Signal Processing and Renewable Energy

March 2019, (pp. 67-84)
ISSN: 2588-7327
eISSN: 2588-7335

Optimal Allocation of Electric Parking and Distributed Generation in distribution system Based on Hybrid Water Cycle-Moth Flame Optimizer Algorithm

Mohammad Hadi Guity Navard[1], Hamid Lesani[2*]

[1]Department of Electrical Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran.
[2]School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran.

Received: 07-Dec-2018, Revised: 01-Jan-2019, Accepted: 05-Jan-2019.

Abstract

In this paper optimal allocation of electric vehicles parking and distributed generations (DGs) with objective of minimizing energy costs is proposed by using a hybrid water cycle-moth flame optimizer (WCMFO) algorithm. The purpose of the study is reduction the losses of distribution system, improvement the voltage profile, minimization the distribution system voltage deviations, and reduction the energy received from the main feeder. The optimization problem is implemented on a 33 IEEE bus distribution system. In this study, due to the optimal combination of WCA and MFO methods, WCMFO method is used to solve the problem with high convergence rate. In this study, the proposed method is compared with WCA, MFO and particle swarm optimization (PSO) methods. The simulation results show superiority of the proposed hybrid method in achieving lower cost and high convergence rate. The results show that with the optimal use of electrical parking and also DGs, the system capacity can be released and the level of upstream system dependency can be reduced. It also reduced the amount of system energy not supplied.

Keywords: Distribution system, PHEV Parking Lots, Energy Cost, Water Cycle-Moth Flame Optimizer Algorithm.

1. INTRODUCTION

Distributed generation technologies, which are in fact a source of electrical energy, are directly connected to the distribution system or to the consumer. Furthermore, they have many economic and technical benefits. These benefits cannot be maximized without determining the optimal capacity and location of distributed generation units [1]. Therefore, optimal location of distributed

*Corresponding Author's Email: lesani@ut.ac.ir

generation is one of the most important issues to be considered in the distribution planning problem. A proper decision can give countless benefits to the distribution system, suppliers and consumers. Reducing losses is one of the main objectives that must be considered in finding the capacity and location of DGs [2-3]. Parking operation of electric vehicles reduces the power system costs in load peak conditions. Placing distributed generation resources and parking lots of electric vehicles in a distribution system without technical planning and optimal location will lead to economic problems for the parking investor and technical problems for the distribution system operator. Also, the optimal use of electric vehicles parking lot for power distribution companies is also very important in terms of losses [4-5]. In [6], the distributed charge control method of electric vehicle has been investigated considering the system effects. In [7], the multi-purpose locating of electric vehicle parking lot is done to improve the voltage profile, reliability and cost reduction, regardless of the battery charging model. In [8] parking locating has been done to reduce the power losses of electric vehicles without the vehicle battery needs to be charged. In [9] Genetic algorithm and Monte Carlo simulation are used to locate and determine the capacity of parking lot of electric vehicles and distributed generation sources for vehicle battery charging. In [10], the determination of the capacity and location of parking lot of electric vehicles and distributed generation sources in the system is considered with regard to the uncertainty of wind power and the output of electric parking lot. In [11], an algorithm was presented to optimal manage parking lot of electric vehicles using PSO. The distribution system power quality assessment considering the charging and discharging of parking lot of electric vehicles was studied in [12].

In this paper, the use of electric parking lots is investigated along with solar panels and diesel generators in 33-bus distribution system. The purpose of this study is determining the location and size of solar panels, parking of electric vehicles and diesel generators. In order to solve the optimization problem, we use a hybrid method named water cycle algorithm-moth flame optimizer (WCMFO) [13-14]. Generally, it is shown that the power of hybrid algorithm is strengthened in achieving optimal global and fast convergence. The superiority of the WCMFO is compared with WCA, MFO and also PSO.

2. PROBLEM FORMULATION

The objective is to locate suitable parking PHEV, PV, wind turbine and diesel generator to power management system. The objective is to reduce the overall system cost. The objective function includes the cost of grid energy losses, the cost of energy received from the main power grid, and energy costs provided by the DG during discharge in PHEV parking. Objective function is defined as follows [5, 15]:

$$\begin{aligned}\min f = \sum_{t=1}^{N} \Big[& C_{loss} P_{loss}(t) \\ & + C_{grid} P_{grid}(t) \\ & + C_{UG}\big(P_{UG}\big(P_{UG}(t)\big) \\ & + C_{DS}\,\big(P_{DS}(t)\big) \\ & + C_{PV} P_{PV}(t) \\ & + C_{gr} P_{gr}(t) \\ & + C_{ens} ENS \Big]\end{aligned} \tag{1}$$

where, *C_loss*, *C_grid*, C_{UG}, C_{DS}, *C_PV*, *C_gr*, and *C_ens* are the cost per kW of losses, the cost per kW of power received from the main network, the cost per kilowatt of UG (utility owned diesel units) power, the cost per kilowatt of DS (placed diesel units) power, the cost of each kWh of solar power, the cost of electric parking and the cost of ENS. Also, *P_loss*, *P_grid*, P_{UG}, P_{DS}, P_{PV}, P_{gr}, *ENS*, respectively represent the power losses, power received from the main network, UG power, DS power, solar power generation capacity, electric power parking and energy not supplied. In addition, P_{gr} is the net power of electric parking spaces that is discharged and charged [5, 15],

$$P_{gr}(t) = P_{disch(t)} - P_{\mathrm{ch}}(t) \tag{2}$$

The relationship between the cost of UG diesel engines, which was installed at 33 bus in base mode, is [5, 15]:

$$\mathrm{C_{UG}}\big(P_{UG}(t)\big) = \sum_{i=1}^{NUG}(a_i + b_i P_{UG-i}(t) + c_i P_{UG-i}(t)^2) \tag{3}$$

where, a_i, b_i and c_i are three cost factors of diesel generator. The *NUG* represents the number of *UG* generators. The cost coefficients and production values associated with *UG* diesel were presented in [15]. The number of *UGs* used in the problem is 3, which are assumed to be in bus 2, 5 and 9. Also, the relationship of DS diesels cost is defined as [5, 15],

$$\mathrm{C_{DS}}\big(P_{DS}(t)\big) = \sum_{i=1}^{NDS}(a_i + b_i P_{DS-i}(t) + c_i P_{DS-i}(t)^2) \tag{4}$$

where, *NDS* represents the number of *DS* diesel generators (in this study, number of 4 *DS* diesel engines with the same coefficients were selected for the network). The cost coefficients and production values associated with *DS* diesel were presented in [15].

Problem constraints are explained in following.

- *Constraints for power balance*

$$P_{DG}(t) + P_{grid}(t) + P_{gr}(t) - P_{loss}(t) - P_D(t) = 0 \tag{5}$$

where, P_D is the system load, P_{loss} refers to power loss, Pgr is the power of PHEV and Pgrid received power from the main feeder and P_{DG} , power generation by DGs is defined as follows:

$$P_{DG}(t) = P_{UG}(t) + P_{DS}(t) + P_{PV}(t) \tag{6}$$

PUG is diesel power generators which installed to optimize the system and P_{DS} diesel power generators, scheduled to be installed after optimization [5].

