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Efficient Networked Microgrid Management Considering Plug-in Electric Vehicles and Storage Units

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ABSTRACT

This article addresses the optimal energy management and operation of networked microgrids considering different types of dispatchable units like fuelcell and microturbine and non-dispatchable units such as wind turbine and solar units. To change the just-consuming role of vehicles into an active role with the ability to make a profit, the vehicle-to-grid technology (V2G) is deployed here. Due to the complex and nonlinear structure of the problem, an effective optimization energy management framework based on the bat algorithm (with a modification) and unscented transform is devised to find the most optimal operation point of the devices from the economic point of view. Due to the high uncertainties injected by electric vehicles pattern behavior in addition to the renewable sources output power variations, the unscented transform is proposed to make the analysis more realistic. The simulation results on an IEEE networked microgrid test system advocate the high capability and proper performance of the proposed method. The results show that the total system operation cost is 53897.004$ and 53711.704$ in the 1st and 2nd scenarios, respectively. Moreover, it is seen that considering uncertainty in the problem has added 0.586% and 0.762% to the cost function value in the first and second scenarios, compared to the deterministic framework.

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I. INTRODUCTION

The traditional electric grid structure is experiencing a fast change due to the high share of distributed generations (DGs) in the form of either dispatchable generators including fuelcell (FC) and microturbine (MT) or snon-dispatchable units including wind turbine (WT) and photovoltaics (PVs). This has created a great opportunity for the last-longing idea of microgrids which can not only support their loads based on the self-supply sources of DGs, but can also benefit the main grid at peak-load hours when the heavy loading bothers the utilities [1, 2]. Due to this great opportunity, different types of AC and DC microgrids are emerging among which the networked microgrids could provide the most interesting and charming features for both the microgrid owners and the power grid utilities. Some of the main rewards of networked microgrids can say as progressed reliability, better voltage profile, more economic power supply, better electrical services, and more support of renewable energy sources and electric vehicles [3, 4]. While these benefits could stabilize the position of microgrid concept in the power system more than before, there are new challenges emerging in the grid which are partly due to the renewable energy sources (RESs) unstable power supply and the much uncertainty they inject and partly due to the electric vehicles high penetration with random charging behaviors [5, 6]. Therefore, in the previous years, many researches were done to check different aspects

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of this new emerging technology and find solution for the potential problems of their future.

In [7], a distributed energy management framework for the networked microgrids is proposed which uses a wireless protocol for data transaction and getting to a consensus point. The diffusion based procedure is compatible with the very wide area covered by the networked microgrid and so makes it possible for an economic power dispatch. In [8], a two-stage stochastic bi-level structure is proposed for the energy management of a high voltage networked microgrid. The proposed bi-level model is deployed for facilitating the interaction between the distribution system and main grid. In [9], the confident consequence of networked microgrids in progressing the hardening of the main grid is investigated. It also explains some of the main experiments in growing DGs at networked microgrids and provides an answer for the broad resiliency enhancement in contradiction of extreme occasions. In [10], a financial dispatch exemplary is presented in the shape of mixed-integer cone programming to guarantee the safety and efficacy of a networked microgrid. It utilizes innovative control techniques for instance tap-changing transformers, switching, etc to energize the microgrid. In [11], authors propose a new management model for scheduling of a multi-carrier energy hub considering (DGs), storage devices with a practical degradation model and heating/cooling. In [12], a centralized architecture is employed for the optimal operation of a networked microgrid. It provides a situation that microgrids can sell/purchase power to/from the utility through a linear quadratic preparation. In [13], authors propose a managing scheme for the networked microgrids which can include different renewable energy sources and handle the power trade happening between the microgrid and the main grid. In [14], a deep neural network model is combined with the reinforcement learning to learn the energy management pattern in a networked microgrid. The objective function is to reduce the demand-side peak load when increasing the selling profit at the same time. In [15], demand response program is used to operate an active distribution grid with a structure of networked microgrid. It evaluates the technical indices of supply-adequacy and voltage profile when improving the reliability at the same time. In [16], an advanced control protocol based on wireless communication is proposed to manage the reactive power sharing between networked microgrids. Therefore, first the amount of reactive power which is needed for the microgrid is predicted and then genetic algorithm tries to minimize the power division error in the microgrid. In [17, 18], a distributed outline is devised for energy managing of multiple microgrids within themselves and with each other.

Based on these explanations, the optimal energy management of networked microgrids has attracted the attention of engineers and power researchers in recent years. Although there are significant works published in the previous years, still the research in this area is at the beginning of the way and there are many unforeseen challenges which need to be studies carefully. Accordingly, this research article aims to assess the interacting behavior of microgrids with each other in a networked microgrid and with the main grid when facing the high penetration of renewable energy sources such as WTs, PVs and non-dispatchable units such as FCs and MTs. In addition, with the very rapid growth of the electric vehicle market, the necessity of studying and then managing these high tech components in the networked microgrids is more than before. To this end, a novel framework based on the vehicle-to-grid technology is suggested which makes it possible for the networked microgrid to make use of the electric vehicles as active power sources. This reduces their costs and improves the power quality to the electric consumers. A stochastic energy management framework based on unscented transform is devised which captures the uncertainties associated with the departure and arrival times of the electric vehicles for scheduling concerns, wind power oscillations, solar radiations, and the forecast error in the hourly load demands of the microgrids' consumers. The objective function incorporates the cost of power supply for DGs, cost of power bought from the neighboring connected microgrid, cost of power trading with the power grid and cost of shut-down or starts-up of the units. Moreover, in order to make the analysis more practical, the V2G cost as a battery degradation issue is modeled in the cost function to reflect the amount of life damage which is received by the battery. Due to the high complexity and very nonlinear formulation of the problem, a new optimization algorithm based on bat algorithm (BA) is devised. In addition, a novel modification method is used to enhance the search ability of the algorithm and help it to get directly to the optimal global solution. The performance of the suggested approach is examined on an IEEE test networked microgrid with several DGs, RESs, and electric vehicles.

