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Impact of plug-in hybrid electric vehicles charging demand on the optimal energy management of renewable micro-grids

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ABSTRACT

This paper suggests a new stochastic expert framework to investigate the charging effect of plug-in hybrid electric vehicles (PHEVs) on the optimal operation and management of micro-grids (MGs). In this way, a useful method based on smart charging approach is proposed to consider the charging demand of PHEVs in both residential location and public charging stations. The analysis is simulated for 24 h considering the uncertainties associated with the forecast error in the charging demand of PHEVs, hourly load consumption, hourly energy price and Renewable Energy Sources (RESs) output power. In order to see the effect of storage devices on the operation of the MG, NiMH-Battery is also incorporated in the MG. According to the high complexity of the problem, a new optimization method called θ-krill herd (θ-KH) algorithm is proposed which uses the phase angle vectors to update the velocity/position of krill animals with faster and more stable convergence. In addition, a new modification method is proposed to improve the search ability of the algorithm, effectively. The suggested problem is examined on an MG including different RESs such as photovoltaic (PV), fuel cells (FCs), wind turbine (WT), micro turbine (MT) and battery as the storage device.

1. Introduction

The increasing concerns on the high dependability of the industry on fossil fuels along with the rising amount of air pollution made severe struggles for replacing the traditional transportation systems with the new electric vehicles (EVs) [1,2]. Recently, the EUs energy policy [3] publicized a letter regarding the serious limitations in the amount of emissions generated by the cars till 2012. Nevertheless, one significant barrier in front of the use of EVs is their high cost that mainly roots from the inappropriate storage devices. In fact, the lack of sufficient technology for building cheap and suitable batteries has guided the EVs industry toward the idea of plug-in hybrid EVs (PHEVs). PHEVs can provide more balance between the cost and performance that makes them more attractive devices with brighter future [4]. The use of internal combustion engine along with the electric battery let the PHEVs travel more distance in comparison with the pure EVs. Along with the several benefits of PHEVs in the transportation systems, the high penetration of these devices can make new challenges in the power systems especially regarding their charging demands. Some of these challenges can be named as increasing the energy losses, reducing the system reliability, reducing the grid power quality of the electrical services, transformer saturation and feeder congestion in both transmission and distribution systems [5–7]. The statistical data report the coincidence of peak load hours of the power grids with hours in which the majority of EVs are charging. This issue can lead to challenges in both the operation and planning of the networks and thus increasing the investment costs. In order to solve this issue, the idea of smart charging was developed [8].

In recent years, renewable energy sources (RESs) have also found much popularity among the researchers and power engineers. The appearance of RESs in the new power systems has resulted in both advantages and disadvantages. In the side of advantages, improving power quality, enhancing the electrical services, reducing power losses and providing the consumers locally (nearness of generation and loads) can be named [9–11]. Cleanness, modularity and fast installation are some of the other attractive aspects of the RESs. In the side of disadvantages, increasing the available strategies of the power systems, incrementing the complexity and nonlinearity of the systems and higher costs for supplying the infrastructure requirements can be named [12–14]. Nevertheless, the nature of RESs is such that their future success

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Nomenclature

$B_{Gi}(t)$ the bid of ith DG at time t
X/θ state variables vector in Cartesian/polar space
$B_{Sj}(t)$ the jth storage device bid at time t
$S_{Sj}(t)$ start-up/shut down cost of jth storage device at time t
$S_{Gi}(t)$ start-up/shut down cost of ith DG at time t
$P_{Grid}(t)$ active power bought (sold) from (to) the utility at time t
$B_{Grid}(t)$ utility bid at time t
$u_i(t)$ state of the ith QUOTE QUOTE unit denoting ON/OFF statuses
N_g number of generating units
N_s number of storage devices
P_g vector including the power generation of all power units
U_g vector including ONN/OFF statuses of all power units
T number of time intervals
$P_{G,i}(t)$ active power production of ith power unit
$P_{G,i,\min}(t)$ minimum active power production of ith power unit at t
$P_{G,i,\max}(t)$ maximum active power production of ith power unit at t
$P_{s,j,\min}(t)$ minimum active power production of jth storage device at t
$P_{s,j,\max}(t)$ maximum active power production of jth storage device
$P_{Grid,\min}(t)$ minimum active power production of the grid at t
$P_{Grid,\max}(t)$ maximum active power production of the grid at t
$P_{L,i}(t)$ the amount of lth load value at time t
N_L total number of load levels
$W_{ess}(t)$ amount of stored energy inside the battery at time t
S probabilistic solution set of output variables
Z input set of uncertain variables
μ_{z_l} mean value of input random variable z_l
σ_{Zl} standard deviation of zl
z_l uncertain input random variable
$X_{\max}/X_{\min}$ maximum or minimum value of vector X
$W_{ess,\max}/W_{ess,\min}$ maximum/minimum stored energy inside the battery
$P_{charge}/P_{discharge}$ permitted rate of charge/discharge during a finite time period (Δt)
$\eta_{charge}/\eta_{discharge}$ battery efficiency during charge/discharge period
$P_{charge,\max}/P_{discharge,\max}$ maximum permitted rate of charge/discharge during a finite each time period (Δt)
$\lambda_m(t)/\lambda_{loss}(t)$ hourly energy price /loss cost ($/MWh)
$\mu_{PHEV}^{\min}/^{\max}$ minimum/maximum hourly PHEV demand (kW)
$\mu_{PHEV}(t)$ hourly mean values of PHEV demand (kW)
$\beta_{PHEV}(t)$ hourly existence coefficient of PHEVs
E total energy demand of PHEVs (kWh)
X^b/θ^b best krill in the population
$V_{r,i}^k/\Delta\theta_{r,i}^k$ velocity of the krill i in the iteration k in Cartesian/polar space
$V_{ind,i}^k/V_{frg,i}^k/V_{dif,i}^k\ \Delta\theta_{ind,i}^k/\Delta\theta_{frg,i}^k/\Delta\theta_{dif,i}^k$ induced/foraging/diffusion velocity of ith krill at the kth movement in Cartesian/polar space
ρ empirical constant factors
N_v number of control variables
$\omega_{ind/frg/dif}$ inertia of induction/foraging/diffusion motion
ε small positive number
rand mathematical operator for random value in the range [0,1]
f_w fitness function of the worst krill in population
N_p number of population
Iter iteration number
Mn_K column-wise mean value of the krill population
φ_1 random value in the range [0,1]
β constant value
F set of deterministic equations
$Z_{l,1}, Z_{l,2}$ estimated locations of input random variable z_l
$\Upsilon_{l,3}$ skewness coefficient of zl
$\xi_{l,k}$ standard location of z_l
$E(S_i^k)$ kth moment of ith output random variable

List of abbreviations

FC fuel cell
WT wind turbine
PV photovoltaic
NiMH-Battery Nickel–Metal–Hydride battery
PHEVs plug-in hybrid electric vehicles
DG distributed generation
MG micro-grid
MT micro turbine
RES Renewable Energy Source
KH Krill Herd
θ-MKH theta-modified KH
PEM Point Estimate Method

has been estimated by the researchers from the last years [15]. Some of the problems that have been arisen in the area of RESs and in the operation of the power systems are addressed by the term micro-grid (MG). By definition, MG is an aggregation of distributed generations (DGs), electrical loads and generation interconnected among them and with the main grid [16]. In recent years, useful works have been implemented in the area of MG. In Ref. [17], a virtual MG was devised to examine the efficiency of an intelligent method for operation management of the MG in one week. The interactive effect between the MG and the main grid was investigated in Ref. [18]. A new method based on mixed-integer linear programming was suggested in Ref. [19] to find the optimal output of DGs in an MG. In order to increase the lifecycle cost of the MG, a three-phase approach including optimal design, sizing and operation of a renewable MG was proposed in Ref. [9]. In Ref. [20], a linear programming approach was presented to optimize the cost of a photovoltaic (PV)-based MG. In Ref. [21], a multi-agent mechanism was proposed to control an MG based on PV RESs. Similar work based on genetic algorithm (GA) was done in Ref. [22]. Here, a three-phase procedure including prediction, storage and management is employed to fully operation of the MG. In Ref. [23], the role of storage devices on the operation of MG was investigated. It was shown that storage devices can reduce the cost of the MG effectively. While each of these works has investigated significant aspects in the MG optimal operation, none of them have assessed the effect of PHEVs on the future MGs. As mentioned before, the ever increasing popularity of the PHEVs is an inevitable issue. The recent statistics estimate more than one million PHEVs in America in the years 2015–2017 [24].