- *Receive feed from the main feeder*

$$\mathrm{C_{grid}} = \mathrm{C_{s1}} \quad \forall \mathrm{P_{grid}}(t) \le P_{grid-max} \tag{7}$$

$$\mathrm{C_{grid}} = \mathrm{C_{s2}} \quad \forall \mathrm{P_{grid}}(t) > P_{grid-max} \tag{8}$$

In this study, a maximum of 30% of the network load per hour can be received from the main network ($P_{grid-max}$ represents the maximum power received from the network). If this is satisfied, according to (7), the cost per kW of power is considered equal to $\mathrm{C_{s1}}$. Otherwise, the power cost for each kilowatt is 10% higher than the amount of $\mathrm{C_{s1}}$, $\mathrm{C_{s2}}$ [5, 15].

- *batteries for PHEV*

The state of charge (SOC) or PHEV battery charge at the moment should be limited between two values.

$$\mathrm{SOC_{min}} \le \mathrm{SOC_i}(t) \le SOC_{max} \tag{9}$$
$$\mathrm{P_{ch}}(t) \le \mathrm{R_{ch}} \tag{10}$$

$$P_{disch}(t) \leq R_{disch} \tag{11}$$

where R_{disch} and R_{ch} indicate the speed of charging and discharging power stored in the battery. SOC or batteries and battery discharge relationship can be expressed as follows (X and Y are binary values) [5, 15].

$$SOC_i(t) = SOC_i(t-1) + P_{ch}(t)X(t) - P_{disch}(t)Y(t) \tag{12}$$

$$Y(t) = \begin{cases} 1 \ if\ the\ batteries\ are\ discharging \\ 0 \ if\ the\ batteries\ are\ not\ discharging \end{cases}$$

$$X(t) = \begin{cases} 1 \ if\ the\ batteries\ are\ charging \\ 0 \ if\ the\ batteries\ are\ not\ charging \end{cases}$$

The values of X (t) and Y (t) can be either 0 or 1. For X (t), the value of 0 and 1 indicate, the lack of charge and the state of charge of the batteries. And, for Y (t), the value of 0 and 1 indicate there is no discharging and discharge mode of the batteries. So, there is the following relationship:

$$X(t) + Y(t) \leq 1 \tag{13}$$

- *The voltage and power constraint*

The voltage and power constraint and also the DGs capacity constraint are as:

$$V_i^{min} \leq V_i(t) \leq V_i^{max} \quad i = 1,2, \dots, nbus \tag{14}$$

$$|S_i(t)| \leq |S_i^{max}| \quad i = 1,2, \dots, nline \tag{15}$$

$$P_{DG-i}^{min} \leq P_{DG-i}(t) \leq P_{DG-i}^{max} \quad i = 1,2, \dots, ng. \tag{16}$$

where, Eqs. (14)-(16) refer to bus voltage, line power and DGs power constraints that V_i^{min} and V_i^{max} is minimum and maximum bus voltage, $S_i(t)$ is power value in line i, S_i^{max} is maximum allowable power of line i, P_{DG-i}^{min} and P_{DG-i}^{max} are minimum and maximum power of DG.

3. SYSTEM ENERGY MANAGEMENT

In energy management plan, the exchange and distribution of power are determined by the availability of solar power units and according to the availability of electric vehicles in parking lots and the amount of SOC vehicles. Total generation size per hour includes the power of solar panels and maximum power supplied by diesel generators (i.e. UGs and DSs). When the total energy generated by the distributed generation sources does not have the potential to supply the entire load, the main feeder has the task of supplying the system (up to 30% of the network charge). For example, if the solar panels are not able to fully load, then the energy stored in the PHEV battery is assisted, and if not enough, diesel generators are used to supply the load [48]. In the absence of full load capacity by solar energy, parking lots and diesel, the rest of the load needs of the main feeder system is provided. On the other hand, if the load demand is less than the total generation and the SOC is less than the maximum SOC, then PHEV batteries will be recharged with allowable charge rates. If (total battery charge production) is greater than zero, then the optimal distribution of the power of diesel system units is determined. Otherwise, if the load demand is greater than the total generation and the SOC is less than the SOC, then the PHEV batteries will be discharged with allowable charge rates.

4. THE OPTIMIZATION PROBLEM

4.1. Water Cycle Algorithm

WCA is originally introduced by Alexander and colleagues in 2012, which is a new super-intelligent algorithm that emulates the

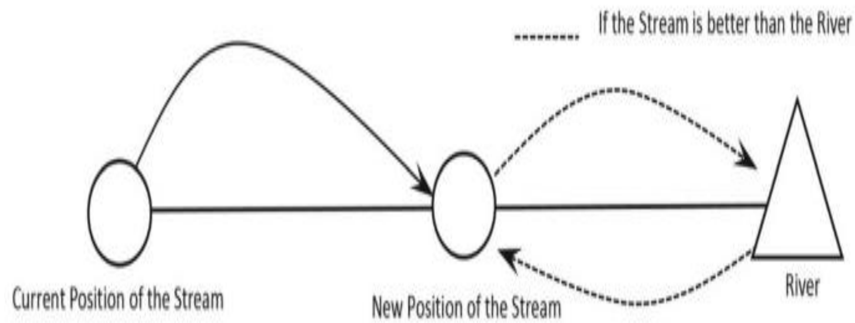

Fig. 1. Update situation of WCA [13].

water cycle of nature to solve optimization problems. The water cycle algorithm is based on strong concept that enables algorithms to effectively solve optimization problems [13].

4.1.1. Water Currents

Like most ultra-intensive algorithms, the WCA uses an array called the water flow to represent decision variables of an optimization problem as follows [13].

$$Raindrop = [x_1, x_2, ..., x_n] \tag{17}$$

where x_1, x_2, ..., xn are decision variables and n is the number of decision variables. The water cycle algorithm is a population-based super-based algorithm; therefore, a set of water currents should first be created as follows [13],

$$\text{Raindrops} = \begin{bmatrix} x_1, & x_2, & \ldots, & x_n \\ x_1, & x_2, & \ldots, & x_n \\ \vdots & & & \vdots \\ x_1, & x_2, & \ldots, & x_n \end{bmatrix} \tag{18}$$

The number of rows is equal to the number of currents in the initial population, which is an initial parameter for the algorithm.

4.1.2. Creating Currents of Water, Rivers and Sea

In the second step, the water cycle algorithm calculates the value of the objective function of each water flow in the initial population, then it arranges these currents relative to their respective target function from best to worst, and the best water flow (first rank in the arrayed population) to title of the sea is chosen. The second to the Nsr-1th streams are known as rivers. Other (Npop-Nsr) are also considered as currents of water (smaller than rivers).

