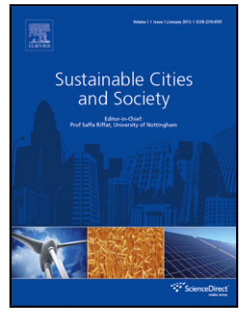
Accepted Manuscript



Title: A Simultaneous Approach for Optimal Allocation of Renewable Energy Sources and Charging Stations based on Improved GA-PSO Algorithm

Authors: Mostafa Rezaei Mozafar, Mohammad H. Moradi, M. Hadi Amini

PII: S2210-6707(16)30603-5
DOI: http://dx.doi.org/doi:10.1016/j.scs.2017.05.007
Reference: SCS 653

To appear in:

Received date: 15-11-2016
Revised date: 8-5-2017
Accepted date: 8-5-2017

Please cite this article as: Mozafar, Mostafa Rezaei., Moradi, Mohammad H., & Amini, M.Hadi., A Simultaneous Approach for Optimal Allocation of Renewable Energy Sources and Charging Stations based on Improved GA-PSO Algorithm.*Sustainable Cities and Society* http://dx.doi.org/10.1016/j.scs.2017.05.007

A Simultaneous Approach for Optimal Allocation of Renewable Energy Sources and Charging Stations based on Improved GA-PSO Algorithm

Mostafa Rezaei Mozafar[1], Mohammad H. Moradi[2], M. Hadi Amini[3,4]

1: Department of Electrical Engineering, Faculty of Engineering, Islamic Azad University, Hamedan, Iran

2: Department of Electrical Engineering, Faculty of Engineering, Bu-Ali sina University, Hamedan, Iran

3: Department of Electrical and Computer Engineering, Carnegie Mellon University, Pittsburgh, PA

4: SYSU-CMU Joint Institute of Engineering, Guangzhou, Guangdong, China

Emails: m.rezaeimozafar@iauh.ac.ir, mh_moradi@yahoo.co.uk, amini@cmu.edu

Highlights

- A novel method is proposed for optimal locating and sizing of RES and EV charging stations simultaneously.
- An optimal strategy for managing electric vehicle charging process is provided.
- A multi-objective optimization problem is formulated based on electric vehicles parameters and the renewable energy sources model.
- GA-PSO hybrid improved optimization algorithm is used to solve the optimization problem.

Abstract
Due to the stochastic nature of renewable energy sources (RES) and electric vehicles (EV) load demand, large scale penetration of these resources in the power systems can stress the reliable network performance, such as reducing power quality, increasing power losses, and voltage deviations. These challenges must be minimized by optimal planning based on the variable output from RES to meet the additional demand caused by EV charging. In this paper, a novel method for optimal locating and sizing of RES and EV charging stations simultaneously and managing vehicle charging process is provided. A multi-objective optimization problem is formulated to obtain objective variables in order to reduce power losses, voltage fluctuations, charging and demand supplying costs, and EV battery cost. In this optimization problem, the location and capacity of RES and EV charging stations are the objective variables. Coefficients which are dependent on wind speed, solar radiation, and hourly peak demand ratio for the management of the EV charging pattern in low load hours are introduced. Genetic Algorithm-Particle Swarm Optimization (GA-PSO) hybrid improved optimization algorithm is used to solve the optimization problem in five different scenarios. The performance of the proposed method on IEEE 33-bus system has been investigated to validate the effectiveness of the novel GA-PSO method to optimal sitting and sizing of RES and EV charging stations simultaneously.
Keywords: Optimization, electric vehicle charging station, renewable energy sources, hybrid GA-PSO algorithm