II. NETWORKED MICROGRID FORMULATION WITH RESS AND ELECTRIC VEHICLES

A. Technologies in the Microgrid

Networked microgrids which simultaneously incorporate several DGs and RESs can provide vital benefits to the utilities and the power consumers including but not limited to more reliable power supply, higher security, improved voltage profile, more economic scheduling and planning schemes, less power losses and more power balance. In the eyes of the main grid operators, the networked microgrid is a quite controllable unit which can be a big help for the utility to get into its main purposes. In fact, networked microgrid idea brings a new concept to the smart grid technology for higher support of the fine idea of RESs and electric vehicles

for a cleaner future. From the consumers' points of view, the networked microgrid is a set of microgrids which are ringed to provide a more stable and reliable power source which probably can benefit them by lower price and higher power quality services. This is a special situation which can benefit both sides of a deal, i.e. the consumers and the utility, simultaneously. Fig. 1 shows the structure a regular networked microgrid. According to this figure, although the networked microgrid concept shows a more complex idea for the microgrids, but the supporting role of microgrids for supplying power through exchange is the key point of its success. With the advent of electric vehicles and RESs, the necessity of studying the optimal operation and management of networked microgrids is felt more than before. Therefore, the next part provides a holistic model to formulate the networked microgrid operation problem in a real environment with high penetration of DGs, RESs, and electric vehicles.

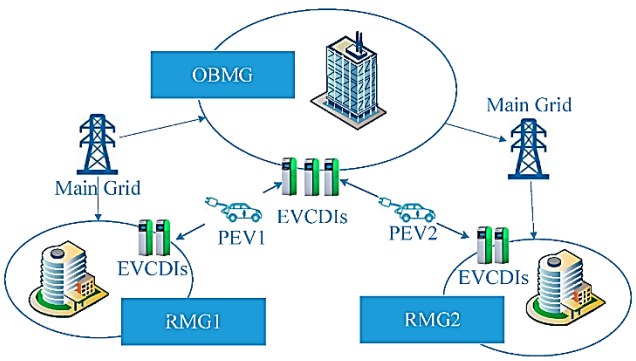


Fig. 1. The idea of multi-microgrids in the structure and technology

B. Problem Formulation

The proposed problem formulation is a single-objective constraint optimization problem which aims to minimize the total cost of the networked microgrid incorporating the cost of power purchasing from internal DGs, cost of power purchasing from the other grids (either main grid or other microgrids and), cost of shut-down and start-up units and cost of V2G due to the repeating charging/discharging of the electric vehicle battery as follows [2]:

$$Min\ \ E(f(X)) = Cost^{DG} + Cost^{sd/st} + Cost^{bat} + Cost^{exch} + Cost^{V2G} \quad (1)$$

$$Cost^{DG} = \sum_{k=1}^{N_{MG}} \sum_{t=1}^{T} \left(\sum_{i=1}^{N_{DG}} [u_{itk}\ E(p_{itk}^{G}) B_{ik}^{G} \right) \quad (2)$$

$$Cost^{sd/st} = \sum_{k=1}^{N_{MG}} \sum_{t=1}^{T} \begin{pmatrix} S_{ik}^{G-off} \max\{0, u_{i(t-1)k} - u_{itk}\} + \\ S_{ik}^{G-on} \max\{0, u_{itk} - u_{i(t-1)k}\} \end{pmatrix} \quad (3)$$

$$Cost^{bat} = \sum_{k=1}^{N_{MG}} \sum_{t=1}^{T} \left(\sum_{j=1}^{N_S} [u_{jtk} E(p_{jtk}^{s}) B_{sk} \right) \quad (4)$$

$$Cost^{exch} = \sum_{k=1}^{N_{MG}} \sum_{t=1}^{T} \left(E(p_{tk}^{grid}) B_{tk}^{grid} \right) \quad (5)$$

$$Cost^{V2G} = \sum_{k=1}^{N_{MG}} \sum_{t=1}^{T} \left(\sum_{t=1}^{T} \sum_{v=1}^{N_v} c_{vtk}^{PEV} P_{vtk}^{PEV} + \sum_{z=1}^{N_{dis}} C_{zk}^{d}(\gamma^{I}, \gamma^{F}) \right) \quad (6)$$

where X is the problem variables, N_{DG} shows the number of generators, T is the number of operation hours, N_{MG} shows the quantity of microgrids, N_S shows the quantity of batteries, N_v shows the number of vehicle fleets, C_{vtk}^{PEV} is charging/discharging cost of electric vehicles, $C_{zk}^{d}(\gamma^{I}, \gamma^{F})$ is the battery degradation cost from initial status of γI to γf, N_{dis} shows the quantity of charge/discharge cycles per the operation time horizon, u_{itk} is the On/Off for i^{th} DG, p^{G}_{itk} is the power generation of i^{th} DG, B^{G}_{ik} is the electricity price offer by i^{th} DG, S_{ik}^{G-on} shows start-up price by i^{th} DG, S_{ik}^{G-off} shows the shut-down price by i^{th} DG, u_{jtk} is the On/Off for j^{th} battery, p^{s}_{jtk} shows the offer of j^{th} battery, B^{S}_{ik} is the electricity price offer of the i^{th} battery, S_{ik}^{S-on} represents the start-up price by i^{th} battery, S_{ik}^{S-off} represents the shut-down price by i^{th} battery, p_{tk}^{grid} is the power generation of the grid, B_{tk}^{grid} is the electricity price offer of the main grid to microgrid k. It worth noting that here we have used the operator $E(.)$ to show the expectation operator.