According to the above discussion, investigating the effect of PHEVs on the optimal operation of the MGs is a vital issue that is not considered in the any of the above works. In fact, the stochastic behavior of PHEVs can affect the operation of the MG severely. As mentioned before, EV's drivers generally tend to charge their vehicles at peak-load hours. In this regard, if the charging demands of these devices are not managed optimally, the MG cost will be increased and in some cases the charging demand can not be supplied by the MG. Therefore, this paper aims to investigate the optimal operation and management of a renewable MG in the presence of PHEVs. A sufficient smart method is proposed to shift the charging demand of PHEVs from peak-load hours to off-peak hours. Using the proposed smart method can reduce the total MG cost when increasing the penetration of PHEVs in the network. For better analysis, the investigated MG includes different types of RESs such as PV, wind turbine (WT), fuel cell (PC), micro turbine (MT) and a battery as the storage device. According to the nature of the problem, it includes several sources of uncertainty (such as WTs output power, PV output power, market cost for the future day, load demand of MG for the future day and PHEVs' charging demand as mobile loads) that should be managed suitably. In this regard, 2m point estimate method (2m-PEM) is used to construct a stochastic framework to capture the uncertainties in the problem. In order to solve the problem optimally, a new optimization procedure based on krill herd (KH) algorithm is devised too. KH algorithm is a newly introduced optimization algorithm that mimics the behavior of krill animals for searching food [25]. In order to increase both the search and convergence abilities of the KH algorithm, a new version of this algorithm called θ-modified KH (θ-MKH) algorithm is proposed. The θ-MKH algorithm: 1) makes use of the polar coordinates instead of the Cartesian coordinates to solve the problem, 2) makes use of a two-phase modification method to increase the diversity of the krill population. As it will be shown later, the proposed θ-MKH will be much more intelligent than the original KH algorithm. The feasibility and satisfying performance of the proposed method are examined on a typical renewable MG. Therefore, the main contributions of this work can be summarized as: 1) investigating the effect of charging demand of PHEVs on the optimal energy management of the MG, 2) introduction of a new powerful optimization algorithm for solving the optimal operation and management of MGs considering RESs, storage devices and PHEVs and 3) introduction of the polar version of KH algorithm called θ-KH suitable for the optimization applications.

The rest of this paper is organized as follows: Section 2 describes the proposed smart charging demand strategy for PHEVs. Section 3 describes the MG formulation including RESs. The 2m PEM as the stochastic framework is explained in Section 4. The proposed θ-MKH is described in Section 5. Section 6 shows the results and simulations on the MG test system. Finally, the conclusions and main remarks are given in Section 7.

2. PHEV smart charging strategy

As the result of low capacity of the available batteries, PHEVs should have fast access to the charging places. This issue forced the public stations to be equipped with charging devices as well as the PHEV owners' houses to have charging facilities [26]. According to the nature of PHEVs, their charging demand is influenced by different variables including charging current/voltage level, number of PHEVs, battery capacities and charging duration time. These effective parameters together make the charging demand of the PHEVs uncertain both in the public station or residential communities. It is demonstrated in the literature that the aggregated total charging demand of PHEVs in the charging station and a residential area tend to follow Weibull probability density function (PDF) and normal PDF, respectively [27]. The mean value and the standard deviation value of these PDFs are determined according to the PHEVs' parameters. As mentioned before, one significant point about the behavior of EV drivers is that they tend to charge their vehicles at peak load hours. This event can result in severe problems for the power systems such as feeder congestion, power loss increment, low reliability, low power quality and transformers saturation. In order to overcome these problems, a smart charging strategy should be devised. In comparison with the uncontrolled charging scheme, the smart charging demand strategy provides high penetration of PHEVs in the network. The proposed smart charging strategy makes use of the market energy price to minimize the energy cost for PHEVs. Generally, peak-load hours coincide the high electricity cost hours and vice versa. Therefore, in contrast to the uncontrolled charging scheme, the smart charging scheme will shift the PHEVs' charging hours to off-peak hours. Economically, this strategy would be the most beneficial and lower electricity price will be more interesting for the consumers. The proposed charging method uses two data sets for managing the PHEVs' charging demand: 1) hourly price data of the electricity and 2) the presence of PHEVs in the charging point. The hourly price data of the market is attained using the well-known forecasting methods. Regarding the second parameter (presence of PHEVs in the charging point), an existence coefficient β_{PHEV} is defined that shows the possibility of a PHEV being in the relevant charging place. Fig. 1 shows the values of existence coefficient for two types of charging places; 1) public station and 2) residential communities. According to Fig. 1, in residential communities, PHEVs are connected to the chargers mostly at night hours or at the end of days. On the other hand, PHEVs tend to be charged at public stations during mid-day hours.

The proposed smart charging strategy will manage the PHEVs charging demand by minimizing the total charging cost using the below equation:

$$\begin{aligned}
&\text{Minimize} \quad \left(\frac{\lambda_m(t)}{\beta_{\text{PHEV}}(t)} \times \mu_{\text{PHEV}}(t)\right) \\
&\text{subject to} \\
&\sum_{t=1}^{T} \mu_{\text{PHEV}}(t) = E \\
&\mu_{\text{PHEV}}^{\min} \le \mu_{\text{PHEV}}(t) \le \mu_{\text{PHEV}}^{\max}
\end{aligned} \tag{1}$$

As it can be seen, the proposed strategy is a linear optimization problem that can be solved using simple linear mathematical methods such as simplex technique. According to the above equation, by knowing the total energy demand of PHEVs in an area for a specific time horizon, the hourly mean value of PHEVs charging demand would be determined for both the residential and

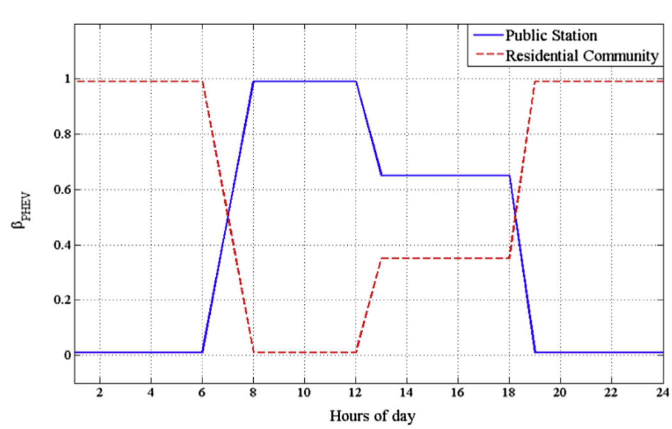

Fig. 1. Existence Coefficient of PHEVs in charging points.

public stations. It is worth noting that the consumers will be also enthusiastic to charge their cars at hours with lower cost.

3. MG formulation

As mentioned before, this paper aims at optimal energy management of an MG including different types of DGs and storage devices as well. The objective function and the relevant constraints are described in the following.

