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Optimal siting and sizing of renewable energy sources and charging stations simultaneously based on Differential Evolution algorithm

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ABSTRACT

Electric Vehicles (EVs) are seen to have some negative impacts on microgrid performance, such as diminishing power quality and efficiency and increasing power losses, voltage variations and even customer energy prices. This paper proposes a new method for evaluating the effect of integrating a large number of EVs on a power system and their impact on the network voltage profile via injecting reactive power into highly-loaded buses. A multi-objective optimization problem is developed to obtain the optimal siting and sizing of charging stations and renewable energy sources (RES). The optimization problem focuses on reducing power losses, improving voltage stability of the system and reducing charging costs of EVs. In order to increase the network load factor some coefficients are introduced. Such coefficients, which depend on wind speed, solar irradiance and hourly peak demand ratio in the load characteristic of day-ahead, help aggregators to charge their EVs in off-peak hours. Differential Evolution (DE) algorithm is used for solving the optimization problem. The performance of the proposed method is evaluated for 69-bus and 94-bus microgrids.

Introduction

Governments and industries are moving toward the use of clean energy sources and reducing environmental pollution. This movement has increased attention toward Distributed Generation (DG) using unconventional and renewable energy sources connected locally to the distribution system. However, adverse impacts of these resources on the grid structure and operation are inevitable. In order to reduce the negative impacts of DGs and to make conventional grids more effective for large-scale systems microgrids have been developed [1].

Renewable energy sources are considered as an important supply alternative for Microgrids. Although the cost of energy from conventional sources is generally lower than that of renewable energy sources a proper supply-mix of renewable energies and fossil fuels can reduce the overall cost of energy in a microgrid [1]. Thus it is essential to examine energy supply options available in Microgrids and to determine the optimal supply mix so that maximum benefits can be achieved. Renewable energy sources combined with EVs provide significant benefits; however, increasing the number of EVs is likely to adversely impact the microgrid performance, such as reducing power quality, increasing power losses and voltage variations, and increasing customer energy prices. Meeting the high demand arising from charging of EVs and satisfying the microgrid operating constraints and reducing the system losses are major issues for distribution operators.

Several studies have looked at the design of optimal hybrid renewable-based microgrids for isolated systems. In [2], an aggregator is proposed as a smart control interface between grid and vehicles. It plays the role of coordinating the charge and discharge operation of multiple vehicles in order to provide the maximum amount of power capacity for a regulation service. The study of [3] discuses different approaches to reduce fuel usage and to minimize CO_2 emission while a high degree of reliability and power quality for Microgrids are considered. A methodology for the design of Microgrid with renewable energy sources is proposed in [4]. The study of [5] looks at control mechanisms for charging demand of electrical vehicles to avoid charging during peak hours. A stochastic modeling for aggregated electrical vehicles and their impact on the optimal load profile of power network is dicussed in [6]. In [7] time-of-use price is utilized for finding optimal charging loads and minimizing charging cost in a regulated market. The study of [8] uses National Household Travel Survey data to expand a probabilistic model for EV loads. Centralized charging of EVs is

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Nomenclature

i,j	bus indices
t	time indice
k	EV index
m	charging station index
P_{loss}	active power losses
P_{gi}	generated active power at bus i
Q_{gi}	generated reactive power delivered to bus i
P_{di}	demand active power at bus i
Q_{di}	demand reactive power at bus i
P_{dc}^{PHEV}	discharging power of an EV
P^{PHEV}	EV charger output active power
Q^{PHEV}	EV charger output reactive power
P_{sub}	power substation
$P_{Station}$	output power of the charging station
P_{Mwind}	output power maximum of wind plant
P_{Mpv}	output power maximum of solar energy
$P_{wind,t}$	output power hourly of wind plant
$P_{pv,t}$	output power hourly of solar energy
P_{Rate}	charged power rate of EV
Y_{ij}	magnitude of the ijth element of admittance bus matrix Y
V_i	magnitude of bus i complex voltage
V_{min}	minimum bus voltage
V_{max}	maximum bus voltage
NB	number of buses
Nst	number of charging stations
Nr	number of lines
δ_i	phase angle of voltage at bus i
θ_i	phase angle of the ijth element of admittance bus matrix Y
$\lvert s_i\rvert$	apparent power at line i
$\lvert s_i^{max}\rvert$	maximum apparent power at line i
C_{SM}	maximum capacity of station
$C_{Station}$	capacity of station
c_p	market price of electricity at off-peak times
$P_{dc,min}^{PHEV}, P_{dc,max}^{PHEV}$	min/max active power discharging capacity of EV
$Q_{dc,min}^{PHEV}, Q_{dc,max}^{PHEV}$	min/max reactive power discharging capacity of EV
$P_{min}^{PHEV}, P_{max}^{PHEV}$	min/max active power charging capacity of EV
$Q_{min}^{PHEV}, Q_{max}^{PHEV}$	min/max reactive power charging capacity of EV
$P_{min}^{RES}, P_{max}^{RES}$	min/max active power capacity of RES
P_i^{RES}	active power of RES at bus i
$T_{m,t}$	time duration for charging EVs of each charging station
t_{disp}	time duration for discharging power of vehicle to grid of each charging station
c_v	Market price of electricity
n_{PHEV}	number of vehicles at each time interval
D_{max}	maximum demand of load
D_t	demand of load during hour t
f_{ch}	Cost of charging EVs
f_{dc}	Benefit of discharging EVs
β	rated electrical power
v_I	cut-in wind speed
v_r	rated wind speed
v_o	cut-out wind speed
v_t	wind speed during hour t
P_S	output power from the PV module
P_{rated}	rated power output of the PV module
R_t	solar radiation during hour t
$R_{standard}$	radiation under standard test condition (1 kw/m^2)
αp	temperature coefficient of power
Tpv	panel temperature
$T_{standard}$	panel temperature under standard test condition (27 °C)

discussed in [9] to minimize power losses of Microgrid using three different objective functions and simplified travel actions.