The battery degradation cost is calculated as a function of the number of cycles (charging and discharging together) that an electric vehicle experiences during its operation. This can be shown as (7). In this equation, the cost of battery degradation from the initial SoC of γ^{I} to the final SoC of γ^{F} is calculated. In (8), the expected cost of battery at a specific SoC value γ^{s} is shown based on the maximum number of cycles which it can experience over its life based on the Wöhler curve which is explained later [5].

$$\sum_{z=1}^{N_{dis}} C_z^{d}(\gamma^{I}, \gamma^{F}) = \sum_{z=1}^{N_{dis}} C_z^{d}(0, \gamma^{F}) - C_z^{d}(0, \gamma^{I}) \quad (7)$$

$$C_z^{d}(0, \gamma^{s}) = \frac{C^{bat} \times \gamma^{s} \times E^{bat}}{N^{c}(\gamma^{s})} \quad (8)$$

where E^{bat} is the battery energy and C^{bat} is the cost battery.

As that is seen in (8), in order to calculate the battery degradation cost, the Wöhler curve is needed. As per definition, the Wöhler curve calculates the number of cycles a battery can experience before getting damaged. Fig. 2 shows the Wöhler curve for a typical battery [5]. Wöhler curve is formulated in a math format which is shown as $Nc(\gamma)=a.\gamma^{b}$ [16] where parameters a and b are found based on the battery type.

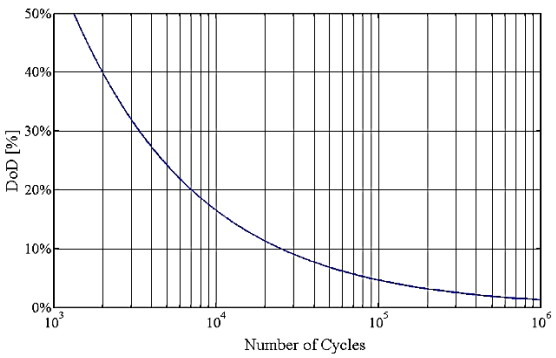


Fig. 2. Wöhler curve for a typical battery [5]

The above cost function (1) is optimized meeting several equality and practical inequality constraints which are explained in the rest:

The generation and demand balance can be met by converging the AC power flow in the microgrids as follows [9]:

$$E(P_{mtk}^{Inj}) = \sum_{n=1}^{N_B} E(V_{tmk})E(V_{tnk})Y_{mnk}\cos\left(\theta_{mnk} + E(\delta_{mtk}) - E(\delta_{ntk})\right) \quad (9)$$

$$E(Q_{mtk}^{Inj}) = \sum_{n=1}^{N_B} E(V_{tmk})E(V_{tnk})Y_{mnk}\sin\left(\theta_{mnk} + E(\delta_{mtk}) - E(\delta_{ntk})\right) \quad (10)$$

where V_{tmk} is bus voltage number m at hour t in microgrid k, Y_{mnk} is feeder admittance linking buses m to n, θ_{mnk} is the admittance phase between busses m to n, δ_{mtk} is bus voltage angle. As it can be seen from the above equation, it is quite nonlinear so it will be solved using the backward-forward sweep approach.

There are limitations due to the capacity for DGs power generation as follows [9]:

$$p_i^{G,\min} \le E(p_{itk}^G) \le p_i^{G,\max} \quad (11)$$

where $p_i^{G,\min}$ / $p_i^{G,\max}$ displays the lower/upper power capacity of unit i.

For the main grid and storage battery, the rule is the same. The maximum and minimum power capacity is as follows [9]:

$$p_j^{s,\min} \le E(p_{jtk}^s) \le p_j^{s,\max} \quad (12)$$

$$p^{grid,\min} \le E(p_t^{grid}) \le p^{grid,\max} \quad (13)$$

where $p_j^{s,\min}$ / $p_j^{s,\max}$ is the lower/upper charge/discharge limit and $p^{grid,\min}$ / $p^{grid,\max}$ is the lower/upper limit of the utility. For the battery storage, the maximum energy storage capacity is calculated according to its initial state of charge (SoC) and the hours it is charging/discharging as follows [9]:

$$E(W_t^{ess}) = E(W_{t-1}^t) + \eta^{charge}E(P_{charge})\Delta t - \frac{1}{\eta^{discharge}}E(P_{\text{discharge}})\Delta t \quad (14)$$

$$\begin{cases} W^{ess,\min} \le E(W_t^{ess}) \le W^{ess,\max} \\ E(P_t^{charge}) \le P^{charge,\max} \\ E(P_t^{discharge}) \le P^{discharge,\max} \end{cases} \quad (15)$$

where W_t^{ess} is the energy stored, η^{charge} and $\eta^{discharge}$ are the charge/discharge efficacy.

According to its materials and diameter, each feeder is capable of transferring a specific amount of power which is shown as follows [9]:

$$|E(P_{lt}^{Line})| < P_l^{Line,\max} \quad (16)$$

where P_{lt}^{Line} is the value of the power flow in line l at time t and $P_l^{Line,\max}$ is the maximum allowed power limit in line l.