3.1. Cost of energy

A typical MG with different types of DGs and storages with interconnection with the main grid should be able to supply its loads all the times. In fact, MG first tries to supply the internal loads by the use of its own power units (DGs and storages) and the additional demand is supplied from the main grid. Nevertheless, sometimes it is more economical to buy electricity from the main grid and operate DGs at minimum capacity. Also, it is beneficial to store energy in the storage devices at light load hours and use it at peak-load hours. These significant decisions should be made by the MG central control (MGCC). MGCC should manage the above key strategies by optimizing the below cost function [16]:

$$\begin{aligned}\operatorname{Min} f(X) &= \sum_{t=1}^{T} \mathrm{Cost}^t \\ &= \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_g} \left[u_i(t) p_{Gi}(t) B_{Gi}(t) + S_{Gi} |u_i(t) - u_i(t-1)| \right] \right. \\ &\quad + \sum_{j=1}^{N_s} \left[u_j(t) p_{sj}(t) B_{sj}(t) + S_{sj} |u_j(t) - u_j(t-1)| \right] \\ &\quad \left. + p_{\mathrm{Grid}}(t) B_{\mathrm{Grid}}(t) \right\}\end{aligned} \tag{2}$$

where X as the control vector that includes the amount of power produced by each power unit (DGs, storage devices or the main grid) and the ON/OFF status of DGs as follows:

$$\begin{aligned}&X = [P_g, U_g]_{1\times 2nT}; \quad P_g = [P_G, P_s]; \quad n = N_g + N_s + 1 \\ &P_G = \left[P_{G,1}, P_{G,2}, \ldots, P_{G,N_g}\right]; \quad P_s = \left[P_{s,1}, P_{s,2}, \ldots, P_{s,N_s}\right] \\ &P_{G,i} = \left[P_{G,i}(1), P_{G,i}(2), \ldots, P_{G,i}(T)\right]; \quad i = 1, 2, \ldots, N_g + 1 \\ &P_{s,j} = \left[P_{s,j}(1), P_{s,j}(2), \ldots, P_{s,j}(T)\right]; \quad j = 1, 2, \ldots, N_s \\ &U_g = [u_1, u_2, \ldots, u_n], \quad u_k \in \{0, 1\} \\ &u_k = [u_k(1), u_k(2), \ldots, u_k(T)]; \quad k = 1, 2, \ldots, n\end{aligned} \tag{3}$$

In this paper, $u_k(t) = 1$ and $u_k(t) = 0$ are used to show the ON & OFF status of the kth power unit at time t, respectively.

3.2. Security limitations

3.2.1. Generation and consumption balance

As the first role, MGCC should balance between the total load demand and the total power generation as below. It is worth noting that PHEVs charging demand can be supposed as variable loads in the MG [16].

$$\sum_{i=1}^{N_g} P_{G,i}(t) + \sum_{j=1}^{Ns} P_{s,j}(t) + P_{\mathrm{Grid}}(t) = \sum_{l=1}^{N_L} P_{L,l}(t) \tag{4}$$

3.2.2. Generation capacity

Each power unit is capable to generate electricity according to its capacity [16]:

$$\begin{aligned}&P_{Gi,\min}(t) \le P_{Gi}(t) \le P_{Gi,\max}(t) \\ &P_{\mathrm{grid},\min}(t) \le P_{\mathrm{Grid}}(t) \le P_{\mathrm{grid},\max}(t) \\ &P_{sj,\min}(t) \le P_{sj}(t) \le P_{sj,\max}(t)\end{aligned} \tag{5}$$

3.2.3. Battery charging/discharging limits

The amount of power that can be provided by the battery at time t is limited to the amount of power stored in the last hours. Also, the battery can charge or discharge according to the specific rates as below [16]:

$$W_{\mathrm{ess}}(t) = W_{\mathrm{ess}}(t-1) + \eta_{\mathrm{charge}} P_{\mathrm{charge}} \Delta t - \frac{1}{\eta_{\mathrm{discharge}}} P_{\mathrm{discharge}} \Delta t \tag{6}$$

$$\begin{cases} W_{\mathrm{ess,min}} \le W_{\mathrm{ess}}(t) \le W_{\mathrm{ess,max}} \\ P_{\mathrm{charge}}(t) \le P_{\mathrm{charge,max}} \\ P_{\mathrm{discharge}}(t) \le P_{\mathrm{discharge,max}} \end{cases} \tag{7}$$

4. 2*m*-PEM as the stochastic framework

As mentioned before, the problem investigated includes many uncertain parameters that necessitate the use of an appropriate framework for modeling them. The forecast error in the WT output power (as the result of wind speed variations), PV output power, load demand of consumers at each hour, market price per kWh and PHEVs charging demand behavior in both the residential and publication stations are the uncertain variables of the problem. In order to model the uncertainties of the variables in the problem, different methods have been proposed in recent years. The most well-known and popular method is Monte Carlo Simulation (MCS) that uses a high number of runs for modeling uncertainty. The main deficiency of MCS is its high computational burden. In order to overcome this issue, different methods were proposed that among the most well-known are approximate methods. Approximate methods replace each uncertain variable with a suitable PDF and then use a limited number of runs instead of high number of runs in MCS. This paper makes use of PEM with $2m$ scheme to model the uncertainties of the problem [28]. The variable m denotes the number of uncertain variables in the problem. The main feature of $2m$ PEM is that it requires just the first few statistical data of the uncertain variables including the mean, variance, skewness, and kurtosis coefficients [29–32]. The $2m$-PEM will convert the stochastic problem into $2m$ deterministic problems with different probabilities. Considering the set of uncertain variables as z, the uncertainties of these variables are transferred to the output through the objective function as below [29]:

$$S = F(z) \tag{8}$$

In this paper, the output variable S is the value of the cost function. First, $2m$-PEM will replace each uncertain variable z_l by a PDF function f_{zl}. Then, each PDF function f_{zl} is replaced by two concentration points $z_{l,1}$ and $z_{l,2}$ that are calculated as below [29]:

$$S_i = F_i(Z_1, Z_2, Z_3, \ldots, Z_m) \tag{9}$$

$$z_{l,k} = \mu_{z_l} + \xi_{l,k} \cdot \sigma_{z_l}; \quad k = 1, 2 \tag{10}$$

$$\xi_{l,k} = \frac{\Upsilon_{l,3}}{2} + (-1)^{3-k} \sqrt{m - \left(\Upsilon_{l,3}^2/2\right)^2}, \quad k = 1, 2 \tag{11}$$

Also, $\Upsilon_{l,3}$ as the skewness coefficient is evaluated as [29]:

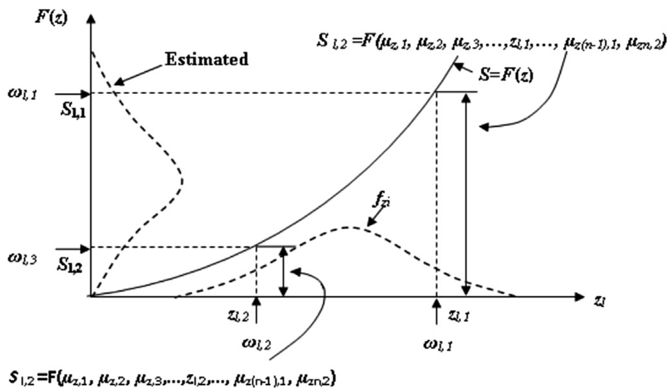

Fig. 2. Conceptual illustration of the 2*m* PEM.

$$\gamma_{l,3} = \frac{E\left[\left(z_l - \mu_{z_l}\right)^3\right]}{\left(\sigma_{z_l}\right)^3} \tag{12}$$

In the above equation, E is the expected operator. Finally, the standard deviation value of S_i can be evaluated using the below equation [29]:

$$\begin{aligned} &E\left(S_i^j\right) = \sum_{l=1}^{m}\sum_{k=1}^{2}\left(\omega_{l,k} \times S_i^j(\mu_{z1}, \mu_{z2}, \ldots, z_{l,k}, \ldots, \mu_{zm})\right) \\ &\sigma = \sqrt{\mathrm{var}(S_i)} = \sqrt{E\left(S_i^2\right) - [E(S_i)]^2} \\ &\omega_{l,k} = \frac{1}{2m} \end{aligned} \tag{13}$$

The schematic diagram of 2*m*-PEM is depicted in Fig. 2.

5. Optimization method based on θ-MKH

The proposed problem is a complex, nonlinear non-convex optimization problem that requires a powerful tool to escape from the local optima. Therefore, this paper suggests a new optimization algorithm called θ-MKH (based on the KH algorithm). The detailed descriptions of this algorithm are given in the following.

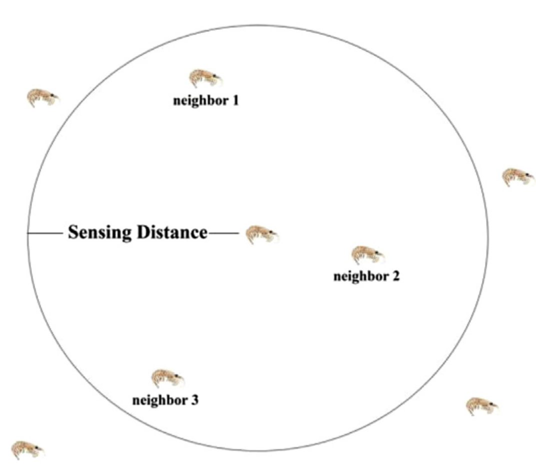

Fig. 3. Conceptual illustration of the induced distance also called sensing distance [25].