In [10], a method is proposed for optimal scheduling of active and reactive power of EVs based on a two step procedure. In the first step, the method performs the active power scheduling aimed to minimize the overall costs that aggregators need to cope for charging. In the second step, the method performs reactive power scheduling aimed to minimize the deviation of the bus voltages from the preferred values. In [11], a model for integration of grid connected vehicles to utility grid is presented.

The study of [12] looks at economic aspects of integrating EVs into power markets. A stochastic model for aggregated EVs and their impact on the optimal load profile of power network is presented in [13]. A novel technique is proposed in [14] for testing integrated power and transportation parts in order to establish the charging station. The study of [15] discusses charging station requirements, such as EV supply equipment, type, location and their quantities based on operation costs.

The impact of different charging stations on two different areas of the United States with two dissimilar area power system capacities are examined in [16]. Optimal capacity and location of charging stations along with expansion of microgrid are given in [17]. The results of [18] highlight the importance of charging strategies on reducing operation costs.

This paper proposes a new method for evaluating the effect of integrating a large number of EVs on a power system and their impact on the network voltage profile via injecting reactive power into highly-loaded buses. A multi-objective optimization problem is developed to obtain the optimal siting and sizing of charging stations and renewable energy sources (RES). The optimization problem focuses on reducing power losses, improving voltage stability of the system and reducing charging costs of EVs. Differential Evolution (DE) algorithm is used for solving the optimization problem.

The contributions of this paper can be outlined as follows:

- An optimal solution for both technical and economic aspects of RES and charging station operation are provided simultaneously. (The siting and number of EVs of each charging station and siting of RES are the problem variables.)
- A multi-objective function including power losses, network voltage deviations and charging costs are proposed to formulate the paper problem.
- A heuristic optimization method, Differential Evolution (DE), is provided to solve the paper problem.

The paper is structured as follows. Firstly, it presents the problem formulation. Then the paper provides system modeling. This is followed by providing a heuristic method to solve the proposed model. Finally, numerical simulations of optimized charging stations are presented and compared with the typical charging scenario.

Problem formulation

The sizing of DGs and active power demand from the charging of the EVs are decision variables of our optimization problem with a nonlinear objective function and equality and inequality constraints. The aim of the proposed objective function is the reduction of power losses, improving voltage stability of the system in a given microgrid and also minimization of charging costs of EVs.

Mathematically, the objective function is formulated as a weighted sum of all three objectives:

$$\mathrm{Min}\, F_T = \tau f_1 + \beta f_2 + \zeta f_3 \tag{1}$$

where τ, β and ζ are weighting coefficients adjusted according to the importance of each objective function. It is assumed that $\tau = 0.5, \beta = 0.3$ and $\zeta = 0.2$. It might be noted that each objective function in equation (1) is normalized via dividing by its base value calculated prior to the optimization process. This normalization makes the objective function dimensionless and it also prevents any scaling problem.

Power losses

The active power losses, f_1, of the network can be formulated as follow,

$$f_1 = P_{loss} \tag{2}$$

where P_{loss} can be calculated by,

$$p_{loss} = \sum_{t=1}^{24}\sum_{i=1}^{NB}\sum_{j>1}^{NB} Y_{ij}[V_{i,t}^2 + V_{i,t}^2 - 2V_{i,t}V_{j,t}\cos(\delta_{i,t} - \delta_{j,t})] \tag{3}$$

These power losses of microgrid can be decreased by effective management of charging stations and RESs.

Total voltage profile index

The total voltage profile index, f_2, of the network can be calculated by,

$$f_2 = \sum_{t=1}^{24}\sum_{i=1}^{NB} |1 - V_{i,t}| \tag{4}$$

By minimizing this index, voltage at the load terminals can be kept within desired bounds. By introducing RESs and EVs into the system, some portion of reactive and real power demanded by customers can be provided which in turn helps in decreasing system losses and improving the network voltage profile.

EVs charging and load supplying costs

This is the third objective function which can be calculated by,

$$f_3 = \sum_{t=1}^{24} (P_{s_{ub,t}} * 1.2 * c_v) + f_{ch} - f_{dc} \tag{5}$$

where

$$P_{sub,t} = \sum_{i=1}^{Nbus} P_{d_{i,t}} + P_{loss,t} - \sum_{k=1}^{n_{PHEV}} P_{dck,t}^{PHEV} + \sum_{k=1}^{n_{PHEV}} P_{k,t}^{PHEV} - P_{wind,t} - P_{pv,t} \tag{6}$$

$$f_{ch} = \sum_{t=1}^{24}\sum_{m=1}^{Nst} P_{Sation,m,t} * c_p * T_{m,t} * \left(\frac{D_t}{D_{\max}}\right) * \left(\frac{P_{M_{wind}}}{P_{wind,t}}\right) * \left(\frac{P_{M_{pv}}}{P_{pv,t}}\right) \tag{7}$$

$$f_{dc} = \sum_{t=1}^{24}\sum_{m=1}^{Nst} P_{Stationm,t} * 1.1 * c_v * t_{disp\,m,t} \tag{8}$$

$$P_{Station,t} = P_{Rate} * n_{PHEV} \tag{9}$$

In the following, the above equations are explained.

Eq. (6) represents the amount of power which can be purchased from the substation. Eq. (7) formulates the cost of EVs charging in which the amount of charged power (on an hourly basis) is multiplied by the amount of tariff in order to improve charging profile. In Eq. (7), the tariff is multiplied by the amount of network demand and is divided by its maximum demand to improve the network load factor. In addition, in order to exploit wind and solar energies, the maximum power of each of these two energy sources is multiplied by the objective function and divided by the amount of hourly power. The goal is increasing the effectiveness of wind and solar energies so that during a low demand period the power is stored in storage devices. Furthermore, in Eq. (7) $T_{m,t}$ is the duration that takes to make EVs fully charged by mth charging station. The value of $T_{m,t}$ depends on the probability of the state of charge (SOC), the battery capacity of EVs and the power rate of each charging level [26].