Nomenclature

i,j	Bus indices	$P_{dc,min/max}^{PHEV}$	Min/max active power discharging of EV
t	time indices	$Q_{dc,min/max}^{PHEV}$	Min/max reactive power discharging of EV
k	EV index	$P_{min/max}^{PHEV}$	Min/max active power charging of EV
P_{Loss}	Active power loss	$Q_{min/max}^{PHEV}$	Min/max reactive power charging of EV
P_{gi}	Generated active power at bus i	$P_{min/max}^{RES}$	Min/max active power capacity of RES
Q_{gi}	Generated reactive power delivered to bus i	P_i^{RES}	Active power of RES at bus i
P_{di}	Demand active power at bus i	$T_{m,t}$	Time duration for charging EVs of each station
Q_{di}	Demand reactive power at bus i	n_{PHEV}	Number of EVs at each time interval
P_{dc}^{PHEV}	Discharging power of an EV	D_{Max}	Maximum demand of load
P^{PHEV}	EV charger output active power	f_{ch}	Cost of charging
Q^{PHEV}	EV charger output reactive power	f_{dc}	Benefit of V2G
P_{sub}	Power amount of substation	T_{cell}	Solar cell temperature
$P_{station}$	Output power of the charging station	T_{amb}	Ambient temperature
$P_{M_{wind}}$	Output power maximum of wind plant	S	Solar radiation
$P_{M_{pv}}$	Output power maximum of solar energy	η	Solar cell efficiency
$P_{wind,t}$	Output power hourly of wind plant	m	Mass of the air bulk
$P_{pv,t}$	Output power hourly of solar energy	ρ	Bulk density of the air
P_{Rate}	Charged power rate of EV	A	Cross-section of wind turbine
Y_{ij}	ijth element of admittance bus matrix y	L	Length in meter
V_i	Magnitude of bus I complex voltage	$c_{1,2}$	Independent random variables
V_{min}	Minimum bus voltage	μ_{md},δ_{md}	Mean and standard deviation of EVs mileage
V_{max}	Maximum bus voltage	E_m	EVs energy consumption per mileage
NB	Number of buses	a, b	Constant coefficients related to EVs model
N_{St}	Number of charging stations	M_d	Expected daily mileage
δ_i	Phase angle of voltage at bus i	$M_{d_{max}}$	Maximum mileage of EVs
θ_i	Phase angle of Y_{ij}	$BCAP$	EV battery capacity
$\lvert S_i \rvert$	Apparent power at line i	$t_{arriv/depart}$	Arrival/departure time of EVs to/from station
$\lvert S_i^{max} \rvert$	Maximum apparent power at line i	$SOC_{desired}$	Probabilistic expected charge level
C_{SM}	Maximum capacity of station	SOC_{init}	Initial level of charge
$C_{Station}$	Capacity of station	chr	Charging rate
π^{TOU}	Market price of electricity at different times	C_b	Battery cost per kWh
N_r	Number of lines	C_r	Cost of battery replacement
t_{disp}	Time duration for V2G of each station	L_c	Battery life cycle

1. Introduction

Nowadays, the world's demand for fossil fuels in both transport sector and electric power generation plants is growing fast. Using these resources not only leads to the high costs but also causes greenhouse gas emissions and environmental pollution [1]. According to studies presented in [2], the demand in the transport sector will increase by 54% until 2035, this considerable demand increases the cost and air pollution. Hence, many countries are looking to replace the green vehicles rather than internal combustion cars [3]. Compared with gasoline vehicles, electric vehicles (EVs) are environmentally friendly and are more cost-effective from an economic point of view. In the structure of these cars, advanced battery, and power electronics equipment are used that enables EVs to be deployed into the network as controllable loads which can play the role of energy storage systems (ESS) to support network [4,6]. This can take place through the vehicle-to-grid (V2G) technology, which was first introduced in 1977 [5]. This promising concept was first utilized by providing a model of income and expenses to participate in the regulation market and ancillary services [7].

Penetration of EVs into the power grid brings challenges, such as thermal constraint violation of transmission lines due to overload and voltage drop in some sensitive network busses, and the uncertainty in the demand [8,9]. According to the previous studies, most of the vehicles are in the parking mode almost 95% of the day. As a result, this capacity can be used for frequency and voltage regulation through V2G [10]. Participation of vehicles in V2G makes revenue for vehicle owners. It also can be used to minimize network challenges by taking advantage of the capabilities of EVs and PHEV[1] charging stations [11,12]. In these stations, vehicles can recharge their batteries, as well as selling the surplus of stored energy to the grid and earn benefit. In this case, managing the charging and discharging of vehicles in various methods is achievable, such as changing energy tariffs at different time slots.

Renewable energy sources in recent years as an alternative to fossil fuel power plants are highly regarded. Because these resources can be installed near the load they can reduce losses, voltage fluctuations [13], and investment costs [14]. The widespread penetration of these resources to the grid can create challenges due to the random nature of their production. Consequently, the energy storage systems with high capacity should be used to support the network. In this context, charging stations can be introduced as ESS through V2G in the network. Charging stations store surplus power produced from RES and inject it into the power grid at the appropriate time, thereby cause these resources be distributed and reduce the stress imposed to the distribution network. In a smart grid with the optimal combination of RES and PHEV charging stations, emission rates are reduced and many technical and economic challenges can be addressed effectively [15].