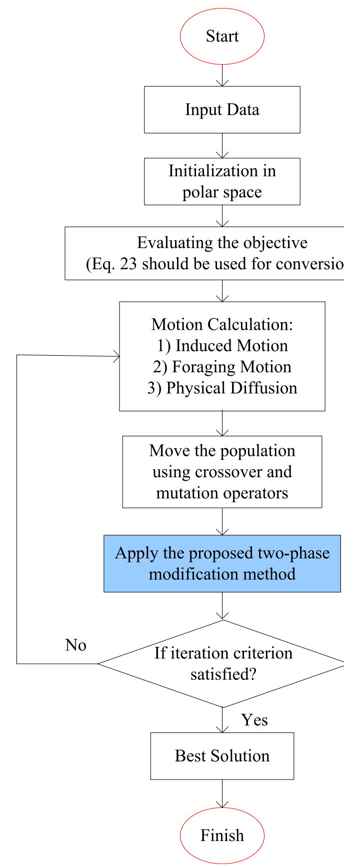

Fig. 4. Flowchart of the proposed θ-MKH algorithm.

5.1. *θ-KH algorithm*

The original KH algorithm is a newly introduced evolutionary algorithm published in 2012 [25]. KH mimics the behavior of krill animals to search for food. In comparison with the other well-known evolutionary algorithms, KH is equipped with some powerful metaheuristic mechanisms taken from the particle swarm optimization (PSO) and genetic algorithm (GA). These features make KH algorithm a powerful optimizer to solve the non-convex optimization problems. In addition, KH has other useful characteristics such as low dependency on the adjusting parameters, fast convergence, easy implementation, usable for solving both continuous and discrete optimization problems and automatic subdivision for solving multi-modal optimization problems. Structurally, KH algorithm starts with a random krill population. After calculating the fitness function value for all krill, the best krill is stored (best krill is the one with the best fitness function value) and then the algorithm tries to improve the krill population as below [25]:

$$X_i^{k+1} = X_i^k + V_{r,i}^k \rho \sum_{j=1}^{N_v} (u_j - l_j) \tag{14}$$

In the above equation, $V_{r,i}^k$ is the velocity of *i*th krill which is affected by three motions: 1) induction motion $V_{\mathrm{ind},i}^k$, 2) foraging motion $V_{\mathrm{frg},i}^k$ and 3) random diffusion $V_{\mathrm{diff},i}^k$ as follows [25]:

$$V_{r,i}^k = V_{\mathrm{ind},i}^k + V_{\mathrm{frg},i}^k + V_{\mathrm{diff},i}^k \tag{15}$$

The induction $V_{\mathrm{ind},i}^k$, foraging $V_{\mathrm{frg},i}^k$ and random diffusion $V_{\mathrm{diff},i}^k$ motions will be discussed later in detail. But in order to avoid

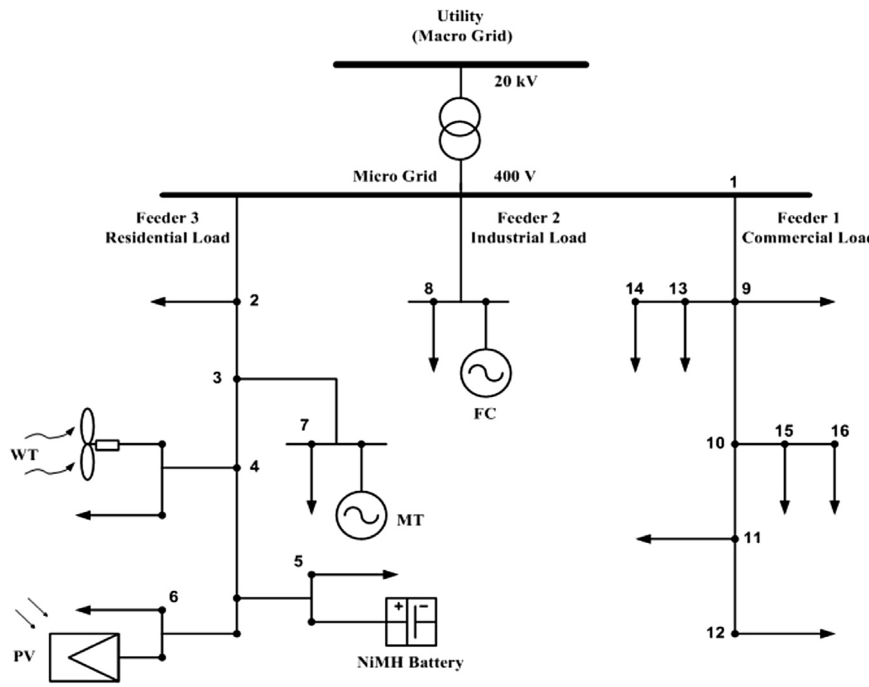

Fig. 5. Single line diagram of the MG test system.

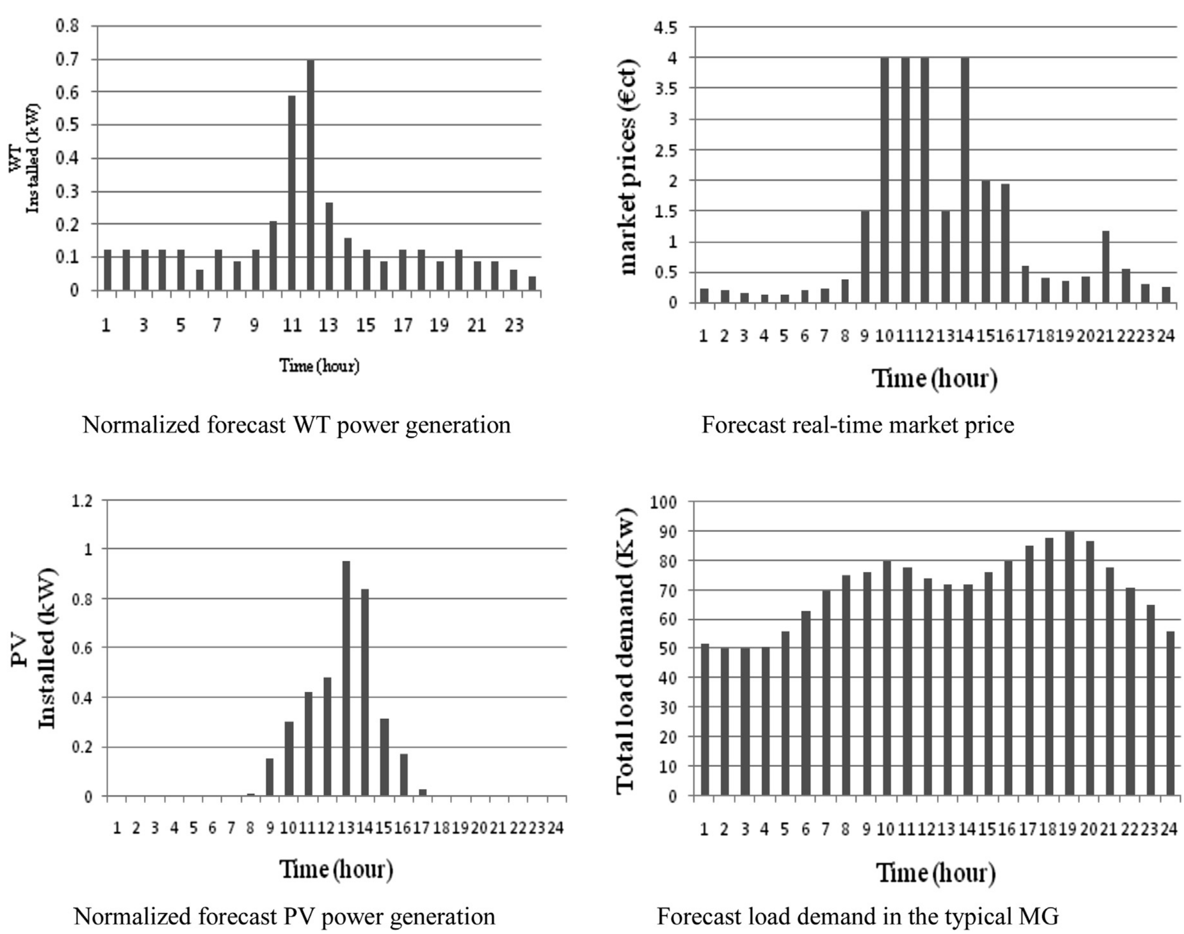

Fig. 6. Forecasted values of the load demand, market price and PV and WT power production [14].