Eq. (8) gives revenue obtained by EV owners in discharging period when Microgrids purchase the EVs' energy 10% more than normal tariff. This in turn aids in increasing the probability of selling EVs' energy. Eq. (9) formulates the amount of power consumed at the station to charge EVs.

Constraints

In the optimization problem, four constraints exist: demand supply balance, bus voltage limit, generation limit and thermal limit.

A.1. Demand supply balance

The active and reactive generated power should be equal to the demand and losses. This can mathematically be expressed as follows [21],

$$P_{gi,t} = P_{di,t} + V_{i,t}\sum_{j=1}^{NB} V_{j,t}Y_{j,t}\cos(\delta_{i,t} - \delta_{j,t} - \theta_{j,t}) \tag{10}$$

$$Q_{gi,t} = Q_{di,t} + V_{i,t}\sum_{j=1}^{NB} V_{j,t}Y_{ij}\sin(\delta_{i,t} - \delta_{j,t} - \theta_{j,t}) \tag{11}$$

A.2. Voltage constraint

The phase angle and magnitude of bus voltages should be kept within allowable ranges [15],

$$V_{\min} \le V_{i,t} \le V_{\max} \tag{12}$$

$$\delta_{\min} \le \delta_{i,t} \le \delta_{\max} \tag{13}$$

A.3. Generation constraint

The output power of a RES in a period t should be kept within its minimum and maximum power limits [20],

$$P_{\min}^{RES} \leqslant P_{i,t}^{RES} \leqslant P_{\max}^{RES} \tag{14}$$

A.4. Thermal constraint

The power flow of each line should be less than its permitted power, denoted by $|S_i^{\max}|$, because of the line heating problem,

$$|S_{i,t}| \quad \leqslant \quad |S_i^{\max}| \quad i = 1, \ldots, Nr \tag{15}$$

System modeling

In the following models of photovoltaic, wind power and EV are given.

Photo voltaic (PV) model

Solar energy is energy obtained directly from the sun. PV is a technology that converts light directly into electricity. PV production has been doubling every two years, increasing by an average of 48% each year since 2002 [20], and is the fastest growing energy technology in the world. PV is best known as a method for generating solar power by using solar cells packaged in PV modules, often electrically connected in multiples as solar PV strings and arrays to convert energy from the sun into electricity. This part shows the computation of the output power of PV modules [21]. In this paper solar radiation profile used in studies has been shown in Fig. 1.

Wind utilization as an energy source

For wind power quantification three basic characteristics are necessary: wind speed and direction, the topographic characteristics of the study locale and the air density [22]. Among these factors, the wind speed is the most important one. The wind speed profile used in this study has been shown in Fig. 2.

EV model

In this paper, two types of EV models are considered to present a power source with a constant active power and a DG with constant active and reactive power. These two models have been addressed in [24]. The constraints associated with these two models corresponding to each bus of the network can be given as follows:

$$P^{PHEV}_{\min} \leqslant P^{PHEV}_{k,t} \leqslant P^{PHEV}_{\max} \tag{16}$$

$$Q^{PHEV}_{\min} \leqslant Q^{PHEV}_{k,t} \leqslant Q^{PHEV}_{\max} \tag{17}$$

$$P^{PHEV}_{dc,\min} \leqslant P^{PHEV}_{dck,t} \leqslant P^{PHEV}_{dc,\max} \tag{18}$$

$$Q^{PHEV}_{dc,\min} \leqslant Q^{PHEV}_{dck,t} \leqslant Q^{PHEV}_{dc,\max} \tag{19}$$

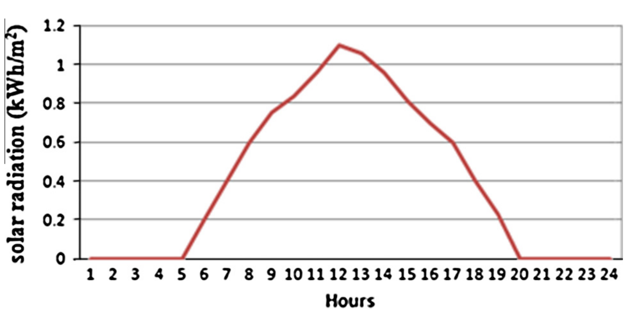

Fig. 1. Solar radiation profile.

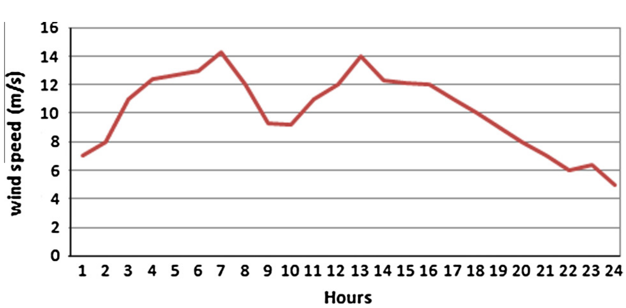

Fig. 2. Wind speed profile.

$$C_{station} \leqslant C_{S_M} \tag{20}$$

It must be noted that charging stations are considered as loads during the period of EV charging. They are also considered as distributed generation (DG) units during the period of EVs discharging.

Methodology

Selection of appropriate values for sitting and sizing variables of DGs and charging stations affect the power flow results; equivalently such variables affect the busses voltage and lines current. This influences the objective functions for example the power loss value which is a function of busses voltage and lines current, as shown in Eq. (3). Therefore, sitting and sizing influence the power loss value as one of the paper objective functions as demonstrated in Eq. (1). To select appropriate buses to install the DGs, the DE algorithm is utilized to minimize Eq. (1). The DE algorithm updates a population (capacity and location) based on Eq. (1) to find optimal buses in microgrid. The paper methodology flowchart of the optimization process is shown in Fig. 3, and the optimization method of DE is given in Fig. 4.

