	0.00	1000.00

4.2. Islanded Multi-Microgrids

Case 0

In this kind of operating mode, each microgrid is scheduled under resource-independent condition to prevent power outages when the power supply from the utility grid is interrupted after an intentional or unintentional islanding decision [34-38], that may be taken in severe weather circumstances, overload conditions, grid equipment damage or other emergency situations. For that reason, microgrids in this case search for optimal operating planning for conventionnel generating units without exchanging power with each other or with the utility grid, without the ESS and without the renewable sources, meanwhile, is trying to achieve minimized operating cost as far as possible. In this case, we investigate the impact of uncoordinated charging where the EVs begin charging immediately when connected to the grid at work place or home and mostly in the peak hours. Most of EVs start charging unfortunately alongside each other and simultaneously with peak demand see Fig. 3. Thus, if the EVs charged in an uncoordinated way, they may generate an extra load coincident with the peak which could enhance undeniably the operating cost or rise the risk of overloading the system. Results of islanded mode optimization are shown in Table 5 where the microgrid power-generating cost is minimized during the whole scheduling period. The obtained results show that every microgrid try to make a profit by running inexpensive generators to meet the load demand and avoid enable generators that are regarded as an unnecessary and costly to participate fully in the daily routine in the operating process (G3 and G4 in Microgrid 1, G5 and G6 in Microgrid 2). Under the deployment of 64,01% of microgrids' full generation capacity at the optimized schedule, these inexpensive conventional generators are trying to produce sufficient energy to meet the demand in every hour of the day. As shown in Figure 4, the total realized operational cost in the islanded mode for both microgrids 1 and 2 is about 23157,1$.

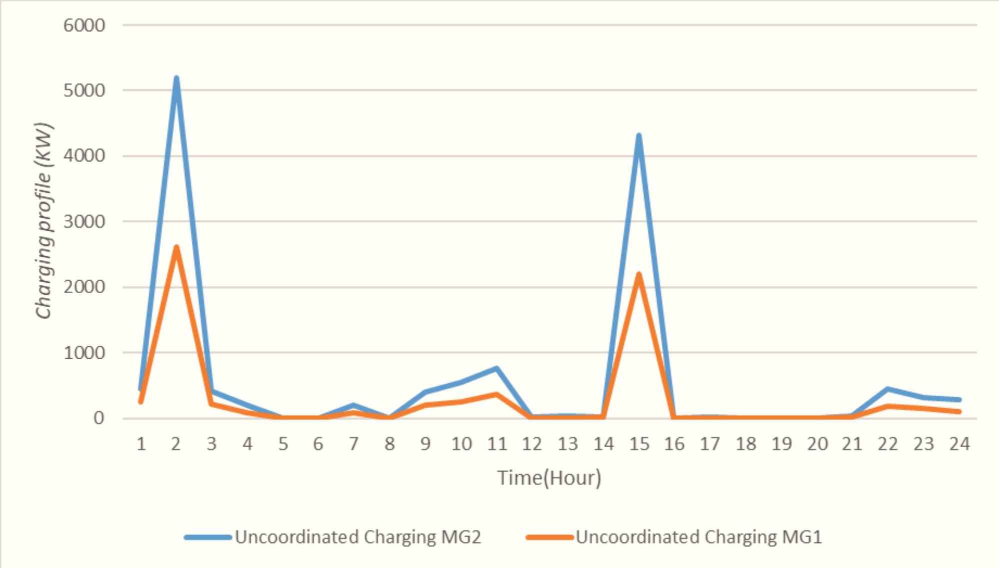


Figure 3. Charging Profile of the Microgrids' Fleets for the Scheduling Day

Table 5. Day Ahead Scheduling of Sources for Case 0 (MW).