4.1.3. Cold Water Currents to Rivers and the Sea

In order to emulate the flow of water flows and rivers into the sea in nature, the water cycle algorithm uses the following equation to update the river's position to rivers [13],

$$x_{stream}^{i+1} = x_{stream}^{i} + R \times C \times (x_{river}^{i} - x_{stream}^{i}) \tag{19}$$

where, R is a random number between 0 and 1 and it is generated by uniform distribution, and C is a continuous number between 1 and 2. When each water stream updates its position relative to its corresponding river, if the water flow target function in its new position is better than its corresponding river,

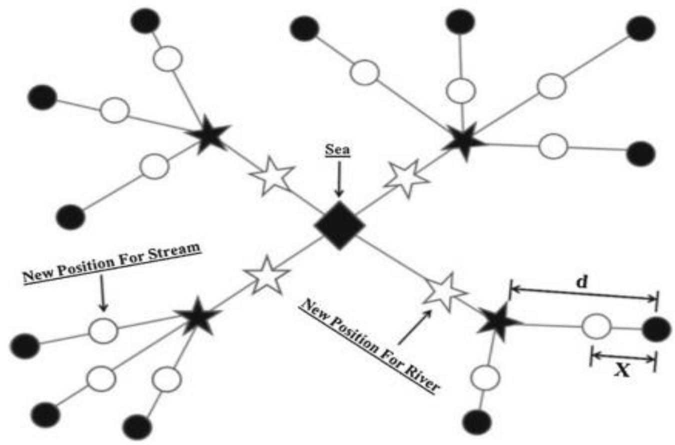

Fig. 2. Water cycle algorithm schematic [13].

the algorithm changes the position of the water flow and the river. To illustrate the process of updating the water cycle algorithm, see Fig. 1.

Note that the water cycle algorithm uses a similar trend to update the position of the rivers to the sea. It is worth noting that the water cycle algorithm allocates water currents to rivers and the sea depending on the intensity of the water flow determined as follows [13].

$$NS_n = round\left(\left|\frac{\mathrm{Cost}_n}{\sum_{i=1}^{N_{sr}} \mathrm{Cost}_i}\right|\right) \times N_{Raindrops} \quad (20)$$

$$, n = 1, 2, ..., N_{sr}$$

4.1.4 Evaporation Conditions

In the water cycle algorithm, evaporation and rainfall conditions are considered to avoid trapping in local optimizations and to increase randomness. Evaporation and rain occur when the distance between the river and the sea is less than dmax; this trend also happens when the distance between each flow of water and sea is less than dmax.

To focus more on exploration, you should consider a large number for dmax, while for exploration, a small amount is preferred for dmax. Therefore, because in first repetitions, the amount of dmax of the wind is large enough to focus on exploration, and in the last repetition it should be small enough to extract the solution space, the dmax value should vary for a period of repetitions. For this purpose, the following equation is used to reduce the amount of dmax linearly over a period of repetitions [13],

$$d_{\max}^{i+1} = d_{\max}^{i} - \frac{d_{\max}^{i}}{\max\ It} \quad (21)$$

where, max *It* is the maximum number of replays.

The precipitation process occurs when the distance between a river or the flow of water and sea is less than dmax to create the new flows such as streams entering rivers and the sea. This process occurs repeatedly to allow stop conditions. Fig. 2 illustrates a water cycle algorithm schematic [13].

4.2 The Moth-Flame Optimization (MFO)

The moths use a mechanism known as transverse orientation for routing. In this way, a moth flies toward moon a license with a constant angle, and the mechanism is very effective to fly in a straight line for very long distances. In this paper, it is assumed that the candidates answer the same butterflies and variables are position of butterflies in space. So, the butterflies in spaces 1 to 3 or even higher-dimensional spaces can fly by changing status [14].
MFO algorithm set of butterflies are expressed in the form of a matrix [14],

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & \cdots & m_{1,\mathrm{d}} \\ m_{2,1} & m_{2,2} & \cdots & \cdots & m_{2,\mathrm{d}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{\mathrm{n},1} & m_{\mathrm{n},1} & \cdots & \cdots & m_{\mathrm{n},\mathrm{d}} \end{bmatrix} \quad (22)$$

where n is the number of licenses and d is the number of variables.

For all the butterflies, the objective function value, is considered as follows [14]:

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ \vdots \\ OM_n \end{bmatrix} \quad (23)$$

A matrix similar to the matrix as follows butterfly is intended for the flames [14],

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & \cdots & F_{1,\mathrm{d}} \\ F_{2,1} & F_{2,2} & \cdots & \cdots & F_{2,\mathrm{d}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{\mathrm{n},1} & m_{\mathrm{n},1} & \cdots & \cdots & F_{\mathrm{n},\mathrm{d}} \end{bmatrix} \quad (24)$$

For all the flames, the objective function value is considered as follows [14],

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ \vdots \\ OF_n \end{bmatrix} \quad (25)$$

Both solutions are the butterflies and flame. The difference between them is how they are updated in every iterations. Search Licenses are real factors that move around the search space, while the butterflies are in the best position ever achieved flames. Flame-license optimization algorithm to approximate the optimal global optimization problems is defined as follows [14],

$$MFO = (I, P, T) \quad (26)$$

In equation (26), I refer the function as an initial population of butterflies and produces a corresponding adjustment values. The function P, which is the main function, makes butterflies move in the search space. T function returns the correct value if the termination criteria are met and if there is no established criteria for termination; it returns false value [14]. With I, P and T, the overall framework for MFO optimization algorithm is defined. The I function produces the initial responses and calculates the objective function value. Each random distribution can be used for this function.

After initialization, P function is carried out until the correct value is performed and so, T function returns right value. P function is the main function that makes the butterflies move in the search space. For mathematical modeling this behavior, the position of each moths to the flame will be updated according [14],

M = S (M_ (i), F_j) (27)

where Mi represents license i, Fj denotes the flame of my j, and S is the spiral function.

Updating butterflies position relative to n different locations in the search space may degrade promising exploration of the best answers. To solve this problem, an adaptive mechanism is provided for the number of flames [14],

$$flame\ no = round\left(N - l * \frac{N-1}{T}\right) \quad (28)$$

where l is the Current number of iterations, N is the maximum number of flames, and T is a maximum number of iterations.

4.3. Hybrid WCMFO Algorithm

As already mentioned, the water cycle algorithm has a great potential for exploring the problem space. In the water cycle algorithm, water flows and rivers update their position to the sea, and this process helps search agents to update their position on the best response. On the contrary, the water cycle Algorithm suffers from the lack of proper operations. Although the MFO optimization algorithm is robust with its spin-ability capability, it is not able to explore the resolution space. This is because each propeller updates its position to its corresponding flame. Therefore, the best-answer information obtained so far by the MFO algorithm is not shared between search factors. The motivation for this research is developing an effective combination of WCA and MFO to take advantages of both algorithms. The proposed hybrid algorithm called WCMFO, the water cycle algorithm is considered as the basic algorithm. The first improvement in the water cycle algorithm is using the rotary motion of the moth to update the position of water flows and rivers. The process of updating the water cycle base algorithm only considers the space between the flow of water and a river when it updates the position of a water stream. In other words, the next position will be the flow of water in the space between the flow of water and its corresponding river. On the contrary, the upgrade process of the MFO optimization algorithm allows the butterflies to update their position anywhere around the corresponding flame. By allowing the flow of water and rivers to update their position with the help of rotating butterflies, the ability to utilize the WCMFO hybrid algorithm increases dramatically.