Differential Evolution algorithm (DE)

The single-objective evolutionary algorithm proposed by Price and Storn in 1995 draws upon ideas from several genetic algorithms and evolutionary methods [23]. One of them is a relatively new element to the general class of evolutionary methods called differential evolution. As other evolutionary methods, DE is a population based technique for finding global optima. The three main operators of DE are mutation, crossover and selection. Much of the power of this method is resulted from a very useful mutation operator that is simple and elegant. Mutations are obtained by computing the difference between two randomly chosen solution vectors in the population and adding a portion of this difference to a third randomly chosen solution vector to obtain a candidate vector. The resulting magnitude of the mutation in each of the variables is different and close to optimal. Two parameters adopted in DE are crossover (CR) and mutation (F). "CR" controls the influence of the parent in the generation of the offspring. Higher values mean

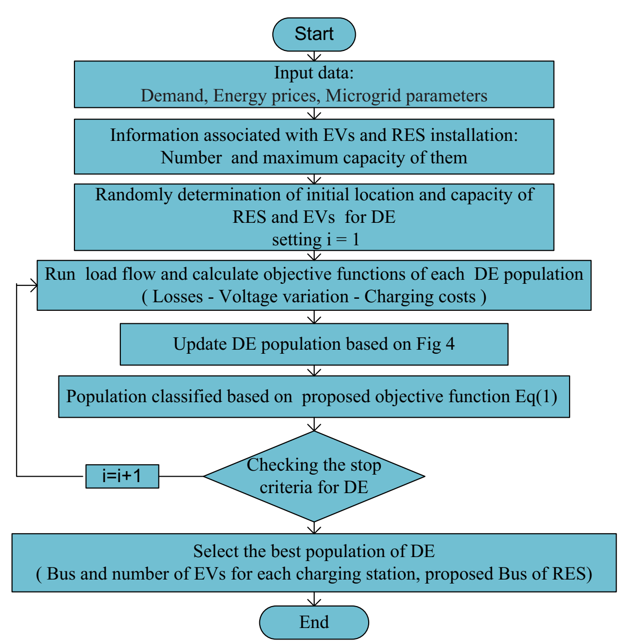

Fig. 3. Framework of sitting and sizing of charging stations and RES.

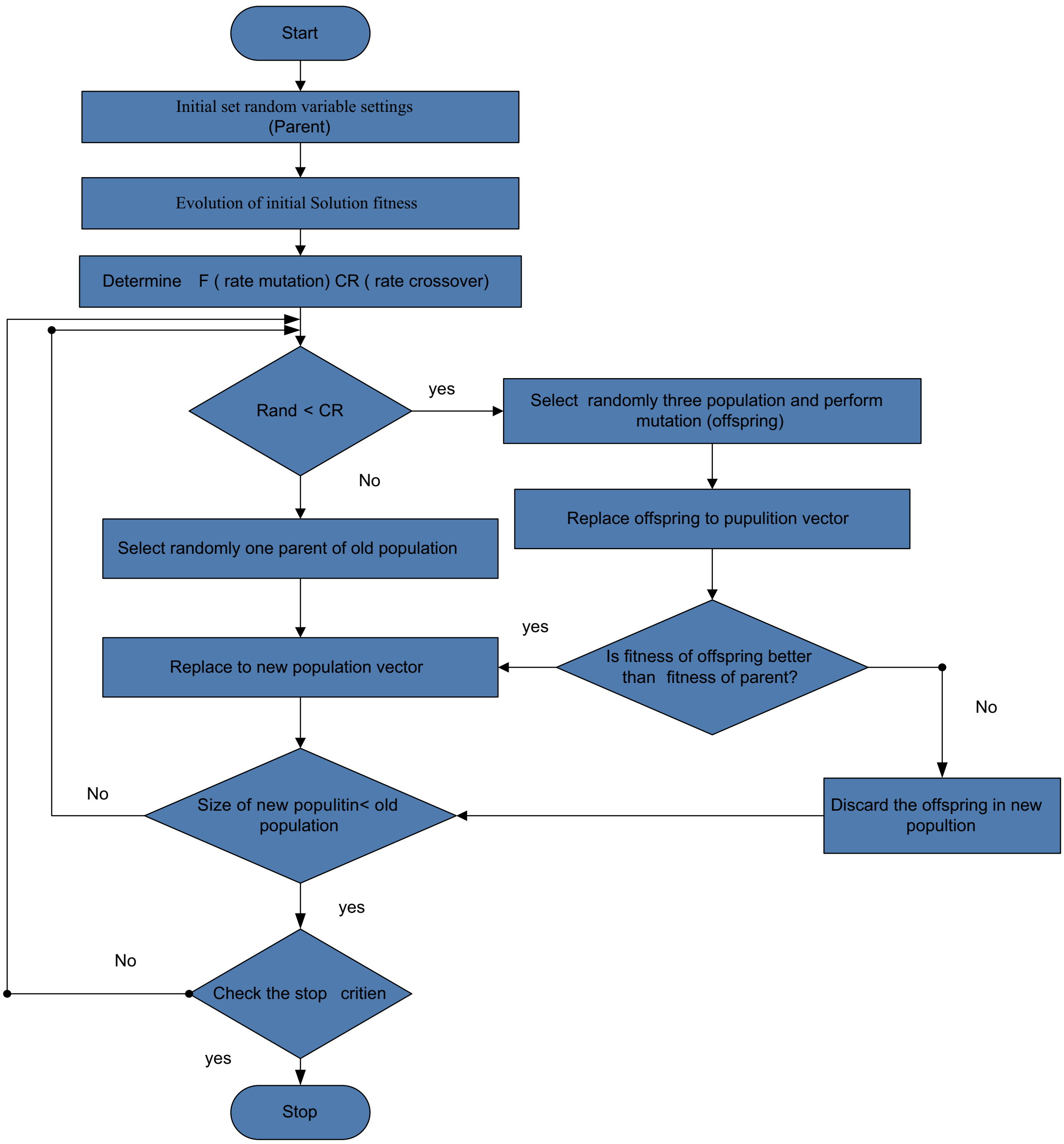

Fig. 4. The DE method for optimal sizing and sitting of station and renewable energy sources.

less influence of the parent in the features of its offspring. "F" scales the influence of the set of pairs of solutions selected to calculate the mutation value.