	Microgrid 1				**Microgrid 2**					
Hour	**G1**	**G2**	**G3**	**G4**	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**
1	5.00	2.25	0.00	0.00	6.00	6.00	1.49	0.00	0.00	0.00
2	5.00	4.42	0.00	0.00	6.00	6.00	4.99	0.80	0.00	0.00
3	5.00	1.95	0.00	0.00	6.00	5.04	1.00	0.00	0.00	0.00
4	5.00	2.39	0.00	0.00	6.00	6.00	1.55	0.00	0.00	0.00
5	5.00	2.06	0.00	0.00	6.00	6.00	2.07	0.00	0.00	0.00
6	5.00	2.08	0.00	0.00	6.00	6.00	3.12	0.00	0.00	0.00
7	5.00	3.52	0.00	0.00	6.00	6.00	2.71	0.00	0.00	0.00
8	5.00	4.27	0.00	0.00	6.00	6.00	1.31	0.00	0.00	0.00
9	5.00	4.73	0.00	0.00	6.00	5.89	1.00	0.00	0.00	0.00
10	5.00	4.59	0.80	0.00	6.00	6.00	2.71	0.00	0.00	0.00
11	5.00	5.00	0.82	0.00	6.00	6.00	3.19	0.00	0.00	0.00
12	5.00	4.70	0.80	0.00	6.00	6.00	4.47	0.00	0.00	0.00
13	5.00	5.00	2.36	0.00	6.00	6.00	4.56	0.80	0.00	0.00
14	5.00	5.00	2.95	0.80	6.00	6.00	5.00	1.71	0.00	0.00
15	5.00	5.00	3.00	3.00	6.00	6.00	5.00	3.00	3.00	1.18
16	5.00	5.00	3.00	1.18	6.00	6.00	5.00	2.42	0.80	0.00
17	5.00	5.00	3.00	1.63	6.00	6.00	5.00	2.97	0.80	0.00
18	5.00	5.00	3.00	1.64	6.00	6.00	5.00	2.79	0.80	0.00
19	5.00	5.00	3.00	1.04	6.00	6.00	5.00	1.12	0.00	0.00
20	5.00	5.00	3.00	0.99	6.00	6.00	5.00	0.93	0.00	0.00
21	5.00	5.00	2.44	0.00	6.00	6.00	3.65	0.00	0.00	0.00
22	5.00	5.00	1.62	0.00	6.00	6.00	1.84	0.00	0.00	0.00
23	5.00	3.28	0.00	0.00	6.00	6.00	1.41	0.00	0.00	0.00
24	5.00	2.84	0.00	0.00	6.00	5.97	1.00	0.00	0.00	0.00