Table 1
The limitations and Bids of RESs and the utility.

Type	Min power (kW)	Max power (kW)	Bid (€ct/kWh)	Start-up/Shut-down cost (€ct)
MT	6	30	0.457	0.96
PAFC	3	30	0.294	1.65
PV	0	25	2.584	0
WT	0	15	1.073	0
Bat	−30	30	0.38	0
Utility	−30	30	–	–

repetition, first we describe the theta version of KH algorithm (θ-KH) here. As mentioned before in the Introduction section, a new version of KH algorithm can be devised that searches for the optimal solution in the polar space instead of the Cartesian space. This idea will convert the feasible search area of each variable to the limited range of $[-(\pi/2), +(\pi/2)]$. As a result, the search process can be done easier with faster convergence. In order to formulate the θ-KH, each krill X_i is replaced by its phase vector θ_i. Similarly, the velocity V_i is replaced by its phase vector $\Delta\theta_i$. Therefore, motions of induction $V^k_{\text{ind},i}$, foraging $V^k_{\text{frg},i}$ and random diffusion $V^k_{\text{diff},i}$ are changed to $\Delta\theta^k_{\text{ind},i}$, $\Delta\theta^k_{\text{frg},i}$ and $\Delta\theta^k_{\text{diff},i}$. Similarly, (14) and (15) can be rewritten as below:

$$\theta_i^{k+1} = \theta_i^k + \Delta\theta^k_{r,i}\rho\sum_{j=1}^{N_v}(u_j - l_j) \tag{16}$$

$$\Delta\theta^k_{r,i} = \Delta\theta^k_{\text{ind},i} + \Delta\theta^k_{\text{frg},i} + \Delta\theta^k_{\text{diff},i} \tag{17}$$

Each of the three motions of induction, foraging and random diffusion are now explained:

Table 2
Comparison of objective function value evaluated for the defined scenarios for 20 trails (deterministic framework).

	Method	Best solution (€ct)	Worst solution (€ct)	Average (€ct)	Standard deviation (€ct)	Mean simulation time (s)
First Scenario	GA [16]	277.7444	304.5889	290.4321	13.4421	–
	PSO [16]	277.3237	303.3791	288.8761	10.1821	–
	FSAPSO [16]	276.7867	291.7562	280.6844	8.3301	–
	CPSO-T [16]	275.0455	286.5409	277.4045	6.2341	–
	CPSO-L [16]	274.7438	281.1187	276.3327	5.9697	–
	AMPSO-T [16]	274.5507	275.0905	274.9821	0.3210	–
	AMPSO-L [16]	274.4317	274.7318	274.5643	0.0921	–
	GSA [34]	275.5369	282.1743	277.8021	2.9283	–
	SGSA [34]	269.7600	269.7600	269.7600	0	–
	HBMO	276.3822	283.493	279.3882	3.2201	12.743
	HS	275.2741	285.4046	279.8321	2.2353	12.842
	KH	274.3740	279.4834	276.1103	2.8764	12.736
	θ-MKH	266.7600	266.7600	266.7600	0	8.003
Second scenario	GA [16]	277.7444	304.5889	290.4321	13.4421	–
	PSO [16]	277.3237	303.3791	288.8761	10.1821	–
	FSAPSO [16]	276.7867	291.7562	280.6844	8.3301	–
	HBMO	275.3823	283.8702	278.4832	4.7703	14.283
	HS	274.5381	282.7473	278.7743	3.7478	13.461
	KH	273.5531	275.3923	274.8372	0.3238	12.213
	θ-MKH	261.2340	261.2340	261.2340	0	8.142
Third scenario	GA [34]	334.8694	345.0211	336.2912	17.6310	14.291
	PSO [34]	327.7211	340.3123	331.2102	13.1244	14.283
	FSAPSO [34]	326.4291	335.4931	331.4301	10.6621	13.281
	GSA [34]	319.6284	331.8401	323.1782	5.0257	3.96
	SGSA [34]	304.1147	304.1873	304.1492	0.0108	1.56
	HBMO	319.3926	331.0954	324.7844	4.7230	13.706
	HS	315.9104	331.3578	320.9722	7.0391	13.832
	KH	317.5642	337.6743	325.8498	7.8844	12.864
	θ-MKH	299.4124	299.4124	299.4124	0	8.233

- Induction motion $\Delta\theta^k_{\text{ind},i}$: This motion simulates the event that the behavior of each krill individual is affected by the neighboring krill:

$$\Delta\theta^k_{\text{ind},i} = \alpha_{\text{ind},i}\Delta\theta^{\max}_{\text{ind},i} + \omega_{\text{ind}}\Delta\theta^{k-1}_{\text{ind},i} \tag{18}$$

$$\alpha_{\text{ind},i} = \sum_{j=1}^{N_s}\left[\frac{f_i - f_j}{f_w - f_b} \times \frac{\theta_i - \theta_j}{|\theta_i - \theta_j| + \varepsilon}\right] + 2\left[\text{rand}(\cdot) + \frac{i}{\text{Iter}}\right] f_i^b \theta_i^b \tag{19}$$

The first term in Eq. (19) is the normalized fitness function value which is multiplied by the induced direction by different neighbors.

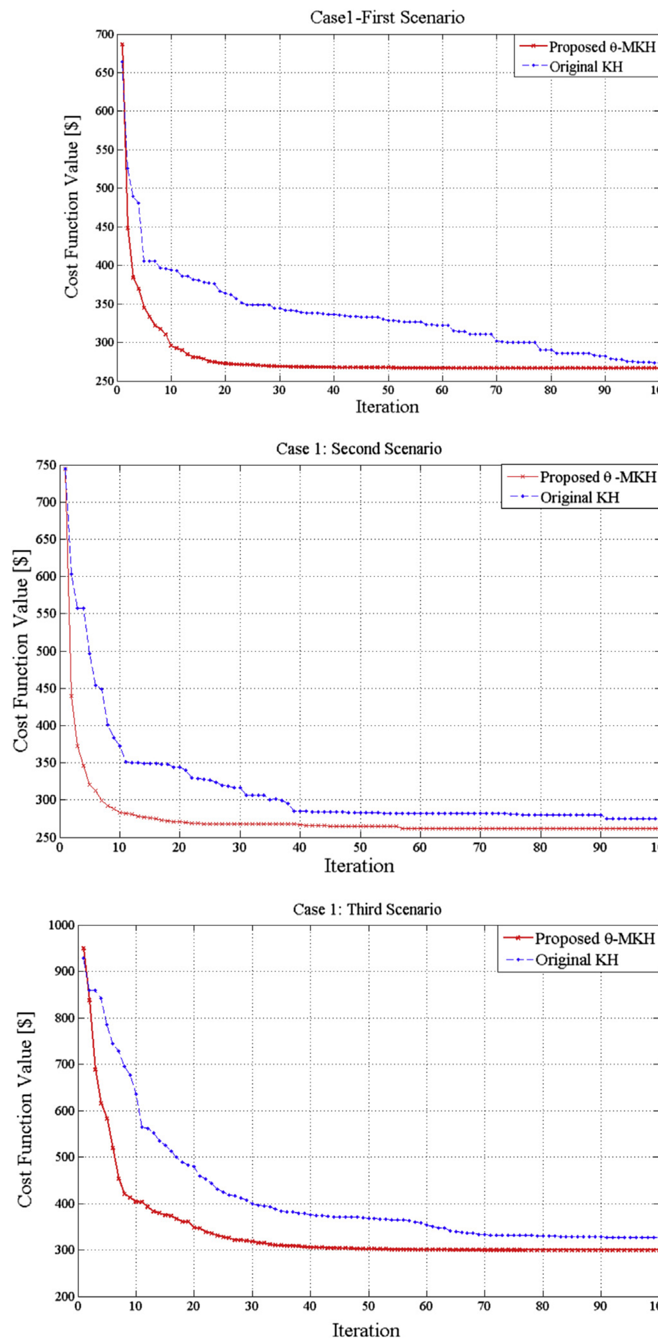

Fig. 7. Comparative convergence diagram of KH and θ-MKH for all scenarios.