This method has been known as one of the most powerful evolutionary algorithms for real number function optimization problems. The DE algorithm can be explained in the following steps which shown in Fig. 4.

Step 1 (initialization): Put the iteration $t = 0$ and generate m population randomly. $[x_i(0),\ i = 1, \ldots, m]$, where $x_j(0) = [x_{j,1}(0), x_{j,2}(0), \ldots, x_{j,n}(0)].x_{j,r}(0)$, will generate in searching space $[x_r^{\min}, x_r^{\max}]$ randomly.
Step 2 (mutation): Generate a random integer for F
Step 3 (fitness): Evaluate each population in the initial population using the objective function.
Step 4 (time update): Update the time counter $t = t + 1$.
Step 5 (new population): Generate a new population by repeating the following steps until the new population is done:

- Generate a random integer for *CR* (crossover).
- (Mutation) Randomly pick three populations from $x_j(t)$ such that $x_{j,r1}(t) \neq x_{j,r2}(t) \neq x_{j,r3}(t)$. A trial vector $y_i(t)$ is defined as $y_i(t) = x_{j,r1}(t) + F\,(x_{j,r2}(t) - x_{j,r3}(t))$.
- (Crossover) Candidate vector $[x_j\ (t),\ j = 1, \ldots, n]$ is obtained via crossover operator involving the vectors $x_{j,i}(t)$ and $y_i(t)$ and is defined as:

$$x_{j,i}(t) = \begin{cases} y_i(t) & \text{if } rand(0,1) \leq CR \\ x_{j,i}(t) & \text{if } rand(0,1) \succ CR \end{cases} \tag{21}$$

- (Selection) The selection process involves a simple replacement of the original parameter vector with the candidate vector if the objective function decreases by such an action. If new population is less than the old population the operation will be continued. Else go to step 6.

Step 6 (end): the operation will stop if one of the stopping criteria was detected, else go back to step 2.

Results

The performance of the proposed method was evaluated in MATLAB for different microgrids. The results for two networks (69-bus and 94-bus) are presented here. System parameters as reported in [26,27] were used for these two networks.

A. 69-Bus microgrid

The first system, a 69-bus microgrid, is demonstrated in Fig. 5 [25] and its load profile is shown in Fig. 6. It was assumed that this microgrid is supplied by the substation. The parameters of the DE technique utilized for solving the problem are provided in Table 1. Noting that, the number of iteration, 50, shown in Table 1, was used as the termination criterion. Due to some technical issues the size of each charging station should be limited. In this paper, the maximum amount for each charging station was assumed to be 1.5 Mw. Moreover, two points in the microgrid for installation of charging stations were considered. The electrical energy price is given in Fig. 9.

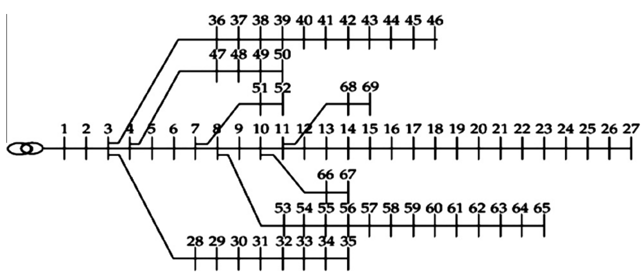

Fig. 5. Single line diagram of 69-bus microgrid.

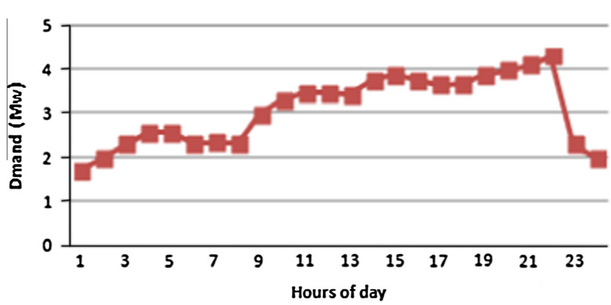

Fig. 6. Load profile 69-bus microgrid.

Table 1
DE parameters.

Pop. size	Crossover (CR)	Mutation (F)	Iteration
30	0.3	0.45	50

Scenario 1: base case

In this scenario, base case, it was assumed that there are no EVs in the system. Also, it was assumed that ζ, the coefficient of the objective function, is equal to zero. The locations of RESs, wind power plant and photovoltaic were obtained by minimizing the objective function, given in Eq. (1), using the DE algorithm and taking into account the optimal power flow value. Table 2 provides the objective function values before installing RES. The results of the proposed DE algorithm for the optimal location of RESs without charging station are presented in Table 3. Fig. 7 depicts voltage profile of the bus 65 before and after installing RESs for a 24 h period. Before RESs installation, for average network load, the voltage level of the bus 65 was low while after installation the voltage was improved (see Fig. 8).

Table 2
Objective function values before RES installation.

Microgrid	f_1 (MW)	f_2 (p.u)
69 BUS	3.238	4.2048
94 BUS	1.794	1.8136

Table 3
Objective function values after RES installation.