Technically, the microgrid voltage should be preserved in the safe zone as follows [9]:

$$V_m^{\min} \le E(V_{mt}) \le V_m^{\max} \quad (17)$$

Regarding the electric vehicle, some constraints need to be considered. When connected to the charger, the electric vehicle may experience three different modes of operation including idle mode U_{vt}^I =1, charging model U_{vt}^c =1,and discharging mode U_{vt}^d =1. Therefore, the electric vehicle may be in only one mode of operation at each time as (18) [5, 11]:

$$U_{vt}^c + U_{vt}^d + U_{vt}^I = U_{vt} \quad (18)$$

There is a limit on the maximum power charging/discharging by the electric vehicle as follows [5, 11]:

$$P_v^{c,\min} \le P_{vt}^c \le P_v^{c,\max} \quad (19)$$

$$P_v^{d,\min} \le P_{vt}^d \le P_v^{d,\max}$$

The sum of energy stored in the electric vehicle is calculated as (20). This energy should not exceed the total capacity of the electric vehicle as in (21) [5]:

$$E_{vt} = E_v^{ini} + \sum_{l=1}^{t}(U_{vt}^c P_{vl}^c \eta_v^c - U_{vt}^d P_{vl}^d \eta_v^d) - \sum_{l=1}^{t}(1-U_{vl})E_{vl}^D \quad (20)$$

$$E_v^{\min} \le E_{vt} \le E_v^{\max} \quad (21)$$

where η_v^c / η_v^d are the charging/discharging efficiency of the electric vehicle and E^D is the energy for PEVs in a fleet to drive.

The electric vehicle is supposed to keep the same amount of energy at the end of the day as the amount of energy it had at the beginning of the day [5]:

$$E_v^{fin} = E_v^{ini} \quad (22)$$

Also, it is supposed that the electric vehicle battery is charged

to its maximum capacity when leaving the home in the morning [5]:

$$E_v^{t'} = E_v^{\max} \tag{23}$$

where *t'* shows the time of the first travel in the morning.

III. Stochastic Framework Based on Unscented Transform

As it was mentioned in the previous sections, the proposed problem contains much uncertainty mainly arising from the RESs such as WT and PV as well the electric vehicles traveling pattern for example departure time and arrival time and the number of vehicles available. More than that, the prediction error in the hourly load demand in the microgrid is a serious issue which due to its low voltage level should be modeled, precisely. Therefore, this paper makes use of unscented transform [19] to construct a strong and reliable stochastic framework for modeling the uncertainties of the above problem. In contrast to the Monte Carlo method which uses a very high number of samples to converge, unscented transform only uses $2p+1$ points, wherein p is the number of uncertain parameters. In order to better perceive the unscented transform, let's consider the whole nonlinear format of our problem as $V_O=F(V_I)$ in which V_I is the output vector of the stochastic input vector V_O. Let's also assume that r is the uncertain parameter with a normal distribution, mean value and standard deviation of $\bar{m}$ and D, respectively. The unscented transform requires to extract $2p+1$ points to model the uncertainty effects through some recursive steps as follows:

Step 1: Find $2p+1$ samples as follows:

$$V_I^{\,0} = \bar{m} \tag{24}$$

$$V_I^{\,\kappa} = \bar{m} + \left(\sqrt{\frac{r}{1-W^0}Q_{VI}}\right)_\kappa \qquad \forall \kappa \in \Omega^\kappa \tag{25}$$

$$V_I^{\,\kappa+p} = \bar{m} - \left(\sqrt{\frac{r}{1-W^0}Q_{VI}}\right)_\kappa \qquad \forall \kappa \in \Omega^\kappa \tag{26}$$

where Q_{VI} represents the input covariance matrix and also W^0 is the initial weigh corresponding to $\bar{V}_I = \bar{m}$.

Step 2: find the weights associated with each sample point as follows:

$$\omega^0 = \omega^0 \tag{27}$$

$$\omega^\kappa = \frac{1-\omega^0}{2p} \qquad \forall \kappa \in \Omega^\kappa, \kappa = 1,2,...,p \tag{28}$$

$$\omega^{\kappa+p} = \frac{1-\omega^0}{2p} \qquad \forall \kappa \in \Omega^\kappa, \kappa+p = p+1,...,2p \tag{29}$$

It should be noted that the sum of the weights must equal 1.

Step 3: find the mean output vector $\bar{V}_O$ and the output covariance matrix Q_{VO} by running some equations as below:

$$\bar{V}_O = \sum_{l\in\Omega^l} \omega^l V_O^l \qquad \forall l \in \Omega^l, l = 1,2,...,2p \tag{29}$$

$$Q_{VO} = \sum_{l\in\Omega^l} W^l (V_O^l - \bar{V}_O)\left(V_O^l - \bar{V}_O\right)^T \qquad \forall l \in \Omega^l, l = 1,2,...,2p \tag{30}$$

Fig. 3 shows the concept of the unscented transform used in this paper for modeling the uncertainty effects.

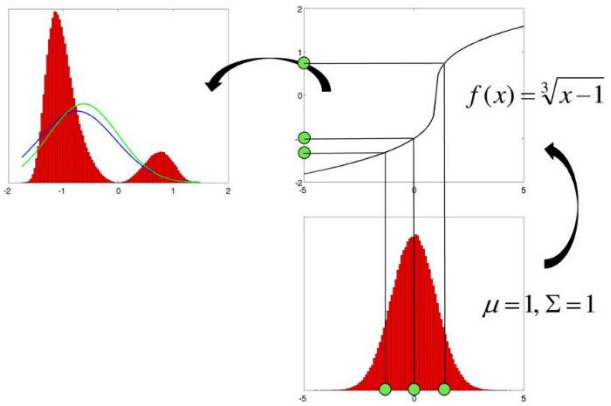


Fig. 3. The nonlinear mapping happening the unscented transform

IV. Modified Bat Optimization Algorithm

As it can be inferred from the problem formulation in section II, the problem structure is a kind of hard one which if not solved by a global search algorithm may fell in the local optima. In order to deal with this issue, this paper proposes a fresh optimization approach, called BA, to solve the problem. In addition, a new modification method is proposed to help the algorithm to improve its shortcoming and escape from the premature convergence. BA was initially developed in 2010 by Xin-She Yang [20] as an evolutionary algorithm mimicking the foraging behavior of bats in nature. Being among the top algorithms in those days, BA was constructed based on the echolocation process of bats in distinguishing between a food and prey. In fact, these mammals send a signal to the air and wait to hear its echolocation. This process is repeated several times so making them capable of routing even in a dark space. This idea brings a nice concept in the mind for making a powerful optimization algorithm, called BA. In the principal body, the BA is constructed based on four ideas: a bat X_b flies with a speed of V_b in the dark space and generates a signal of the frequency f_b with magnitude A_b. 2) the signal power (represented by its magnitude A_b) reduces as time is spent from high to a low level. 3) the echo assistances the bat to differentiate between a food and a prey. 4) the frequency f_b and rate r_b change in an unconscious course.