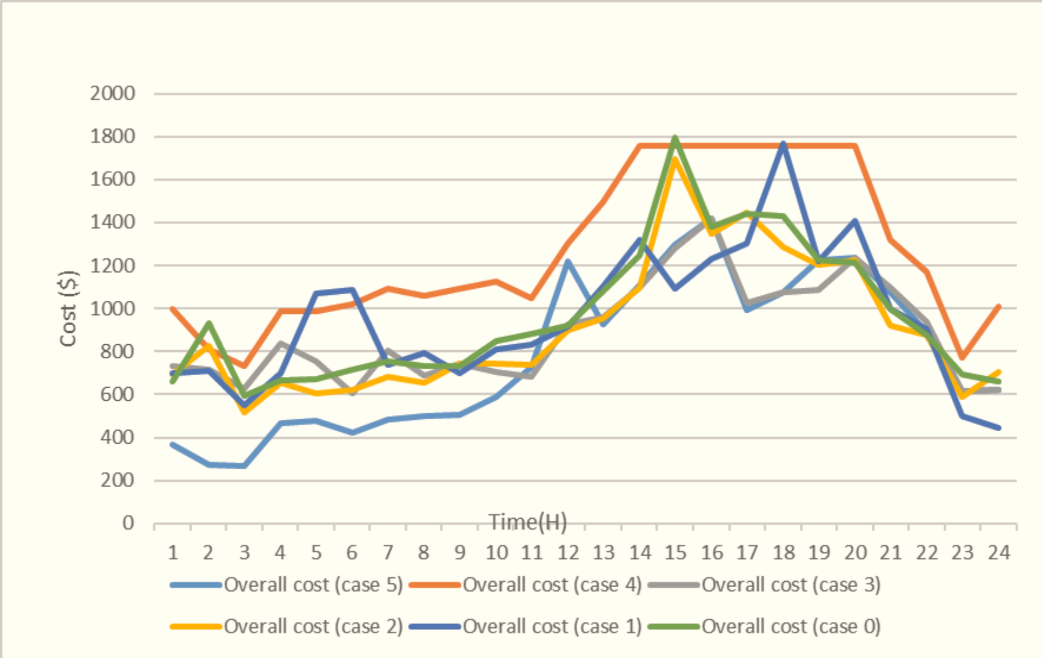


Figure 4. The Hourly Operating Cost for the Whole System in All Cases

Case 1

As the precedent case, we consider both microgrids are scheduled under the same conditions in Case 0 (without the ESS, the renewable sources and any ability of exchanging power). The only change is the coordinated strategy of EVs which is smartly control the charging and discharging profile of each EV plugged into the grid., which is expected to avoid any risk of overloading microgrids and to reduce the overall operating cost. Figures 5 and 6 illustrate the good distribution of charging and discharging acts of the EV batteries' fleet during the scheduling time. Table 6 represents the commitment status, and the power contribution of each conventional generator in microgrid 1 and 2 obtained by using the proposed approach in the islanded mode. In which the proposed approach nevertheless shows a great flexibility of avoiding costly generators in both microgrids and giving an adequate scheduling. The total operation costs of two microgrids in Case 1 (22906,9$) is reduced by the amount of 250,2$ per day compared with the previous total operating costs of Case 0 which corresponds to 7756,2 per month and 93074,4$ per year see Fig 4. This undeniably reduction in the operating cost is because the entry into operation of the coordinated EV charging strategy which has a positive impact on the local power-generating savings, and the load demands for both microgrids by maintaining the right balance between satisfying EV owners and delivering power to the grid to relieve the load on the peak hours.