System	Optimal placement of sources	f_1 (MW)	f_2 (p.u.)
69-bus	53 27	1.0664	1.0568

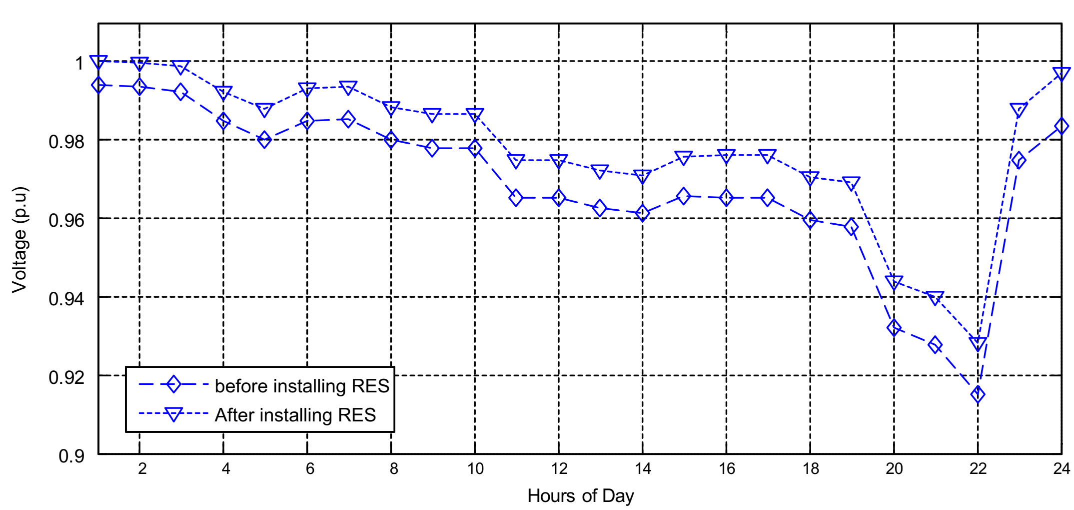

Fig. 7. Voltage profile of bus 65 before and after RES installation.

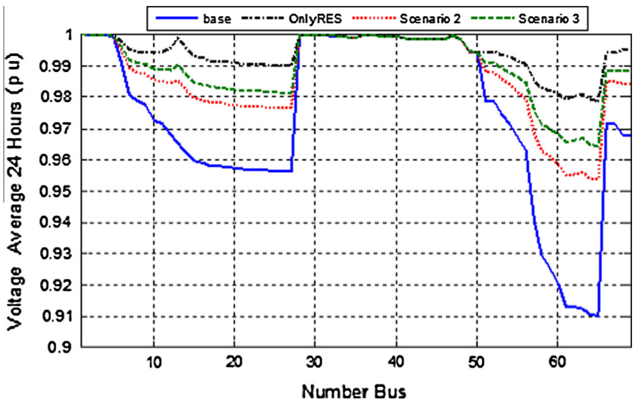

Fig. 8. Voltage profile of 69-bus network (24-h average).

Scenario 2: installing RESs and EVs without reactive power generation

In this scenario EVs were considered in the system. It was assumed that each charging station enables to return 40% charged energy of EV's battery to the grid. It was also assumed that batteries are not able to deliver reactive power to the grid. The two stations were assumed to have 500 cars capacity and each vehicle was assumed to have a battery with 20 kW h storage capacity. To encourage vehicle owners discharging tariff to the grid was considered to be 10% more expensive than the normal charging tariff.

The objective function was assumed to comprise EV's costs (according to TOU tariff), power losses and voltage profile. A three-level TOU was used to capture the peak price (19–22 pm), off peak price (23 pm – 8 am) and average price (19–22 pm), as shown in Fig. 9.

Table 4 shows that the amounts of network loss with and without discharging capability were 1.4352 and 2.0352, respectively. This demonstrates that stations with discharging capability are more efficient for network loss reduction. Accordingly, without accommodating the charging station properly more network losses might be happened which adversely affects the system performance. Table 4 also shows that the discharging capability of charging station increases the number of EVs (station capacity).

Fig. 10 illustrates the load profile, in an hourly basis, before and after EVs installation. This figure demonstrates an increase in the network load factor which is equivalent to a reduction in the network energy loss. Fig. 11 shows an improvement in the voltage of bus 65 after the installation of RESs and charging station.

Scenario 3: RESs and EVs with reactive power generation

In practice, where reactive power sources are located far from the load energy losses are anticipated to increase and the network efficiency is anticipated to decrease. This is the reason for locating the reactive power producer near the load. EVs can readily provide reactive power at the load side. The study of [25] proves that EVs are able to produce reactive power irrespective of the battery SOC at any time even during the charging period [19].

In this scenario, it was assumed that EVs are able to produce active and reactive power, simultaneously. This makes the working region of all vehicles square shape similar to the model proposed in [25]. It was also assumed that 40% of the charged energy of

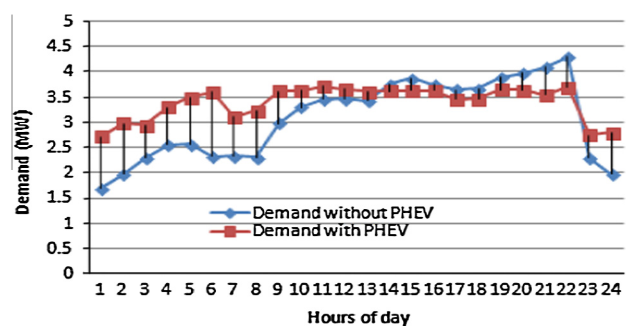

Fig. 10. Load profile before and after EVs installation.