Initially, a set of bats are generated randomly in the feasible region of the problem. Each bat contains some numbers

showing the optimal value of the control variables of the problem. After calculating the cost function value for any bat, the dominant bat X_g is saved and the remained bats need to get progressed as follows:

$$\begin{aligned} \mathbf{V}_b^{Iter+1} &= \mathbf{V}_b^{Iter} + f_b(X_g - X_b) \qquad ;b=1,\ldots,N_{Bat} \\ X_b^{Iter+1} &= X_b^{Iter} + \mathbf{V}_b^{Iter} \qquad ;b=1,\ldots,N_{Bat} \\ f_b &= f_b^{\min} + \varphi_1(f_b^{\max} - f_b^{\min}) \qquad ;b=1,\ldots,N_{Bat} \end{aligned} \tag{31}$$

Where N_{Bat} is the size of bat population; $f_b^{\max}$ / $f_b^{\min}$ are the lower/upper limits for the frequency of b^{th} bat. Also, φ_1 to φ_6 are random parameters in the range (0,1] in this article.

In addition to the above movement, bat algorithm is equipped with a random search as well. After generating a random value β, it is compared with the signal rate r_b. In the case that it is bigger than the signal rate, then the bat will fix its position in the near surrounding as follows:

$$X_b^{Iter+1} = X_b^{Iter} + \varepsilon A_{mean}^{Iter} \qquad ;i=1,\ldots,N_{Bat} \tag{32}$$

Where ε is a random value in the range of [-1,1] and A_{mean}^{old} is the average value of the bats' frequency loudness. If β is smaller than r_i, a bat X_b^{rand} is generated, randomly. This new bat is verified only if the following two conditions are guarantied:

$$\begin{aligned} &\beta < A_b \\ &f(X_b) < f(Gbest) \end{aligned} \tag{33}$$

Based on the fourth rule of BA, the signal features are updated in an unconscious course:

$$\begin{aligned} A_b^{Iter+1} &= \alpha A_b^{Iter} \\ r_b^{Iter+1} &= r_b^0[1-exp(-\gamma \times Iter)] \end{aligned} \tag{34}$$

Where α and γ are adjusting parameters.

Some special characteristics of the BA are simple concept, high searching ability, few adjusting parameters, no need to differentiation, compatible with mixed integer nonlinear programming, etc. But it still suffers from the premature convergence when facing complex and multi-modal optimization problems. Therefore, this article suggests a new modification method to help BA improve its performance and find the global solution with high probability. These modifications are explained in the following.

Sub-modification method 1**:** Since X_g is the best bat in the population, it can be a good guide for the other bats to accelerate their improvisation process. Therefore, (35) is proposed to improve the population in each iteration. Here the population mean value M_{bat} is evaluated as a scale for the acceleration:

$$X_b^{Iter+1} = X_b^{Iter} + T_F \times \phi_4 \times \left(X_g - M_{bat}\right) \tag{35}$$

Where T_F is a random integer value. Based on (35), the BA can increase its convergence rate using a very good guide of its best bat in every iteration.

Sub-modification method 2**:** This modification method exchanges the control variables between bats to simulate a kind of interaction between them. This is like a knowledge sharing process which helps bats to make use of the others' experiences in finding food. Such an idea can be simulated by the crossover operator as follows:

$$X^{Test1} = \begin{cases} x_{b,j} & ;\ \varphi_4 < \varphi_5 \\ x_{gj} & ;\ \varphi_4 \geq \varphi_5 \end{cases} \tag{36}$$

$$X_b = [x_{b,1}, x_{b,2}, \ldots, x_{b,n}]$$

$$X_g = [x_{g1}, x_{g2}, \ldots, x_{gn}]$$

V. Simulation Results

In this section, the performance and capabilities of the proposed stochastic method for optimal operation and management of a networked microgrid are examined. The test system is shown in Fig. 4. It consists of four microgrids connecting with each other and exchanging power with either each other or the main grid. The voltage level is 12.66 (kV). There are several DGs installed in the networked microgrid so that microgrids can supply their own power. Therefore, a PV is installed in bus 10 of microgrid one, a battery unit is installed in bus 36 of microgrid one, an MT is installed in bus 63 of microgrid one. There is one WT installed in bus 10 in the microgrid two. There is a wind turbine in bus 18 of microgrid 3. Finally, microgrid number 4 has an FC installed on bus 43 and an MT on bus 53. According to the figure, the networked microgrid is capable of power exchange with the main grid. There are three electric vehicles fleets considered in the networked microgrid traveling on different paths. The travel pass of the electric vehicle fleets number one is all inside the microgrid number one, between the buses 4 and 37. Electric vehicle fleet number two travels between the first and the second microgrids, though the buses 13 and 42. Finally, the electric vehicle fleet number three travels between the third and the fourth microgrid. Tables I and II show the specifications of the electric vehicle fleets including their charging/discharging capacity and departure and arrival time and location. According to Table II, each electric vehicle experiences two travels in a day one from home to the work office and then a second one from the work office heading to the home. Therefore, during the hours that they are in the parking (either the office parking or home parking), the vehicles are unused and can attend the V2G plan to earn money and reduce the microgrid costs.