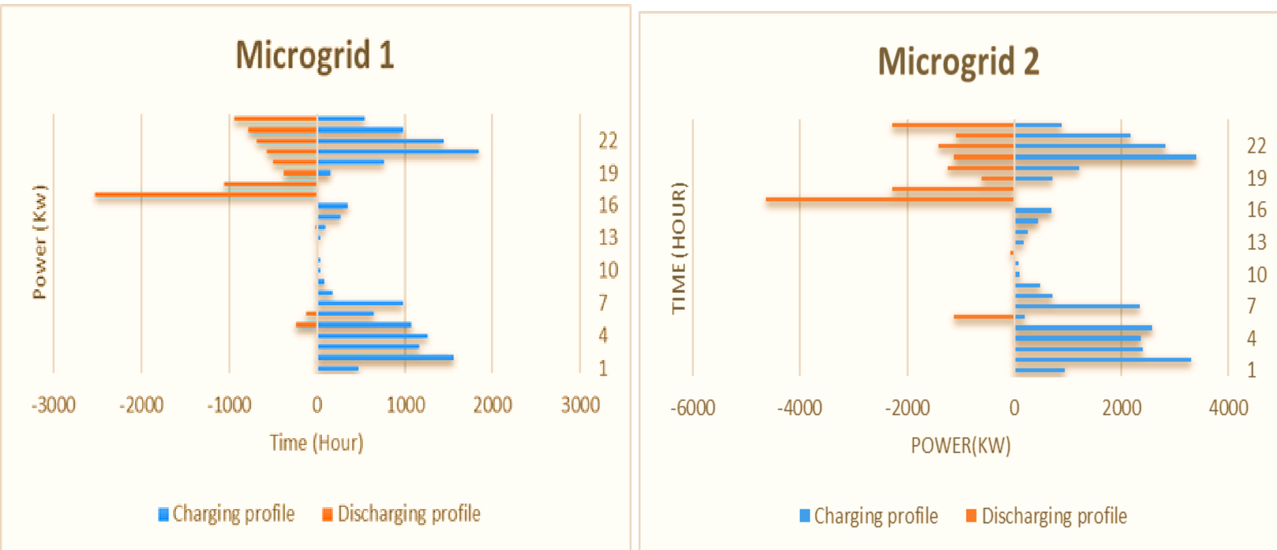


Figure 5-6. Charge/Discharge of Batteries' Fleet in Both Microgrids Over the Scheduling Day

Table 6. Day Ahead Scheduling of Sources for Case 1 (MW).

	Microgrid 1				Microgrid 2					
Hour	**G1**	**G2**	**G3**	**G4**	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**
1	5.00	2.55	0.00	0.00	6.00	6.00	2.24	0.00	0.00	0.00
2	5.00	2.65	0.00	0.00	6.00	6.00	2.35	0.00	0.00	0.00
3	5.00	1.58	0.00	0.00	6.00	5.35	0.00	0.00	0.00	0.00
4	5.00	2.39	0.00	0.00	6.00	6.00	0.00	1.49	0.00	0.00
5	5.00	3.97	0.00	0.00	6.00	6.00	0.00	3.00	2.94	0.00
6	5.00	4.54	0.00	0.00	6.00	6.00	5.00	2.23	0.80	0.00
7	5.00	3.35	0.00	0.00	6.00	6.00	2.42	0.00	0.00	0.00
8	5.00	4.80	0.00	0.00	6.00	6.00	2.33	0.00	0.00	0.00
9	5.00	4.43	0.00	0.00	6.00	5.26	1.00	0.00	0.00	0.00
10	5.00	4.31	0.80	0.00	6.00	6.00	2.09	0.00	0.00	0.00
11	5.00	4.58	0.80	0.00	6.00	6.00	2.35	0.00	0.00	0.00
12	5.00	4.65	0.80	0.00	6.00	6.00	4.43	0.00	0.00	0.00
13	5.00	5.00	2.51	0.00	6.00	6.00	4.87	0.80	0.00	0.00
14	5.00	5.00	3.00	1.14	6.00	6.00	5.00	2.46	0.00	0.00
15	5.00	5.00	2.56	0.00	6.00	6.00	4.51	0.80	0.00	0.00
16	5.00	5.00	3.00	0.00	6.00	6.00	3.74	0.80	0.80	1.00
17	5.00	5.00	3.00	0.00	6.00	6.00	5.00	1.14	0.81	1.00
18	5.00	5.00	3.00	3.00	6.00	6.00	5.00	2.99	2.84	1.01
19	5.00	5.00	3.00	1.02	6.00	6.00	5.00	1.06	0.00	0.00
20	5.00	5.00	3.00	2.04	6.00	6.00	5.00	2.92	0.00	0.00
21	5.00	5.00	2.42	0.00	6.00	6.00	3.67	0.00	0.00	0.00
22	5.00	5.00	1.81	0.00	6.00	6.00	2.16	0.00	0.00	0.00
23	5.00	1.56	0.00	0.00	6.00	3.89	0.00	0.00	0.00	0.00
24	4.93	1.00	0.00	0.00	6.00	3.09	0.00	0.00	0.00	0.00

4.3. Cooperative Islanded Multi-Microgrids

In this operational mode, microgrids can exchange power with each other during the islanded operation, in other way they can share unused and/or inexpensive the counterpart's generators to meet the load demands, mitigate the risk of committing costly generators, avoid operationally deficient, reduce the total operating cost, and make them in a fully independent position far away from utility grid.