The improvement of the latter, created in the basic water cycle algorithm, is based on the rainfall process development. As already mentioned, randomization plays an important role in super-search algorithms. To increase randomness in the WCMFO algorithm, two processes are considered. The first is the rainfall process, like the water cycle algorithm. When the distance between a river or the flow of water and sea is less than dmax, the WCMFO algorithm executes the precipitation process to create new responses. The second process is to allow water currents to circulate randomly in the space of the reaction, using a random stroke (flying levy). Consider a repetition of the water cycle algorithm, if the water currents update their position and can't find a better response, then the position of the rivers and the sea will not change until the next repetition. In the WCMFO hybrid algorithm, the water currents are allowed to update their position using levy flying, in order to increase the algorithm randomization,

$$x_{i+1} = x_i + Levy(\text{dim}) \otimes x_i \quad (29)$$

where x_{i+1} is the next position of the water flow, xi is the current water flow and dim dimensions of the problem or the number of decision variables. Fly levy is calculated as,

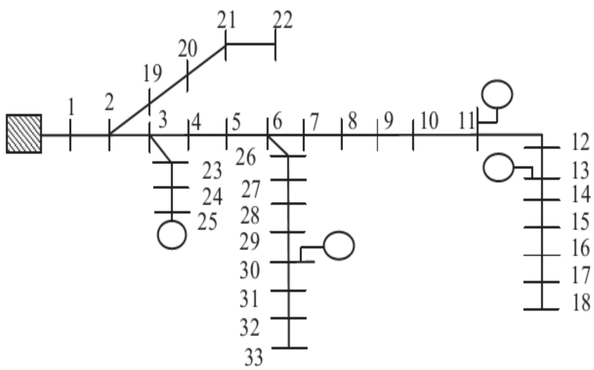

Fig. 3. Single-line diagram 33 bus distribution system [10].

$$Levy(x) = \frac{0.01 \times \sigma \times r_1}{|r_2|^{\frac{1}{\beta}}} \tag{30}$$

where r_1 and r_2 are random numbers between 0 and 1. In Eq. (30), parameter σ is obtained as follows,

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})}} \right)^{\frac{1}{\beta}} \tag{31}$$

4.4. WCMFO Implementation

WCMFO algorithm for solving placement placement PHEV and renewable sources used. Optimization variables include parking installation location or PHEV or DG and the DG capacity.

Problem solving steps are listed in following:

1) produce randomly the initial possible answers.
2) apply energy management and check operation constraints for every license.
3) calculate the results of energy management by using a cost function.
4) select the best answer and change the position of populations.
5) back to step 2 in case of not reaching the last repeat.

5. THE RESULTS OF THE SIMULATION

IEEE standard 33-bus [10] system is selected to implement the proposed method, along with an energy management system. The mentioned system is used to implement electrical parking locating along with distributed generations including solar arrays and diesel units. Fig. 3 shows a single-line diagram of the 33-bus system.

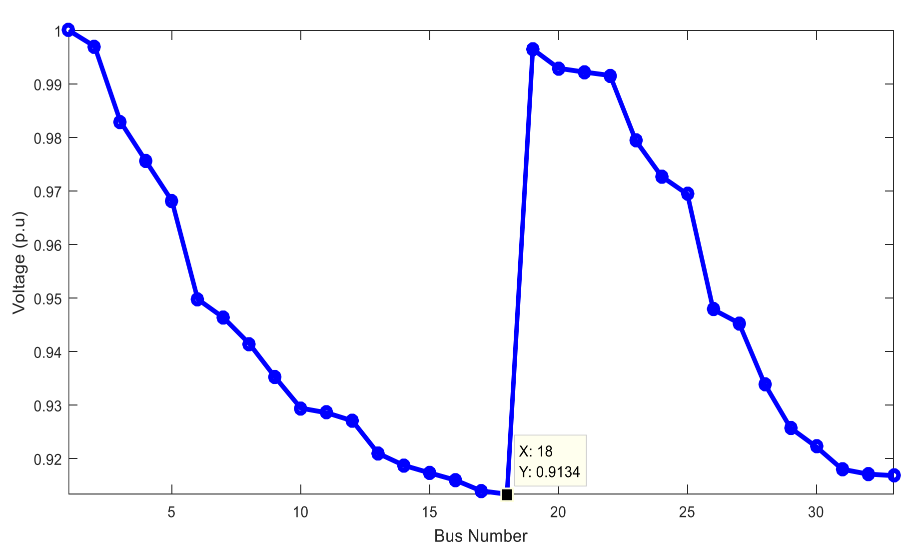

Fig. 4. The 33-bus system voltage profile in base mode.

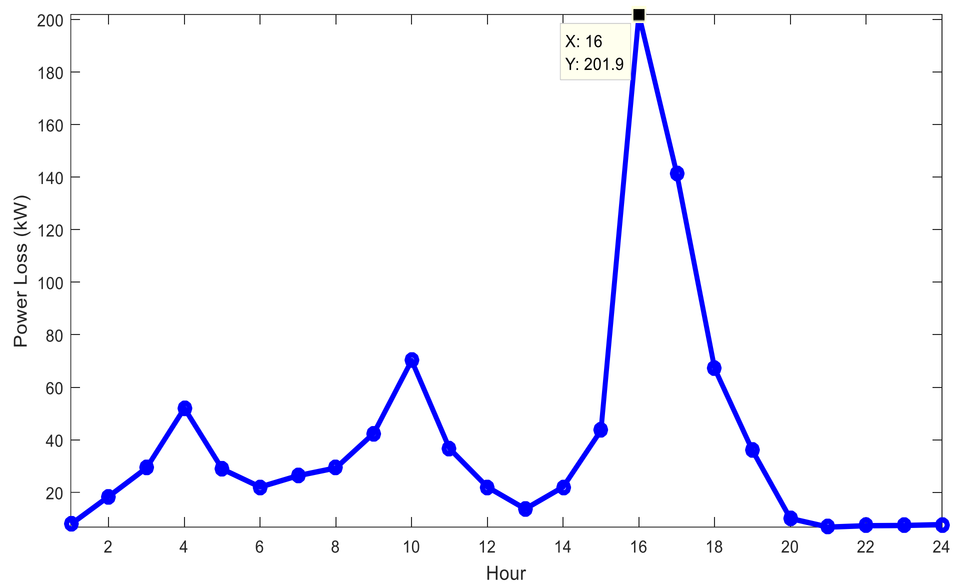

Fig. 5. Network losses in the 33-bus system base.

Table 1. ***Candidate buses for the installation of DGs and electrical parking of 33-bus system [10].***

Candidate Bus	6	8	29	30	27	13	610	--
DG Type	PV	PV	PV	DS	DS	DS	DS	--
Candidate Bus	24	21	31	32	28	17	15	12
Parking Type	G_C	G_C	G_C	G_R	G_C	G_C	G_R	G_R

Table 2. ***The value of the objective function obtained from different methods of the 33-bus system.***

Method	Objective Function Value (M$)
WCMFO	**0.43823**
MFO	0.43827
WCA	0.43845
PSO	0.43833

In the base mode of the system, as shown in Fig. 4, the system voltage profile is plotted in conditions of load peak and the most severe voltage deviation, which the lowest system voltage is 0.9134 p.u in bus 18 which is out of voltage allowed range.