Therefore, the neighbors' vector can be attractive or defensive depending on positive or negative sign.

The krill θ_j is in the neighboring of krill θ_i if it is in the below surrounding region:

$$R_{\text{Vicinity}} = \frac{1}{5N_p}\sum_{j=1}^{N_p}\left|\theta_i - \theta_j\right| \tag{20}$$

A schematic representation of the induced distance around each krill is shown in Fig. 3.

- Foraging motion $\Delta\theta_{\text{frg},i}^{k}$: This motion simulates the foraging movement of krill for food. This motion is done based on the food current location and the krill previous experience about the food location as below:

$$\Delta\theta_{\text{frg},i}^{k} = 0.02\left[2\left(1-\frac{i}{\text{Iter}}\right)f_i\frac{\sum_{i=1}^{N_s}\frac{\theta_i}{f_i}}{\sum_{i=1}^{N_s}\frac{1}{f_i}} + f_i^b\theta_i^b\right] + \omega_{\text{frg}}\Delta\theta_{\text{frg},i}^{k-1} \tag{21}$$

According to the above equation, first the center of the food is virtually determined (taken from center of mass) and then the food attraction can be determined.

- Random diffusion $\Delta\theta_{\text{diff},i}^{k}$: This motion simulates a random process in terms of a maximum diffusion speed and a random directional vector:

$$\Delta\theta_{\text{diff},i}^{k} = \upsilon\times\omega_{\text{diff}} \tag{22}$$

The KH algorithm is also equipped with the crossover and mutation operators from GA to improve its population. More information can be found in Ref. [25]. Each time that the objective function should be calculated, the phase vector θ_i should be converted to its Cartesian framework X_i. This process is implemented using the below equation:

$$X_i^k = \frac{X_{\max}-X_{\min}}{2}\sin\theta_i^k + \frac{X_{\max}+X_{\min}}{2} \tag{23}$$

The above formulation is the tool required for calculating the equivalent Cartesian vector for θ_i.

5.2. Modification method

In this section we introduce a two-phase modification method to improve the search ability of the KH algorithm. These two modifications can improve the performance of KH by increasing the diversity of the krill population in each iteration. The first part of the modification method uses the *Lévy flight* technique to make a local search around each krill. By definition, a *Lévy flight* is a random walk in which the step-lengths are distributed according to a heavy-tailed probability distribution [33]. It is demonstrated in the literature that *Lévy flight* has powerful ability in the optimization applications [33]:

$$\theta_i^{k+} = \theta_i^k + \varphi_1 \oplus \text{Lévy}(\Gamma) \tag{24}$$

$$\text{Lévy}(\Gamma)\sim\tau = k^{-\Gamma};\quad \left(1<\Gamma\le 3\right) \tag{25}$$

The second modification method tries to shift the mean of the krill population toward the best krill in each iteration. In this way, at first the mean value of the krill population Mn_K is calculated. Then the position of each krill is updated as below:

$$\theta_i^{k+1} = \theta_i^k + \text{round}\left(1+\text{rand}\right)\left(\theta^b - \text{Mn}_K\right) \tag{26}$$

The above movement will increase the convergence of the proposed algorithm, effectively. The complete flowchart of the proposed θ-MKH algorithm is depicted in Fig. 4.

5.3. Application of θ-MKH to solve the MG operation problem

In order to apply the proposed θ-MKH on the energy management of the renewable MGs, the below steps are required:

Step 1: Input data including the MG data (such as load data, cost of energy, topology, etc), DGs data (including output power of WT and PV and their standard deviation values for stochastic analysis, capacity limits of MT and FC (fuel cell), etc), algorithm data (including initial size of krill population, iteration criterion, adjusting parameters) and PHEV charging data (including the daily charging demand of PHEVs in both residential and public stations). In this step, the hourly charging demand of PHEVs can be determined using the proposed smart charging method as described in Section 2.
Step 2: Convert the constrained optimization problem into an unconstrained one by the use of penalty factors. In this regard, all the equality and inequality constraints are met by applying penalty factors.
Step 3: Generate the initial population of krill. In our problem, each krill is a vector that determines the optimal status and output power of the units as shown in (3). Regarding the θ-MKH, the initial phase angle (θ_i) and relevant incremental angle ($\Delta\theta_i$) for each krill is generated as follows:

$$\begin{aligned}&\theta_{i,j} = \psi_5\left(\theta_{j,\max}-\theta_{j,\min}\right)+\theta_{j,\min};\quad j=1,2,\ldots,N_\nu\\ &\Delta\theta_{i,j} = 0.1\times\theta_{i,j};\quad i=1,2,\ldots,N_p\end{aligned} \tag{27}$$

As described before, in this paper, θ is the phasor scheme of the control vector X.

Step 4: Transition from the phase angle space to the Cartesian space as shown in (23).
Step 5: Evaluate the expected value of the cost function. It is worth noting that considering m random variables in the problem, the $2m$-PEM technique will solve the problem $2m$ times. Here, the expected and standard deviation values of cost function are calculated as described in Section 4.
Step 6: Store the best krill in the population. In this paper, the best krill is the one with the least expected value of the cost function.
Step 7: Apply the modification process as explained in Section 5.1 to each of the krill, separately. In this step, the krill population is updated once.
Step 8: Apply the proposed modification method as explained in Section 5.2. Here the krill population is updated once more.
Step 9: Update the position of best krill and store it.
Step 10: Check the termination criterion. If the termination criterion is satisfied, finish the algorithm, otherwise return to step 7.

6. Simulation results

This section makes use of a typical MG with different types of RESs including an FC, a WT, an MT, a PV and a NiMH-Battery as the storage device. Fig. 5 shows the single line diagram of the MG connected to the main grid through a transformer [16]. The analysis is done for 24 h to determine the optimal output power of each unit at different hours.

DGs are supposed to work at unit power factor, thus no reactive power is produced. The forecast data for load value (neglecting EVs charging demand), market price, PV output power and WT output power are shown in Fig. 6.

The cost of kW power produced by DGs and the main grid and their capacities data are shown in Table 1. Regarding the WT and PV power sources, since they should produce their maximum power after the first time installation (first time capital investment), the MGCC should buy all the power of these DGs at each hour. Meanwhile, this strategy is a useful policy for supporting RESs in the networks.

Regarding the optimization algorithm, the size of the krill population is 25 and the termination criterion is to reach 200 iterations. These values are found after several running of the algorithm experimentally. Other adjusting parameters of the algorithm are taken in the scale from Ref. [25] as follows: maximum induced speed is 0.01, maximum diffusion speed is 0.05, the position constant factor is 0.3 and all the inertia weighting factors including ω_{ind}, ω_{frg} and ω_{dif} are assumed to be 0.8. About PHEVs, one public charging station is supposed in the MG and the residential charging demands of PHEVs are distributed in the other load centers. We have considered similar total charging demand value of 250 kW for charging at residential locations and public station during the day in the MG. As described in Section 2, this 250 kW charging demand can be considered in the MG optimal scheduling problem in either uncontrolled or smart manner. In the case of smart charging of PHEVs, μ_{PHEV}^{min} and μ_{PHEV}^{max} are assumed to be 0 and 50 kW for residential locations and 5 kW and 70 kW for public stations, respectively. Therefore, in order to see the performance of the smart charging strategy as well as the PHEVs effect on the system, three different cases are defined: 1) neglecting PHEVs charging demand in the system, 2) considering uncontrolled PHEVs charging demand and 3) considering smart PHEVs charging demand. For each case, three different scenarios are defined to highlight the performance of DGs, effect of considering start-up or shut-down of DGs and NiMH-Battery role. In this way, the first scenario considers all DGs to operate without shut-down and the battery initial charge is infinitive (enough electricity charge for one day long). The second scenario will let DGs shut down or start up according to the economical preferences and the battery charge is infinitive. The third scenario is similar to the second scenario but the initial charge of the battery is zero. It is clear that the second scenario is the most flexible scenario when the third scenario has a severe limitation on the battery charge and discharge process. In order to see the high ability of the proposed θ-MKH in the optimization process, all the three scenarios of the first case (neglecting PHEVs) are repeated for 20 trails. The analyses are implemented in both the deterministic and stochastic frameworks. The purpose of the deterministic framework is to show the satisfying performance of the θ-MKH.