Case 2

The stacked bar chart is presented in Fig 7. it displays detailed information about the total contribution of each of the conventional generator and RSS system in 24h scheduling horizon for microgrid 1 and 2. From that chart, it is remarked that the conventional generators are producing power at their full capacity to meet a big part of demand in both microgrid. And some generators are most time switched off or generate less amount of power, especially at the peak time. Furthermore, the hourly amounts of exchanged power between both microgrid over time, which microgrid1 delivers an overall amount of 14,29 MW to microgrid2, whereas microgrid2 purchases an overall amount of 8,00 MW to microgrid1. Whether it could simply be deduced from the cheap production costs in microgrid1 which gives more reliability and operational flexibility to the whole system and guarantee the low-cost production facility to meet the load demands. As shown in Fig 4, it's remarkable that the overall operating cost is about 21728,87$ which is notably reduced by a percentage of 6,16% and 5,14% compared with Case 0 and 1, respectively. This reduction is the fruit of decreasing the deployment of a considerable part of generation capacity in the microgrid that has the cheaper generators in the multi-microgrid system, integrating renewable sources, optimally scheduling ESS, profiting the positive effects of both exchanging power in-between microgrids, and the good management of power exchanges which makes the power flows either from or towards EVs more efficient and useful.

Case 3

As the precedent-setting case, microgrids can exchange power under the same conditions in Case 2 with adopting the efficient strategy for charging and discharging of EVs batteries. Figure 8 presents a stacked bar chart different levels of power production in the microgrids 1 and 2 alongside with the RSS within a 24-hour time horizon. While these structural changes in the system, the microgrids have shared an overall amount of 16,41 MW evenly through the day (10,73 MW from microgrid 1 to microgrid 2; 5,67 MW from microgrid 2 to microgrid 1). The operation of a smart strategy for charging and discharging of EVs will progressively lead to daily savings on the overall system operating costs of 21273,32$ up to 1883,76$ per day a reduction of about 8% compared to the first case, see Fig 4. Which presents an important potential savings for EVs contribution, based on delivering energy in the high-cost operation periods and scheduling their charging cycles in the low-cost operation periods.

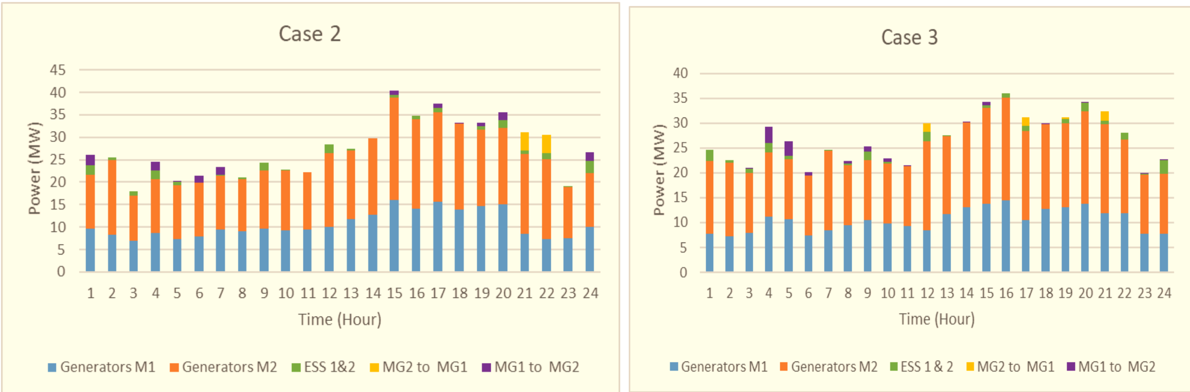


Figure 7-8. Commitment Statuses of Conventional Generators, ESS and the Amounts of Energy Exchanged Among Microgrids for Case 2 and 3