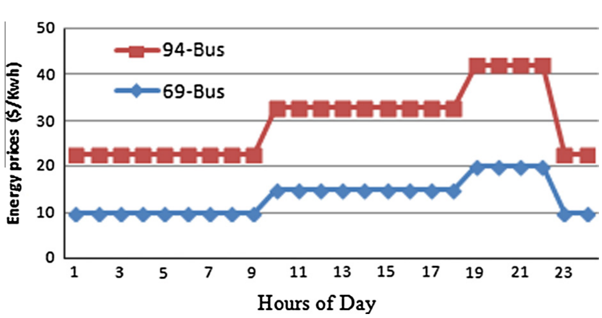

Fig. 9. Network electricity price for a 24 h period.

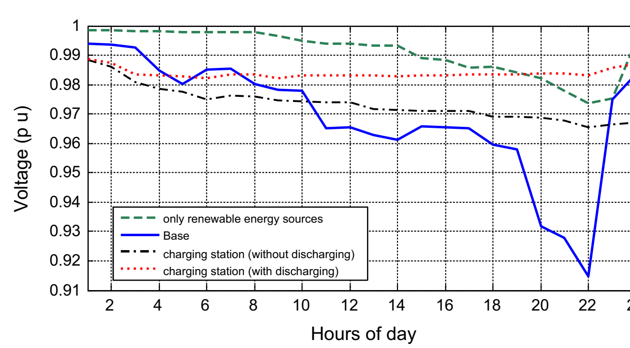

Fig. 11. Voltage profile of bus 65 for different scenarios.

Table 4
Objective function values for 69-bus after RES and charging station installation.

System 69 BUS	Placement of sources	Placement of charging stations	Sizing of charging stations (MW h)	A number of EVs	f_2 (p.u.)	f_1 (MW)
Scenario 2 (without discharging)	24	29	0.570	205	1.3025	2.0352
	61	36	0.740	227		
Scenario 2 (with discharging)	16	23	1.10	336	0.7032	1.6765
	61	63	0. 850	283		
Scenario 3	18	22	1.1	315	0.5761	1.3850
	63	61	0.960	298		

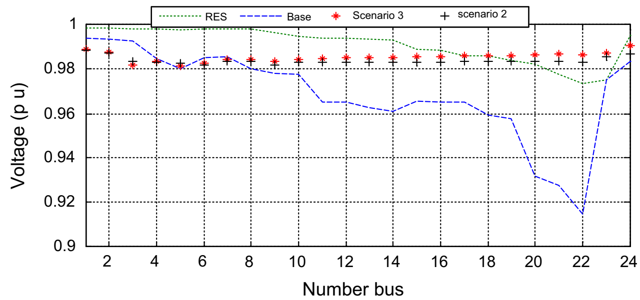

Fig. 12. Voltage profile after discharging active and reactive power of EVs to grid (bus 65).

Table 5
Economic analysis by considering RES and EVs (69-bus).

Cases	Costs of power losses ($)	Benefit of discharging power of EVs ($)	Purchased power from the grid ($)
Base	391,668	–	93,810,417
Only RES	128,943	–	48,152,637
Scenario 2 (without discharging)	284,497	–	62,920,514
Scenario 2 (with discharging)	173,602	4,312,560	54,628,514
Scenario 3	140,966	4,617,316	52,753,913

batteries can be returned to the grid as a tertiary service. The voltage profile of these three scenarios can be compared in Fig. 8 which shows an improvement in the voltage level of buses with reactive power injection.

Fig. 12 demonstrates the voltage profile of the network with discharging the active and reactive power of EVs to the grid. The results show an improvement in the voltage profile of the buses. Table 4 summarizes the values of cost functions for these three scenarios. This table shows that the network losses corresponding to Scenario 3 were reduced compared with Scenario 2 which demonstrates an improvement in the system performance.

Results discussion from economic perspective

To provide an insight into the benefit of the proposed method from economic perspective a cost-benefit analysis was conducted via evaluating five cases for a 69-bus network, as shown in Table 5. These five cases, from Case 1 to Case 5, were, respectively, based on, only RES, Scenario 2 without discharging, Scenario 2 with