Also, in Fig. 5, the net losses curve is plotted over 24-hours of system load peak. As it is seen, the maximum active losses of system in the base mode without any DG and charge parking are 201.9 MW.

In this section, we present the results of locating DGs and electrical parking’s with the aim of minimizing system costs, using the WCA, MFO and WCMFO combination algorithm. The maximum power of each solar array in the 33-bus system is 200 kW and there is a linear relationship between output power and radiation. In this study, 3 solar arrays with a maximum capacity of 600 kW were used. In Table 1, the candidate buses are expressed for the installation of solar arrays, DS diesel generators and electrical parking. In the 33-bus system, a maximum of four 200 kW diesel generators can be installed. For electrical parking, a maximum of eight commercial and residential parking according to Table 1, can be installed.

The optimization results of the objective function using WCA, MFO and WCMFO algorithms are presented in Table 2. Also, to evaluate the proposed approach, the problem is accomplished by the Particle Swarm Optimization (PSO) method. PSO has very high convergence speed and accuracy as well. The obtained results are compared and analyzed from the viewpoint of the objective function as well as the size of the equipment according to Table 5.3. Each of the

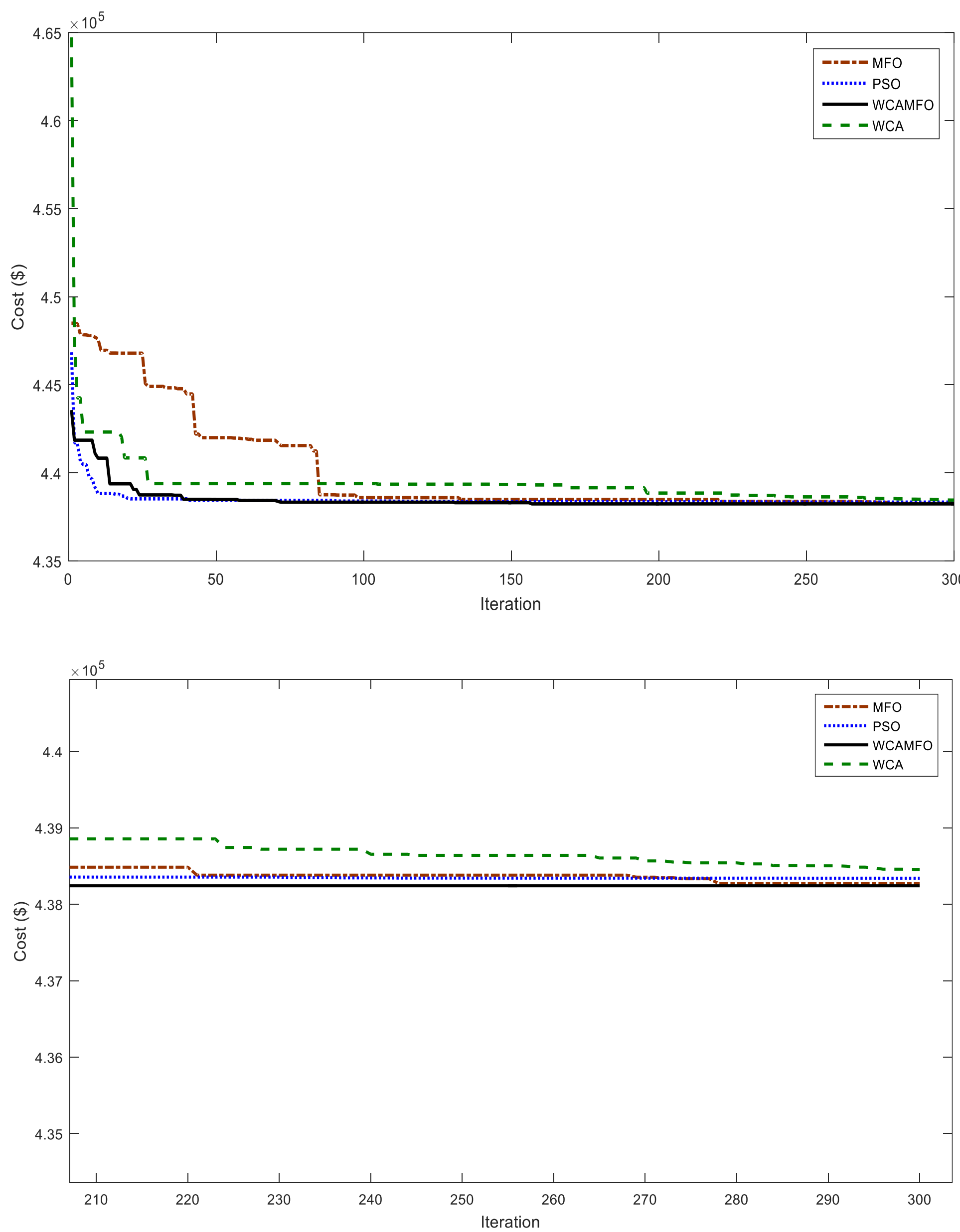

Fig. 6. Convergence curve of the proposed method along with other methods for solving the 33-bus system.

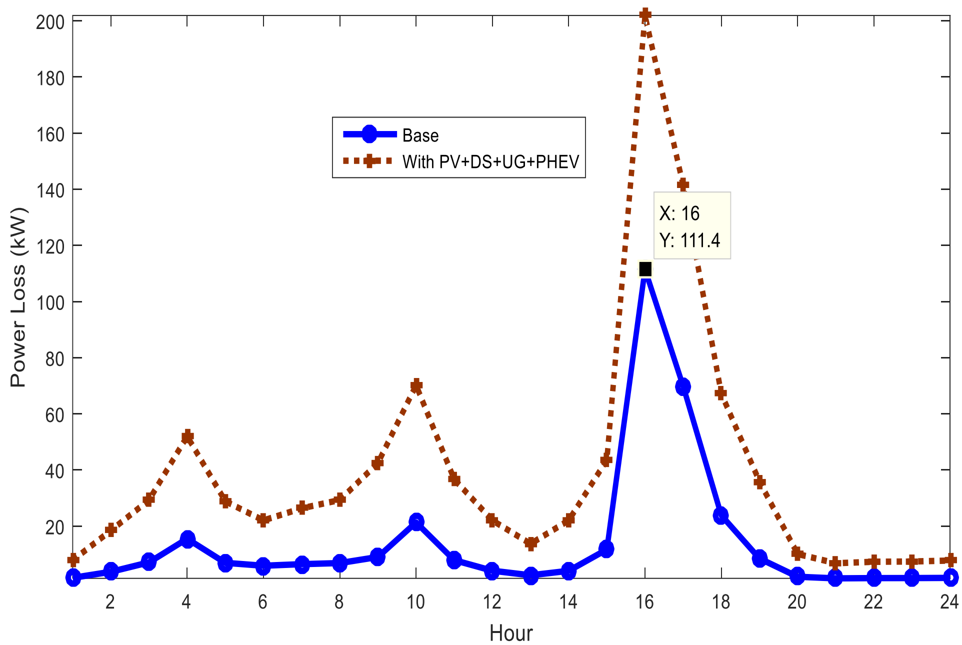

Fig. 7. Power losses curve during 24 hours before and after 33-bus system optimization.

optimization methods have been executed 30 times and the best objective function has been chosen as the best answer for each method. It is observed that WCMFO is able to obtain less cost by using DGs and electrical parking at 0.43823 million dollars. Also, the convergence curves obtained from different methods are shown in Fig. 6 where WCMFO has been able to achieve approximately less cost per 300 iterations. Combining WCA and MFO methods decrease the convergence tolerance of the combined algorithm.