4.4. Cooperative Connected Multi-Microgrids

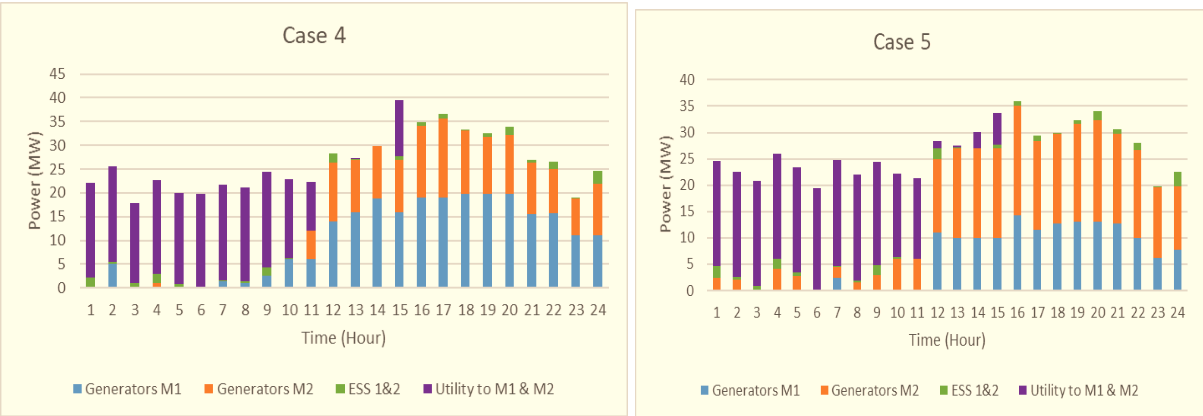
In the following two cases, the microgrids operate in the grid-connect mode with the ability of exchanging power alongside each other and purchasing power from the utility grid as conditions dictate. Microgrids encompass multiple types of conventional generation resources, renewable sources, ESS, efficient strategy for charging and discharging of EVs batteries (see Figure 5-6). Microgrids 1 and 2 are designed to purely manage their local resources when the utility grid is offering a limited cost-effective or less energy-saving potential. Two other stacked bar charts are presented in Fig 9-10. It shows the results of applying our approach with detailed information about the contribution of conventional generators, RSS, the amounts of exchanged power between microgrids 1 and 2 and the power purchased from the utility grid over the scheduling horizon in cases 4 and 5. Figures 11 and 12 indicate clearly not only the amounts of energy exchanged locally in-between microgrids, but also the electricity purchased from the utility grid in both cases 4 and 5.

Case 4

In this case, the microgrids had been designed to switch off most of generators (G1 is excluded in microgrid 2) especially in the first 10 time slots in the scheduling time, where the electricity price is less than 27.09$. For that reason, the multi-microgrid system decreases its deployment of the microgrids' full generation capacity to 39,48% and then the overall operating cost to 19030,32$ compared with Case 0 which the system totally powered by its local resources to meet the local load demand as illustrated in Fig 4. Which refers to purchase smarty power when the electricity price is lower than the electricity that it could be generated locally.

Case 5

The total amount of delivered power from the utility grid, in this case, to microgrid 1 is about 115,98 MW, meanwhile, Microgrid 2 has purchased an amount of 104,88 MW from the utility grid. It should be noted that the total exchanged energy in-between the two microgrids in this operation mode is 30,99 MW (microgrid1 delivers 22,89 MW to microgrid2, whereas microgrid2 purchases an overall amount of 8,1 MW to microgrid1), with a diminution of 18% compared with Case2. This diminution is due to microgrids' recourse to purchase power from the utility gird when the electricity price is lower than the electricity generated in the counterpart microgrid. We have assumed a high decrease of the overall operating cost of 11,7% and 18% compared respectively with Case3 and Case1. Where the overall operating cost is about 18775,73$ (see Fig 4) with deploying approximately more than the half of the microgrids' maximum generation capacity. Microgrids had realized net benefits under this case up to 4381,37$ per day, 135822,2 $ per month and 1 629 866,687 $ per year compared to the base Case 0 which can reveal that the algorithm is smart enough to control the flows exchanged between the microgrids, efficiently determinate the purchased energy from the utility grid and precisely allocate the cheapest power generators at each hour. These results indicate the hugely disproportionate numbers between this case and the other five cases. Additionally, they also indicate the impact of effectiveness of a model when microgrids are set up to be in the connected mode where variant resource availability, Optimal scheduling of ESS system and the renewable resources allow microgrid to get some adequate and quick needed supplies which makes the cost and efficiency of the whole operation a lot better.