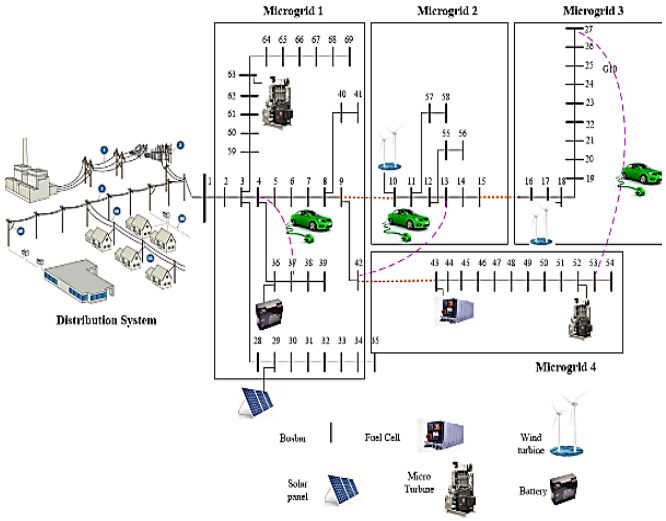


Fig. 4. Networked MG system incorporating RESs, DGs and electric vehicles

TABLE I
PEV FLEET TRAVEL CHARACTERISTICS

Fleet Number	First Trip				Second Trip			
	Departure		Arrival		Departure		Arrival	
	Time	Bus	Time	Bus	Time	Bus	Time	Bus
One	6	5	8	35	15:00	35	17:00	5
Two	8	52	9	29	18:00	29	19:00	52
Three	8	15	9	41	13:00	41	14:00	15

TABLE II
FEATURES OF THE ELECTRIC VEHICLE FLEETS

Fleet Number	Capacity (kWh)		Charge/Discharge rate (kW)	
	Min	Max	Min	Max
One	263	1973	7.3	496
Two	219	1644	7.3	292
	210	1812	7.3	313

Regarding the DGs, their characteristics are shown in Table III. For the storage unit, the charging/discharging rate is 200 kW/hour and the maximum storage capacity is 2000 kWh. Some data in Table III (such as prices) are borrowed from [21]. The problem is solved for 24 hours. For non-dispatchable units such as WT and PV, their forecast power is plotted in figures 5 and 6. It is well accepted that RESs due to their non-dispatchable nature may generate as much power as they can. Also figures 7 and 8 show the load power factor of the grid and the market price, respectively.

TABLE III
Features of the Distributed Units Deployed In The Microgrid

Unit	Type	Cost Coefficient ($/kWh)	Min-Max Capacity (kW)	Start-up Or shut-down Cost
WindUnit1	ND	1.0734	0, 1600	0
WindUnit 2	ND	1.073	0, 1920	0
SolarUnit	ND	2.584	0, 2300	0
Fuelcell	D	0.294	90, 1400	0.96
MicroTurbine1	D	0.457	120, 1500	1.65
MicroTurbine2	D	0.457	120, 1700	1.65
Utility	-	-	500, 2500	-