The optimum size of the system components, including the size of solar arrays, DS diesels, as well as electrical parking obtained by various optimization methods, is presented in Table 3. In the proposed method, one PV is installed in the bus 29 with a maximum capacity of 200 kilowatts. 4 parking lots are also installed at buses 15, 12, 31 and 21 with 1131, 1003, 1075 and 1138, automobile respectively, in the 33-bus system. In addition, there is 2 DS diesel at buses of 13 and 30 each with a capacity of 200 kilowatts.

After applying the results of the proposed algorithm to the 33-bus system, the system is considered for power and voltage losses during 24-hours of load peak. In the base state, the total number of losses during 24 hours was 950.39 kW which after optimization, the amount of losses has fallen to 335.93 kW (64.65 % drop. The active power losses during 24 hours are plotted in Fig. 7, the highest amount of losses is at 16 o'clock which has dropped from 201.9 kilowatt to 111.4 kW and showed 44.82% improvement.

Without using DGs and electrical parking in the 33 bus system, at 4, 10, and 16 oclock, the voltage has dropped out of allowed range. After optimal use of solar arrays, diesel generators, as well as electric parking places, the voltage was at normal range for all 24

Table 3. ***Location, equipment type and capacity obtained from 33-bus different system optimization methods.***

MFO			PSO		
Capacity	Installation Bus	Component	Capacity	Installation Bus	Component
167	6	PV	153	6	PV
130	8	PV	91	8	PV
165	29	PV	1189	12	G_R
1735	12	G_R	1463	15	G_R
1343	17	G_C	1329	31	G_C
1300	26	G_C	1684	24	G_C
863	31	G_C	200	30	DS
819	21	G_C	--	--	--
200	10	DS	--	--	--
WCAMFO			WCA		
Capacity	Installation Bus	Component	Capacity	Installation Bus	Component
200	29	PV	197	8	PV
1131	15	G_R	1808	15	G_R
1003	12	G_R	1494	17	G_C
1075	31	G_C	316	28	G_C
1138	21	G_C	573	32	G_R
200	13	DS	1923	31	G_C
200	30	DS	200	13	DS
--	--	--	200	30	DS

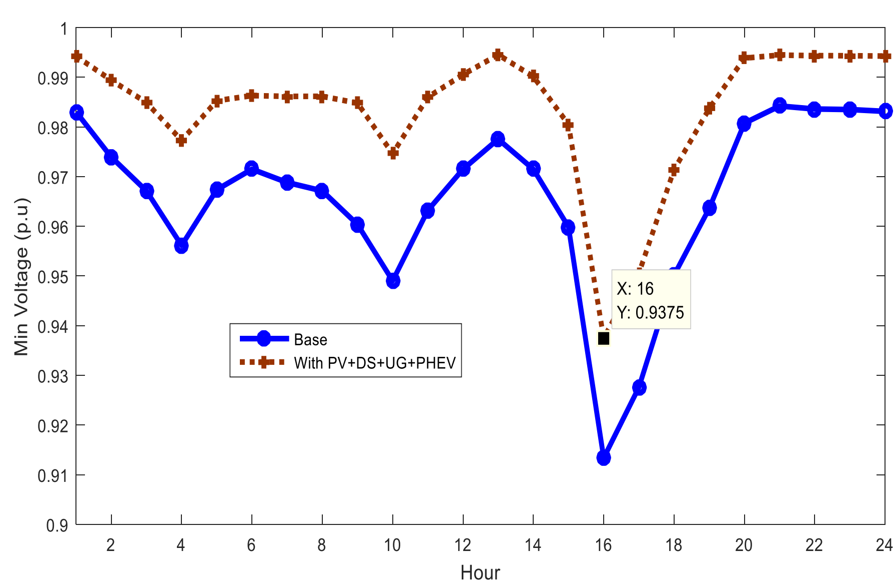

Fig. 8. The minimum voltage profile curve at 33-bus system for base and optimum mode.

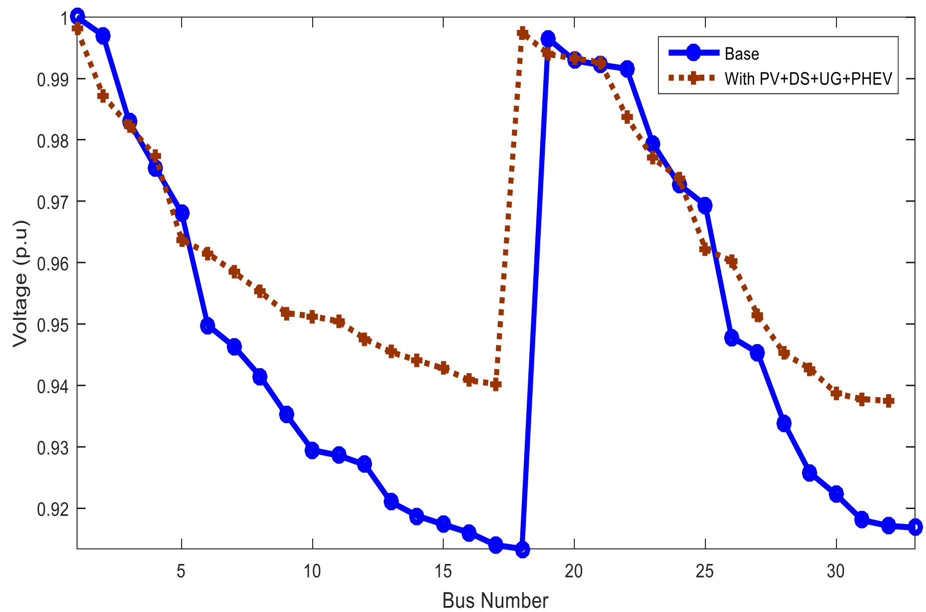

Fig. 9. The voltage profile of system buses in peak conditions and worst case of 33-bus system.