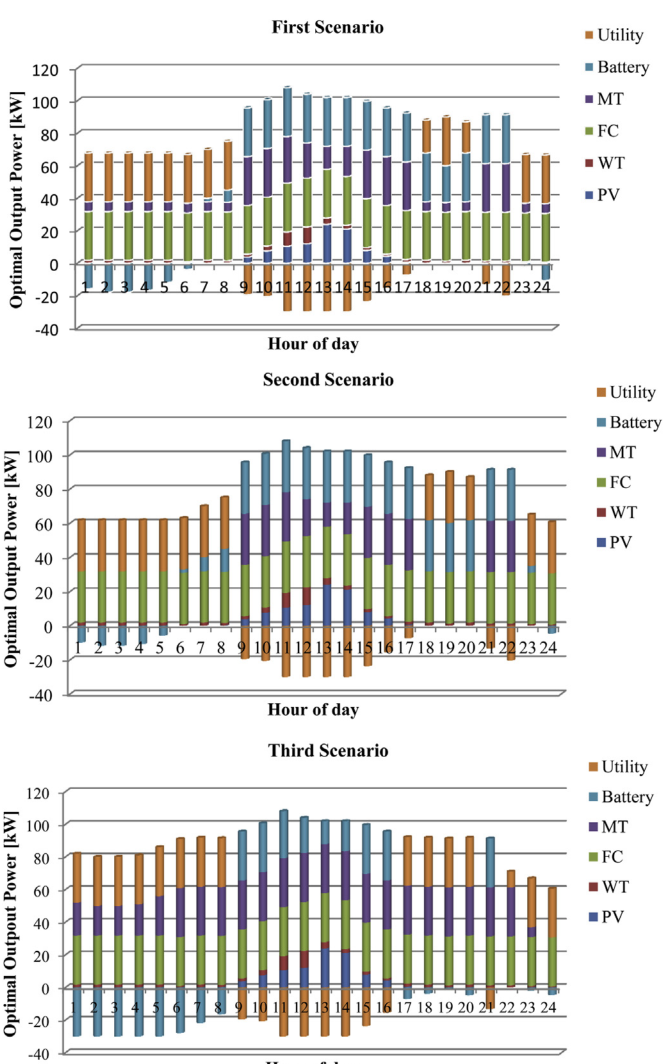

Fig. 8. Optimal operating point of power units in the three scenario of the first case in the deterministic framework.

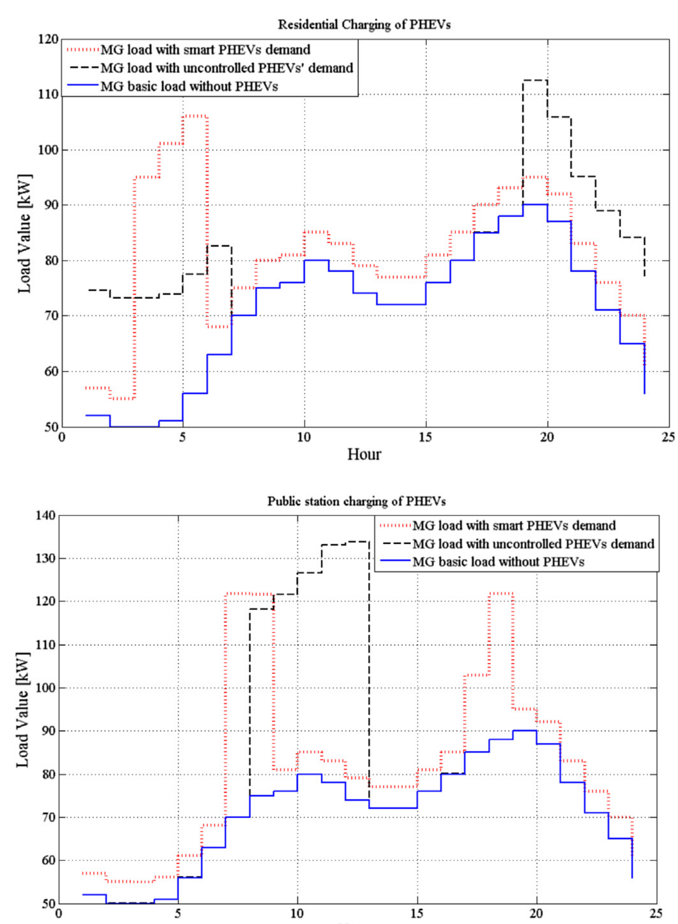

Fig. 9. Load Curve of the MG smart/uncontrolled PHEVs' charging strategy in a) residential places, b) public station.

Therefore, only the first case is simulated in the deterministic framework. Table 2 shows the simulation results for different scenarios of the first case (neglecting PHEVs) in the deterministic framework. For better comparison, the results of other well-known algorithms for optimizing the cost function are shown in Table 2. As it can be seen, the θ-MKH could reach more optimal solution than the other algorithms for all the three scenarios. The second scenario as the most flexible scenario has the least cost value and the third scenario as the most rigid scenario has the most cost. As regards the stability of the algorithms, the results of the best solution, worst solution, average value and standard deviation value for the 20 trails are shown in Table 2. From these results, the high stability of the proposed θ-MKH is deduced easily.

In order to see the high convergence of the algorithm, Fig. 7 shows the comparative plot of the convergence diagram of KH and proposed θ-MKH for the best solution and for all three scenarios. According to the diagrams shown in Fig. 7, the proposed algorithm has successfully converged to the optimal solution in the first iterations.

The optimal output powers of the units for the three scenarios of the first case are shown in Fig. 8. Negative values of power for battery show battery is in the charging mode and negative values of power for the main grid show selling power to the grid. According to Fig. 8, the second scenario has decided to shut down the MT in the first hours for reducing the cost of the MG. Also from the results of the third scenario, it is seen that the battery had to charge in the first hours of the day to be able to discharge at later hours. This event has resulted in incremental cost for the third scenario.

As far, the analysis was implemented in the deterministic framework. From now on, the stochastic framework based on 2m-PEM is employed to model the uncertainties of the random variables. The uncertain parameters of the problem are 1) output power of WT, 2) output power of PV, 3) load demand of the MG, 4) market energy price and 5) PHEVs charging demand. We have considered normal distribution function for modeling the uncertainty of these parameters. It is clear that other PDFs can be used in the similar manner. The standard deviation of the random variables are assumed to be 0.05 for WT output power, 0.04 for PV output power, 0.08 for loads of the MG, 0.03 for market energy and 0.15 for charging demand of PHEVs.

In the first step, the charging demand of PHEVs in both public stations and residential communities should be managed using the proposed smart charging strategy explained in Section 2. As mentioned before and according to Fig. 1, PHEVs tend to be connected to residential chargers through hours 1–6 and 18–6 with higher probability than the other hours. On the opposite point, PHEVs have higher tendency to be connected to chargers at public stations at mid-day hours. These two charging schemes for PHEVs create the "worst case" scenario of coincidental of the peak electrical demand of the grid with PHEV charging demand that is called here as *uncontrolled* charging method. By the use of the proposed smart charging method that was described in Section 2, the above two charging schemes should be amended. According to Eq. (1), this amendment is done according to both the existence coefficient of PHEVs and the electricity cost at different hours. As mentioned before, in this paper, it is supposed that the mean values of the charging demand of PHEVs for both residential and public stations are 250 kW in the area limited to the MG land. Since the load demand of MG is increased, we have increased the maximum power capacity of the utility to 60 kW in Table 1. In other words, the capacities of all power units are kept similar to the first case and just the utility maximum capacity is increased. One significant constraint in the proposed smart charging strategy is that at each hour, the summation of the MG load and PHEVs' maximum charging demand (both residential and public station) should not exceed the maximum power production of the power units (PV, WT, FC, MT, battery and the utility). Fig. 9 shows the comparative loading effect of considering PHEVs' charging demand in both smart and uncontrolled charging methods. According to this Fig. 9, the proposed smart charging method has shifted the PHEVs' charging demand to off-peak load hours with lower cost.