D: Dispatchable, ND: nondispatchable

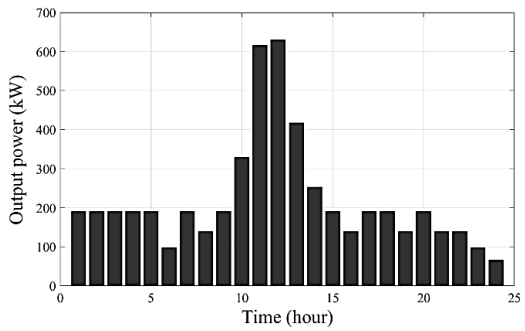


Fig. 5. Forecast wind turbine output power pattern

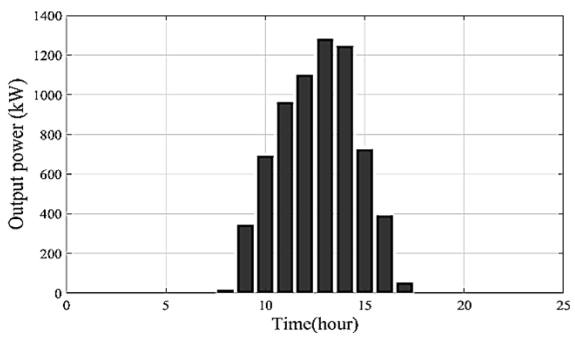


Fig. 6. Forecast photovoltaic unit output power generation

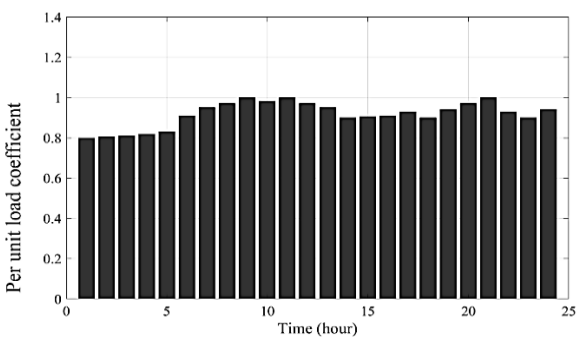


Fig. 7. System load factor over 24 hours based on the IEEE peak load value

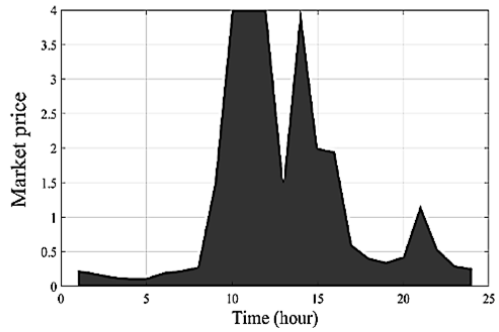


Fig. 8. Electricity market price offered by the main grid

Two different scenarios are simulated in this paper to reveal the capabilities of the proposed method. In the first scenario, electric vehicles are ignored and DGs and batteries are only considered. DGs can also switch On or Off depending on their preferences. In the second scenario, electric vehicles charging and possible discharging demands are considered in the microgrid. Table IV and V show the optimal power dispatch of the networked microgrid in the first and second scenario. According to these results, the microgrids number two and three have to purchase their extra power needs from the first microgrid since they only have RESs of WT and PV as DGs inside their areas. This reveals the significant role of microgrid number one in bridging between the main grid and other microgrids which can increase its profits. The situation is different for microgrid number four since it has dispatchable DGs of FC and MT and thus can only rely on internal productions for the power supply. This provides a more economic position for this microgrid to reduce its cost and attend the power trade when benefits. For microgrid number one, it has both adequate internal power generation capacity and a direct connection to the main grid. Therefore, this makes it the most stable microgrid which can reduce its costs by optimal managing of its units and the main grid. For the battery, it is seen that the battery is charged at the beginning of the day to get discharged later at the peak-load times. This is a very economic plan for making the maximum advantage of the storage units.

TABLE IV
Optimal Power Dispatch Of Units In Scenario One

Time (h)	Wind turbine 1 (kW)	Wind turbine 2 (kW)	Photovoltaics (kW)	Fuel cell (kW)	Micro Turbine 1 (kW)	Micro Turbine 2 (kW)	Storage Unit (kW)
1	190.4000	228.4800	0	0	0	0	0
2	190.4000	228.4800	0	0	0	0	-29.8166
3	190.4000	228.4800	0	0	0	0	-61.6241
4	190.4000	228.4800	0	0	0	0	-96.5816
5	190.4000	228.4800	0	0	0	0	-78.3473
6	97.6000	117.1200	0	0	0	0	-32.0543
7	190.4000	228.4800	0	0	0	0	-120.1656
8	139.2000	167.0400	18.4	0	0	0	-22.8289
9	190.4000	228.4800	345.0	1226.5	1079.1	548.3	184.3805
10	329.6000	395.5200	692.3	1035.9	1237.7	226.4	-191.2522

Table IV continued

11	616.0000	739.2000	961.4	472.1	126.7	916.0	-29.2607
12	630.4000	756.4800	1099.4	372.3	232.1	469.1	128.4086
13	417.6000	501.1200	1278.8	770.8	363.7	411.8	-131.7213
14	252.8000	303.3600	1246.6	979.3	4381	243.6	-41.7469
15	190.4000	228.4800	724.5	1201.0	1203.7	0	-107.0821
16	139.2000	167.0400	388.7	1290.3	722.0	601.1	151.6652
17	190.4000	228.4800	50.6	1052.5	1500.0	442.6	71.4839
18	190.4000	228.4800	0	1400.0	1222.2	0	137.0802
19	138.8800	166.6560	0	1129.5	0	1700.0	127.1509
20	190.4000	228.4800	0	1093.9	603.1	1700.0	-127.8503
21	138.7200	166.4640	0	1378.4	831.3	1212.1	75.1165
22	138.7200	166.4640	0	1399.9	741.8	894.1	195.0461
23	97.6000	117.1200	0	1336.0	0	0	0
24	65.6000	78.7200	0	0	0	0	0

TABLE V
Optimal Power Dispatch of Units in Scenario Two

Time (h)	Wind turbine 1 (kW)	Wind turbine 2 (kW)	Photovoltaics (kW)	Fuel cell (kW)	Micro Turbine 1 (kW)	Micro Turbine 2 (kW)	Storage Unit (kW)
1	190.4	228.48	0	0	411.1801	0	-0.0137
2	190.4	228.48	0	0	264.2646	0	-2.6450
3	190.4	228.48	0	223.7159	0	0	-17.6346
4	190.4	228.48	0	0	0	0	-85.1593
5	190.4	228.48	0	0	0	0	-1.4869
6	97.6	117.12	0	0	0	243.9681	10.9565
7	190.4	228.48	0	0	0	244.5895	9.9259
8	139.2	167.04	18.4	0	0	0	20.7859
9	190.4	228.48	345.0	792.5566	1053.9803	363.5021	37.8371
10	329.6	395.52	692.3	721.9271	571.0821	392.4715	-82.7094
11	616.0	739.20	961.4	467.8826	0	422.9153	55.9942
12	630.4	756.48	1099.4	0	884.4738	357.0653	-79.4686
13	417.6	501.12	1278.8	0	760.7829	666.2651	-34.7672
14	252.8	303.36	1246.6	378.7729	0	656.9597	-90.9020
15	190.4	228.48	724.5	1014.6598	638.2393	781.7054	50.4240
16	139.2	167.04	388.7	1025.3934	720.9894	1340.4373	-54.6269
17	190.4	228.48	50.6	1399.7238	561.0359	637.0073	-14.5553
18	190.4	228.48	0	1400	0	437.5930	74.7302
19	138.88	166.656	0	0	0	0	93.0087
20	190.4	228.48	0	0	0	382.9724	83.6701
21	138.72	166.464	0	436.2503	1500	1028.4159	26.6084
22	138.72	166.464	0	719.7058	1040.1948	1036.9315	-0.1097
23	97.6	117.12	0	275.4172	634.9327	0	-0.02351
24	65.6	78.72	0	0	0	0	0.05193

Table VI shows the optimal operating point of electric vehicle fleets in the second scenario. According to this table, the electric vehicles are neither in charging mode nor discharging mode when they are on the road. Owing to the V2G technology, now the vehicles are changing their role from just-consuming components into active players which could discharge at heavy loading condition. It is seen that vehicles could actively attend the V2G plan when parked in the parking and are unused. This is a wise strategy for making the maximum advantage of these devices for benefiting the microgrid. For sure it has some unwanted costs which is modeled as the battery degradation cost in the objective function.