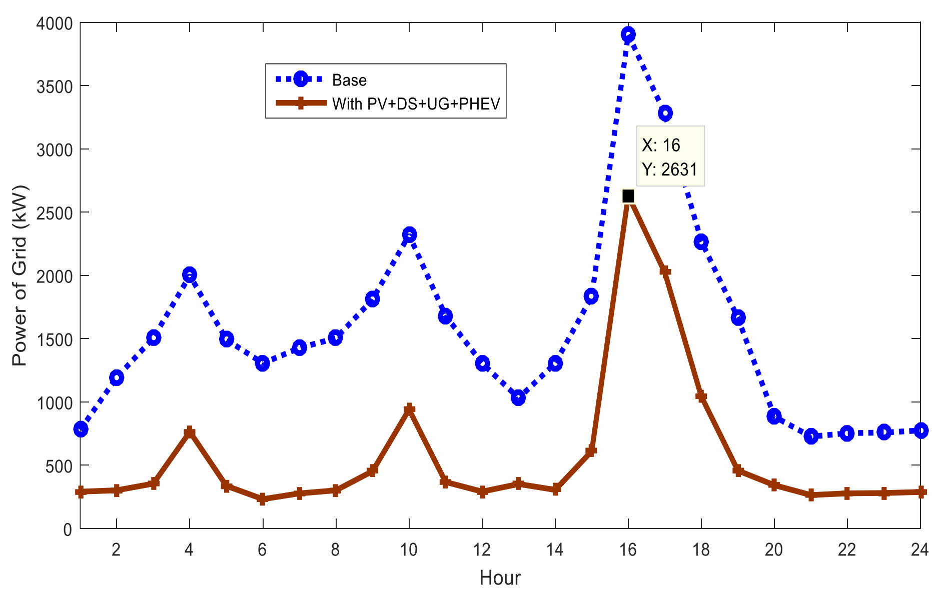

Fig. 10. Power received from the main feeder over day and night in the 33-bus system.

hours and the minimum voltage increased from 0.9134 p.u to to 0.9375 p.u (see Fig. 8). In addition, the voltage profile of the system buses is plotted in Fig. 9 at load peak hour occured at 16 o'clock.

As results show, using optimization makes the voltage profile smooth and improves the system performance significantly. In Fig. 10, the power purchased from the upstream system is presented. Prior to optimization, at 71% of the day time, the allowed ceiling of the power received from the main feeder (1.110 MW) is not met and all system loads and system losses are provided from the main feeder. After

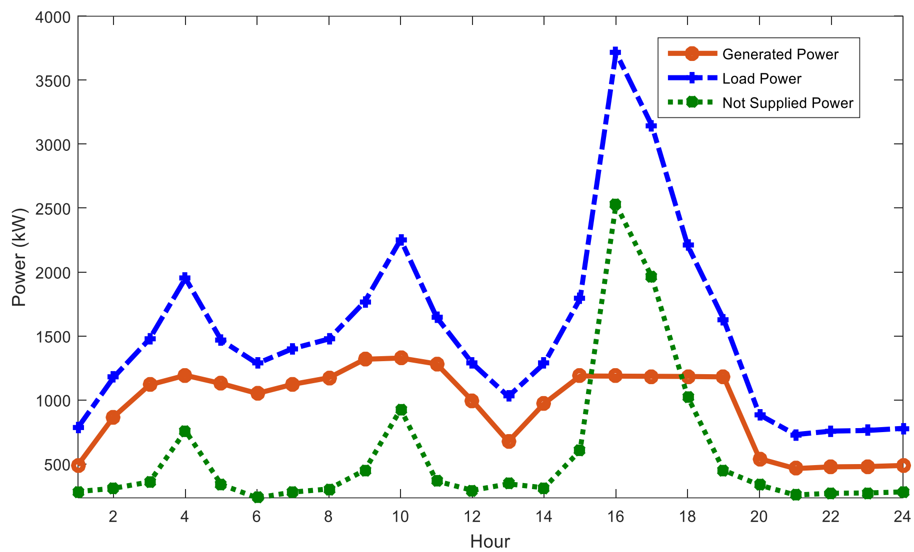

Fig. 11. Generated power in the system by distributed generation sources and electrical parking of 33-bus system.

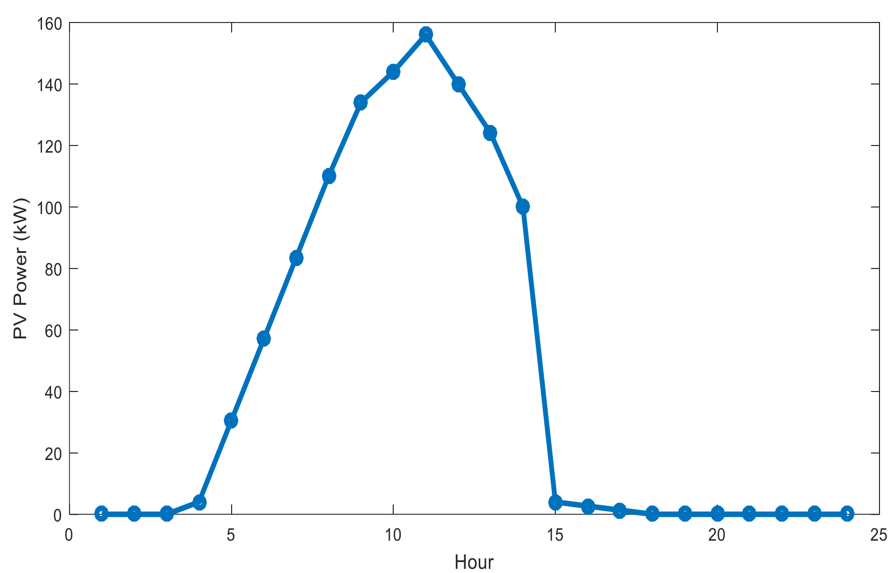

Fig. 12. Generated power of solar panels at different hours on the 33-bus system.

optimizing and installing DGs and energy management of electrical parking of automobile, only at 16 o'clock this allowable ceiling of the power received from the feeder has been violated because of the system's load peak.

In optimization mode, some system loads are supplied by distributed generation sources and electric parking lots and the remaining is received from the main feeder. Fig. 11 shows the total grid load and the total power generated by DGs and electrical parking lots, as well as the power not provided by system subscribers. In most cases, the installed DG resources are not

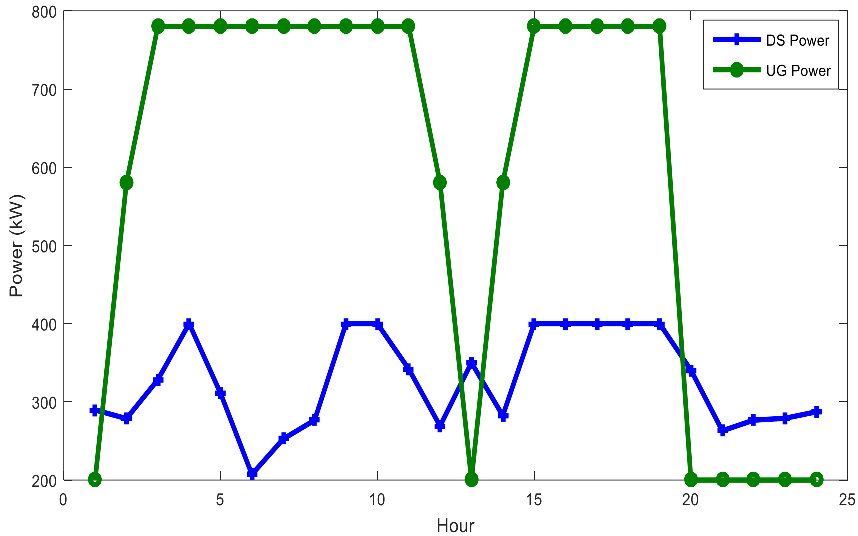

Fig. 13. The power generated by UG and DS diesel generators on 33-bus system.