Figures 9-10. Commitment Statuses of Conventional Generators, ESS and the Amounts of Energy Exchanged Among Microgrids and with the Utility Grid for Case 4 and 5

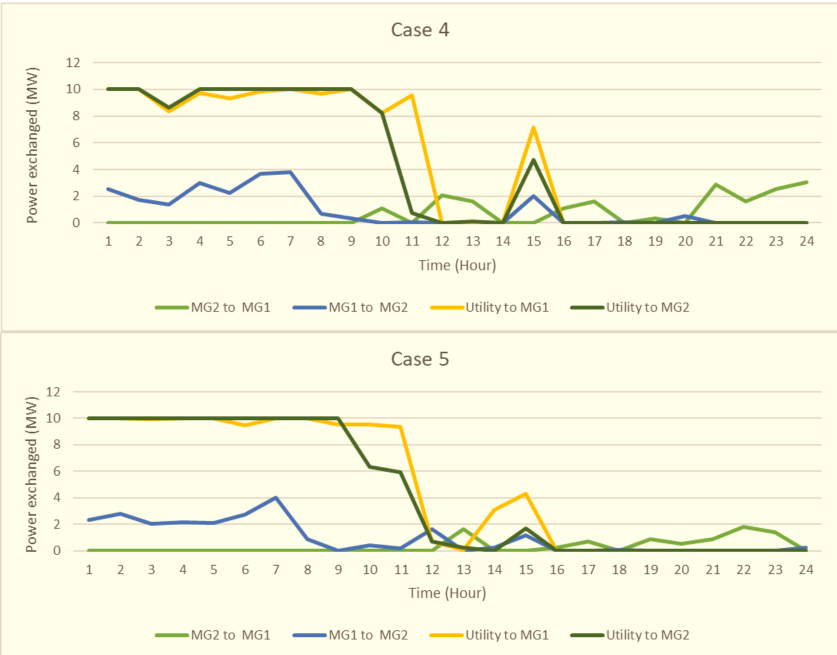


Figure 11. The Power Exchanged in-between Microgrids and with the Utility Grid for Case 4-5

5. Conclusion

This paper assesses the effectiveness and the robustness of smartly managing the charging and discharging of EVs batteries under different multi-microgrids operating modes (islanded, integrated, grid-connected modes) with variant combinations of several non-renewable and renewable sources (conventional generators, wind turbines, PV systems) and energy storage system. Six different cases were studied in this paper, each case represents a distinct operating mode with a specific EV charging/discharging strategy (uncoordinated for cases 0, 2 and 4, coordinated strategy for Cases 1,2,3) to gradually evaluate the improvement in system reliability and flexibility. Adequate robust optimization is developed in this paper to optimally scheduling the resources commitment, ESS, the power shared among microgrids, and the amounts of energy purchased from the utility grid which it was deployed the Genetic Algorithm to find the optimal schedules while minimizing the operating cost at every mode's dictated conditions over the scheduling time. Thus, a more resource deployment and imposed conditions decrease the expense of higher robustness and quality of solutions created. There were also quantitative analyses and numerical simulations on a test system conducted to validate the effectiveness of the proposed methods and their high performance to provide the optimal charging/discharging of EV batteries that guarantee the load shedding and deliver a low-cost solution for an optimal schedule of all microgrids.

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