TABLE VI
Electric Vehicle Fleets Performance for 24 Hours

Time (h)	Electric Vehicle Fleet Number 1	Electric Vehicle Fleet Number 2	Electric Vehicle Fleet Number 3
1	139.41601	192.9079	0
2	480.38419	174.7460	1.8396
3	-308.6526	-291.9977	0
4	275.2524	292	288.4197
5	496	292	311.7763
6	0	292	247.3129
7	0	0	287.0541
8	-153	-180	0
9	-331.0259	-279.4162	-180
10	-301.8570	-128.5881	-275.5103
11	-90.9377	-226.1966	-221.6559
12	332.8514	-108.1917	-264.4336
13	-248.7874	0	169.8892
14	-338.8346	-155.5431	-180
15	259.2956	53.4450	-125.3398
16	-85.5866	91.43379	261.2915
17	0	-107.2613	-274.8871
18	0	0	162.6318
19	-153	-180	311.6599
20	400.1334	63.7333	-147.2028
21	-189.5206	-155.9086	-160.3014
22	-270.9295	155.6934	-312.9647
23	0	-20.48481	-211.3681
24	0	-216.1296	-1.4083

The convergence characteristics of the proposed MBA for a hundred and fifty iterations considering electric vehicles and RESs (second scenario) are shown in Fig. 9. As it can be seen from this figure, the proposed algorithm shows a robust convergence in optimizing the cost objective function. Also, it is seen that it could converge before a hundred iteration which is a very good performance.

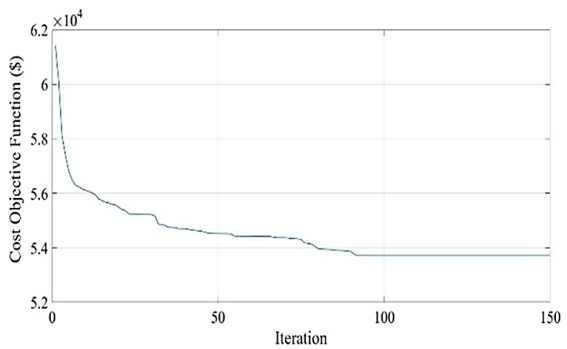


Fig. 9. Convergence characteristics of the algorithm over a hundred iteration in the second scenario

In order to better perceive the appropriate capability of the proposed stochastic framework, Fig. 10 shows the comparative cost function value plots in the first and second scenarios with and without considering the uncertainty effects. Here, the stochastic framework uses unscented transform to model the uncertainties of the WT, PV, load demand and vehicle behaviors. The first conclusion from this figure is that the electric vehicles can help to reduce the cost function if designed well by the V2G technology. This is a quite great result since it was expected that the vehicles appearance in the networked microgrid will increase its cost. But on the contrary, the cost was reduced since they can now play the role of a mobile storage to reduce the heavy loading effects on the microgrids. The second conclusion comes around the uncertainty effects. It is seen that modeling the uncertainty has increased the cost values. This could be expected since with uncertainty, the analysis is now more realistic and thus it is assumed to pay money for remaining in the safe zone. In overall, the results advocate the appropriate and reliable presentation of the proposed stochastic framework.

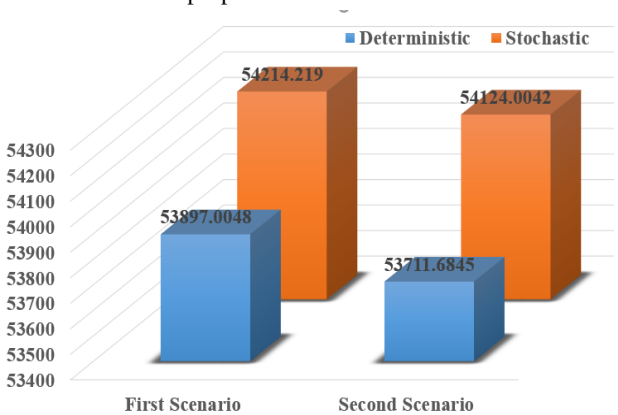


Fig. 10. Stochastic framework and the deterministic optimizing cost function in the networked microgrid.

VI. CONCLUSION

Networked microgrid idea include many returns not only to the customers but also to the power grids and the single microgrids. This article tries to investigate the optimal energy management in a networked microgrid considering the most advanced technologies of DGs such as WT, PV, FC and MT as well as electric vehicles and storage units. We used a stochastic framework to not only solve the optimal economic dispatch of the units but also capture the uncertainty effects of RESs, electric vehicle and load demand. The new framework is constructed based on unscented transform and MBA to provide a very good tool for managing a networked microgrid. The main paper outcomes can be summarized as below:

- The simulation results on a test networked grid with four interconnected microgrids through two different scenarios show that the model developed in this paper is capable to provide appropriate performance for the microgrids. It was seen that storage unit attends the economic program of the networked microgrid and can mitigate the total costs

by charging the cheap load hours and discharge at peak-load hours. All renewable sources attended the power dispatch plan as forecasted.

- It is seen that V2G technology may have some degradation cost but can change the passive role of electric vehicles from just-consumers into the active role of mobile storages. This could reduce the networked microgrid costs by letting the vehicles attend the V2G plans when parked in the parking of office or home.
- From the optimization point of view, the proposed MBA shows robust performance in optimizing the cost function. The total cost of operation of the networked microgrid in the first and second scenarios (incorporating uncertainty effects) 54214.219$ are 54124.0042$ respectively.
- From the uncertainty point of view, modeling the uncertainty increased the operating costs but will provide a safe zone for the reliable operating of the microgrids. Although the stochastic framework based on UT added 0.586% and 0.762% to the cost function value in the first and second scenarios, the new results are more realistic and trustable for the test system.

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