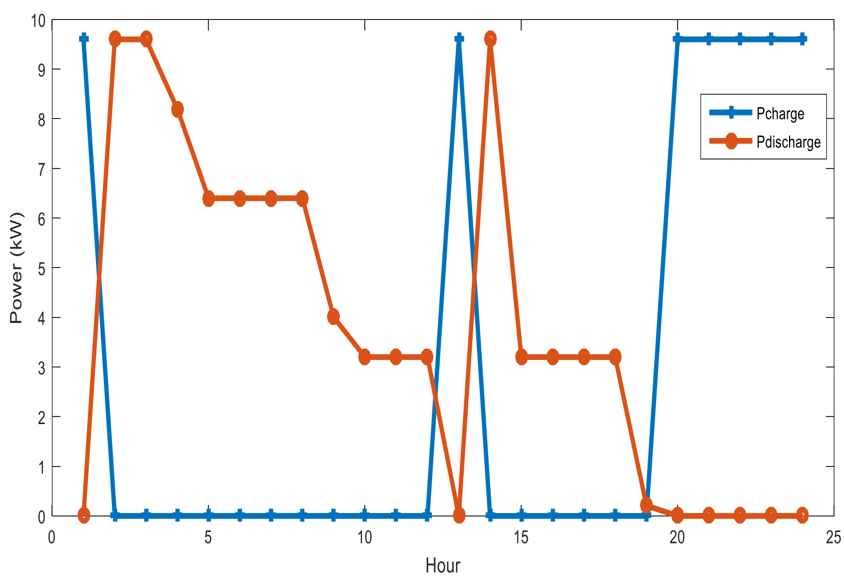

Fig. 14. The charged and discharged power by cars in PHEV parking lots of 33 bus system.

sufficiently able to supply hourly load especially in load peak hours. Also in Fig. 11, the lack of need of subscribers is very clear with the green line, especially at 16 o'clock. In this case, the program has the ability to buy more power from the upstream system to supply the load with higher probability. As the cost of power purchased from the system should be minimized, there is a trade-off between the cost and the ability to supply customers load.

Fig. 12, shows the power curve of solar arrays over 24-hours period. Solar arrays generate power during mid-day hours and at 60% of the day and night, they cannot generate the power.

When the power of solar arrays cannot respond to load demand; diesel generators enter the circuit and inject the power into system. Fig. 13 shows the power generated by the DS and UG diesel generators. The UG diesels engine have a maximum of 780 kW and according to the optimum DS diesel capacity obtained by the WCMFO method, with 2 selected diesels, a maximum of 400 kW have injected into system.

Fig. 14 illustrates the charging and discharging curves of electric parking spaces. As the charging and discharging of cars at different hours is done and the parking lots are discharged at the peak hour (16:00), the DG, and power generation should continue working until 19:00. And the car battery charge has to be reached its minimum and at 19 o'clock later. When the system load has dropped, Electrical parking have been recharged again.

6. CONCLUSION

In this paper optimal allocation of electric parking, diesel units and also solar panels is presented in a radial distribution system with the objective of energy costs reduction. For this purpose, hybrid WCMFO algorithm is proposed. In this study, the optimization variables are considered as the optimal location, the size of the electric parking, diesel units and solar panels. The proposed method is implemented on the 33 bus distribution system. To evaluate the performance of the hybrid WCMFO method, the problem is compared and analyzed using WCA, MFO and PSO algorithms. Simulation results showed that the proposed method in optimization problem yielded a better objective function, and less energy cost in comparison with other methods. The simulation results showed that with the optimal location of electric parking lots and distributed generations, the system losses are significantly reduced and the power purchased from the main feeder after optimization has decreased significantly. In addition, it is observed that the system voltage profile is improved and the ENS of customers is reduced.

REFERENCES

[1] Markel, A. J., Bennion, K., Kramer, W., Bryan, J., & Giedd, J. (2009). Field testing plug-in hybrid electric vehicles with charge control technology in the xcel energy territory (No. NREL-TP-550-46345). National Renewable Energy Laboratory.

[2] Tang, Y. (1996). Power distribution system planning with reliability modeling and optimization. IEEE Transactions on Power Systems, 11(1), 181-189.

[3] Pepermans, G., Driesen, J., Haeseldonckx, D., Belmans, R., & D’haeseleer, W. (2005). Distributed generation: definition, benefits and issues. Energy policy, 33(6), 787-798.

[4] Quinn, C., Zimmerle, D., & Bradley, T. H. (2012). An evaluation of state-of-charge limitations and actuation signal energy content on plug-in hybrid electric vehicle, vehicle-to-grid reliability, and economics. IEEE Transactions on Smart Grid, 3(1), 483-491.

[5] El-Zonkoly, A., & dos Santos Coelho, L. (2015). Optimal allocation, sizing of PHEV parking lots in distribution system. International Journal of Electrical Power & Energy Systems, 67, 472-477.

[6] Karfopoulos, E. L., & Hatziargyriou, N. D. (2013). A multi-agent system for

controlled charging of a large population of electric vehicles. IEEE Transactions on Power Systems, 28(2), 1196-1204.

[7] Moradijoz, M., Moghaddam, M. P., Haghifam, M. R., & Alishahi, E. (2013). A multi-objective optimization problem for allocating parking lots in a distribution network. International Journal of Electrical Power & Energy Systems, 46, 115-122.

[8] Shariatpanah, H., Sabourikenari, M., Mohammadian, M., & Rashidinejad, M. (2012, May). Optimal placement and determine parking capacity of electric vehicles to improve VSM and congestion. In Smart Grids (ICSG), 2012 2nd Iranian Conference on (pp. 1-6). IEEE.

[9] Moradijoz, M., Ghazanfarimeymand, A., Moghaddam, M. P., & Haghifam, M. R. (2012, May). Optimum placement of distributed generation and parking lots for loss reduction in distribution networks. In Electrical Power Distribution Networks (EPDC), 2012 Proceedings of 17th Conference on (pp. 1-5). IEEE.

[10] Liu, Z., Wen, F., & Ledwich, G. (2011). Optimal siting and sizing of distributed generators in distribution systems considering uncertainties. IEEE Transactions on power delivery, 26(4), 2541-2551.

[11] Su, W., & Chow, M. Y. (2011, July). Performance evaluation of a PHEV parking station using particle swarm optimization. In Power and Energy Society General Meeting, 2011 IEEE (pp. 1-6). IEEE.

[12] Clement-Nyns, K., Haesen, E., & Driesen, J. (2011). The impact of vehicle-to-grid on the distribution grid. Electric Power Systems Research, 81(1), 185-192.

[13] Khalilpourazari, S., & Khalilpourazary, S. (2017). An efficient hybrid algorithm based on Water Cycle and Moth-Flame Optimization algorithms for solving numerical and constrained engineering optimization problems. *Soft Computing*, 1-24.

[14] [Mirjalili, S. (2015). Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. *Knowledge-Based Systems*, *89*, 228-249.

[15] El-Zonkoly, A. (2014). Intelligent energy management of optimally located renewable energy systems incorporating PHEV. *Energy Conversion and Management*, *84*, 427-435.