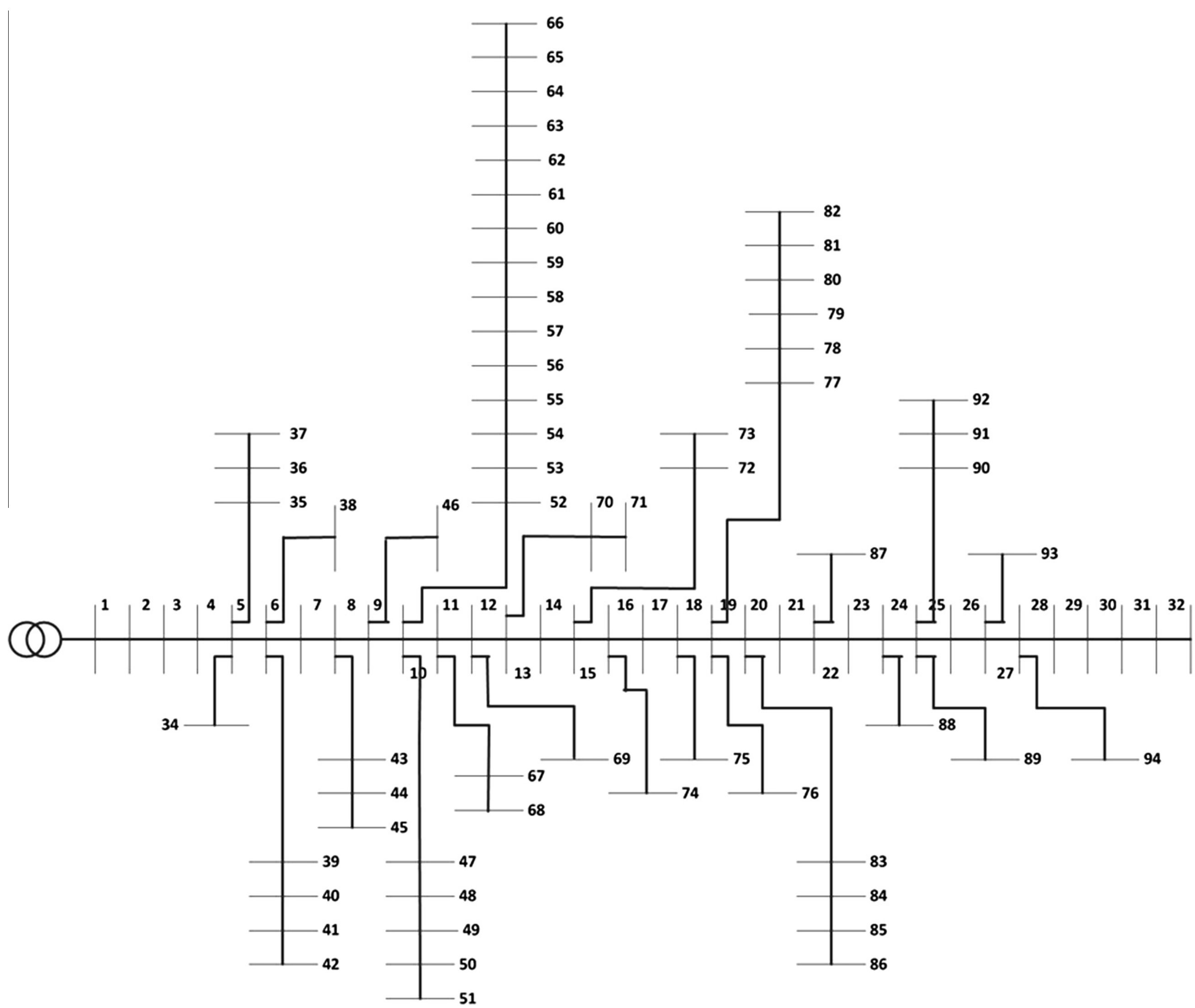

Fig. 13. Single line diagram of 94-bus microgrid.

Table 6
Objective function values of 94-bus after RES and charging stations installation.

System 94 BUS	Placement of sources	Placement of charging stations	Sizing of charging stations (MW h)	A number of EVs	f_2 (p.u.)	f_1 (MW)
Base case	67 31 51	–	–	–	0.9427	0.4731
Scenario 2 (without discharging)	67 30 34	16 10 69	0.608 0.716 0.503	217 253 182	1.0575	1.1665
Scenario 2 (with discharging)	26 36 11	14 77 35	1.04 0. 952 0.745	371 340 266	0.8256	0.9614
Scenario 3	93 34 87	34 47 10	1.25 1.03 0.860	446 367 307	0.6621	0.7852

Table 7
Economic analysis by considering RES and EVs (94-bus).

Cases	Costs of power losses ($)	Benefit of discharging power of EVs ($)	Purchased power from the DGs ($)
Base	459,894	–	1,529,109,799
Only RES	151,404	–	78,488,798
Scenario 2 (without discharging)	332,862	–	102,560,437
Scenario 2 (with discharging)	277,763	7,115,724	71,017,068
Scenario 3	222,726	7,618,571	68,580,086

discharging and Scenario 3. In the first case, the load cost without installing RES and charging stations was assessed. In the other cases, the load cost with the optimal capacity and location of charging stations and RES was assessed. Table 5 gives the optimization results corresponding to the charging stations with and without discharging active and reactive power. This table also gives the purchased energy saving for the 69-bus system. The time period of simulation was assumed to be one year. The results demonstrate a decrease in the cost of power losses and an increase in the revenue follow from the use of discharging active power of EVs to the grid. As such, the selection of station capacity directly influences the revenue value.

B. 94-Bus microgrid

The second system was an autonomous 94-bus microgrid as shown in Fig. 13. The line and load data of the network were based on [26]. Three DGs were set on buses 21, 56 and 74 with maximum capacity of 1 KVA and with power factor of 0.8. It might be noted that rather than using substation in this case DG units were used where the maximum amount of each charging station was considered equals to 1.5 Mw. Three points in the microgrid to install the charging stations were considered. Also, three buses for installing RES with 1 Mw capacity were considered. Similar to the first system, three scenarios were examined. The electrical energy price is given in Fig. 9 and the values of objective function, before installing RES, are illustrated in Table 2. Table 6 summarizes the values of objective functions for the different scenarios, after installing RES. This table shows that in Scenario 3 the network loss is less than that of Scenario 2 demonstrating an improvement in the microgrid performance. Table 7 gives the optimization results corresponding to the charging stations with and without discharging active and reactive power. The results demonstrate that in Scenario 3 a lower amount of power is required to be purchased from DG units. This is because EVs enable to inject active and reactive power to the microgrid more effectively.

Conclusions

Electric vehicles' chargers are seen to be beneficial for both consumers and grid. In this paper, the use of EVs on the Microgrid performance was explored. A multi-objective optimization problem comprising the amount of charging/discharging cost, power loss and voltage profile was developed. Differential Evolution algorithm was adopted to solve the paper optimization problem. The performance of the proposed method was simulated in MATLAB for different microgrids. The simulation results provided the optimal place and size of charging stations along with the number of EVs based on optimal load factor, power loss and voltage profile. The paper shows that an appropriate EVs scheduling improves the network voltage profile via removing voltage drops in highly-loaded buses. The paper also shows that the use of the proposed coefficients in the paper objective functions increases the load factor while it shifts the EVs demand into hours with high speed of wind and solar radiation level. Additionally, the paper demonstrates that discharging of EVs improves the load factor and reduces the energy cost for both consumers and microgrid. Finally, the paper shows that the use of EVs as active and reactive power sources helps improving the hourly demand, reducing energy costs and improving voltage profile in the network by utilizing optimal charging stations for EVs.

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