Table 3
Comparison of objective function expected value for the three cases evaluated in the 2m-PEM stochastic frameworks.

Framework	Cost value in scenario 1	Cost value in scenario 2	Cost value in scenario 3
Case 1 (neglecting PHEVs charging demand)	267.3241	262.8736	300.6742
Case 2 (considering uncontrolled PHEVs charging demand)	1022.1814	1016.6576	1046.3222
Case 3 (considering smart PHEVs charging demand)	540.6673	528.2249	682.2380

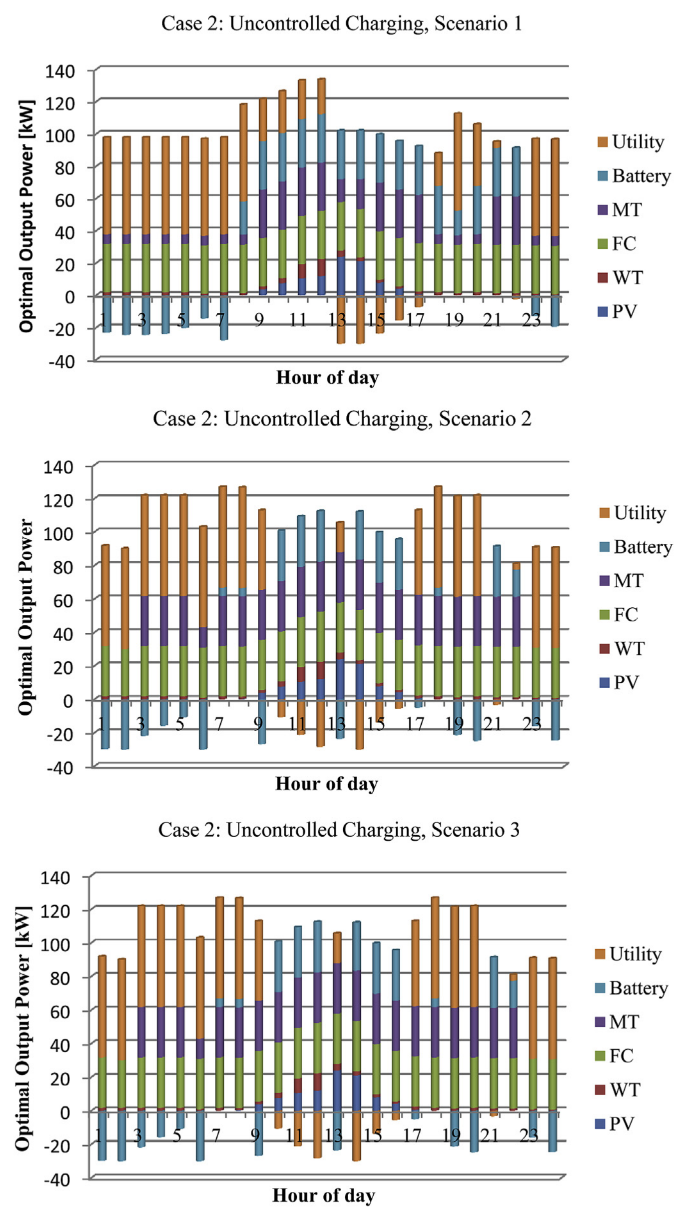

Fig. 10. Optimal operating point of power units in the three scenario of the second case in the stochastic framework.

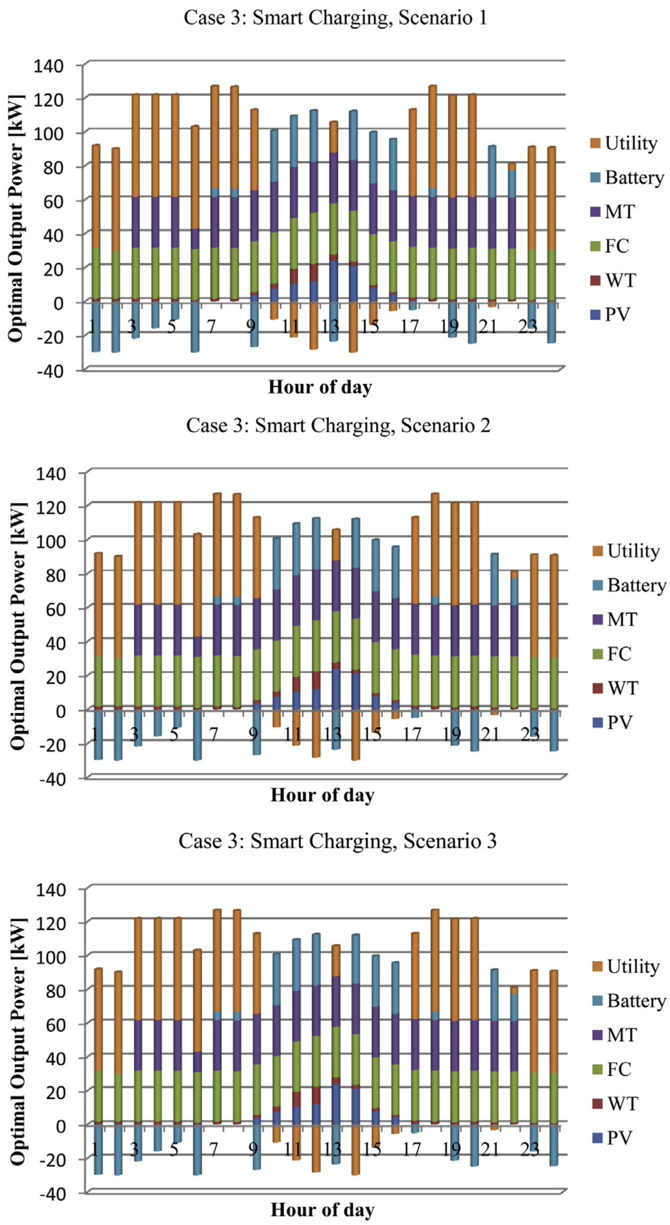

Fig. 11. Optimal operating point of power units in the three scenario of the third case in the stochastic framework.

In the following, the simulation results of the three cases are shown comparatively. According to the results of Table 3, the proposed smart charging method has reduced the total cost of the MG effectively. It should be noted that this amount of reduction in the MG cost is reached just by smart management of the PHEVs demand. This event can result in higher penetration of PHEVs in the system that is a significant goal for the future networks. By comparing the results of Case 1 with those of Cases 2 and 3, it is seen that PHEVs charging demand has resulted in higher cost which could be guessed before. Figs. 10 and 11 show the expected optimal output of power units for Cases 2 and 3 for all scenarios.

7. Conclusion

This paper addressed the impact of PHEVs' charging demand on the renewable MGs from the optimal operation and management point of view. In this way, a smart charging strategy was proposed to manage the charging demand of PHEVs in the public charging stations and residential communities. Also, an intelligent stochastic framework based on 2m-PEM and a new version of KH algorithm called θ-MKH algorithm were suggested. For better understanding, three different cases each having three different scenarios were defined. Also, both the deterministic and stochastic analyses were implemented. The simulation results on a renewable grid-connected MG including different types of RESs such as WT, FC, MT, PV, battery and PHEVs showed the satisfying performance of the proposed intelligent framework. From the optimization view, the proposed θ-MKH could reach more optimal solution for the MG than the other well-known algorithms in the area for all scenarios. According to the results, considering PHEVs in the system using the proposed smart charging strategy can reduce the total cost of the MG notably. This amount of reduction in the cost function value can support the high penetration of EVs in the MG. However, without smart management, the MG cost is increased severely which can even result in loss of some of the loads in the peak-load hours.

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