Several studies are reported in the literature regarding the application of V2G in power systems and charging stations and RES. Ref. [16] shows that by replacing gasoline cars with EVs and using V2G capabilities in the network with high penetration of renewable energy, the total network capacity can be increased by 30-75% until 2020. In [17] a multi-objective optimization-based approach is proposed to allocate the optimal amount of electrical energy

[1] Plug in Hybrid Electric Vehicle

to the EV parking with regard to peak demand, the cost of charging and subscriber behavior is presented. According to [18], a new model is developed to achieve a maximum average charge of vehicles through energy management. In this model, vehicles have the V2G capability, and the network efficiency and reliability is improved using EV integration. In [19] a method for optimality of EVs and to achieve the maximum benefit of the aggregator is provided. In [20] EVs are used for frequency regulation. Ref. [21] allocated EV parking through multi-objective optimization problem with the study of distribution system indices, including the distribution system reliability, system losses and the cost indices and regardless of load forecasting error in the optimization model and load flow equations. A novel two-stage method to find optimal location of EV parking lots and RES considering both the economical and technical constraints using GA and PSO algorithms is proposed in [22]. The results show that using this method and the simultaneous presence of EVs and RESs in the network, make a reduction in costs and improve network operation. In [23], a comprehensive optimization objective function is defined to optimal sitting of PHEVs in smart distribution network with regard to reliability indices. In this paper a PHEV owner behaviour is modelled to calculate the hourly charge demand of PHEVs per day. The impact of EVs on the environment and economy is investigated in [24]. In [25][26], a model to calculate bills in smart energy systems based on demand response is provided. By exploring the recent papers, simultaneously optimal determination of the site and size for RES and charging station and EVs charging scheduling have not done. Moreover, the objective function is defined simply as single or double objective and most of them have worked in the field of reducing losses and costs. Meanwhile, in more articles a single model of EVs is used for transport section modelling and the EV owner’s behaviour, EV specifications and costs related to the vehicles battery are neglected.

In contrast to recent studies, in this work, simultaneous determination of the site and capacity of RES and EV charging stations is obtained. Furthermore, optimal planning of the EV’s charging process is considered to utilize the vehicles for power network improvement. A multi-objective function to minimize active power losses, voltage fluctuations, the power supply, EV charging costs, and expenses related to the vehicle’s battery is defined. Load flow calculations are performed on IEEE 33-bus network in five different scenarios using backward-forward algorithm for a 24-hour period. To solve the optimization problem and calculate the appropriate values for the objective variables, weighting coefficients method and modified GA-PSO optimization algorithm in MATLAB software are used. In order to validate the effectiveness of improved GA-PSO, the objective function of the paper is solved with DE[2] algorithm and results which are obtained for two algorithms are compared together. The results show the effectiveness of this approach to achieve the goals set and less computation requirement and thus less time spending to find the optimal solution compared to previous methods.

This paper is organized as follows. Section 2 explains the detailed system model. Section 3 is devoted to the formulation of the proposed approach. Section 4 explains the simulation results. Section 5 concludes the paper.

[2] Differential Evolution

2. System Model

2.1 Solar cell model (PV[3])

PV is the direct conversion of light into energy technology as well as the widely-used method to produce electricity from sunlight radiation. Using this technology since 2002 is increased by annual growth of 48% [28]. Due to the effect of temperature on the performance of solar cells, it is important to consider the temperature while studying the behavior of these cells. Therefore, the NOCT[4] index is introduced, that represents the cell temperature in a condition which ambient temperature is 20°c, solar radiation is 0.8 $\frac{\mathrm{KW}}{\mathrm{m}^2}$ and wind speed is $1\frac{\mathrm{m}}{\mathrm{s}}$. For determining the cell temperature;

$$T_{cell} = T_{amb} + \frac{NOCT - 20°}{0/8}.S \qquad (1)$$

where T_{cell} is the temperature in centigrade degree, T_{amb} is the ambient temperature and S is the solar radiation (sun=1 $\frac{kw}{m^2}$).

$$cell\ output\ power = P \times [\eta\ \times (T_{cell} - 25)] \qquad (2)$$

Eq. (2) gives the solar cell output power which η is the solar cell efficiency in energy conversion. Solar radiation profile considered in this study has been shown in Fig. 1.

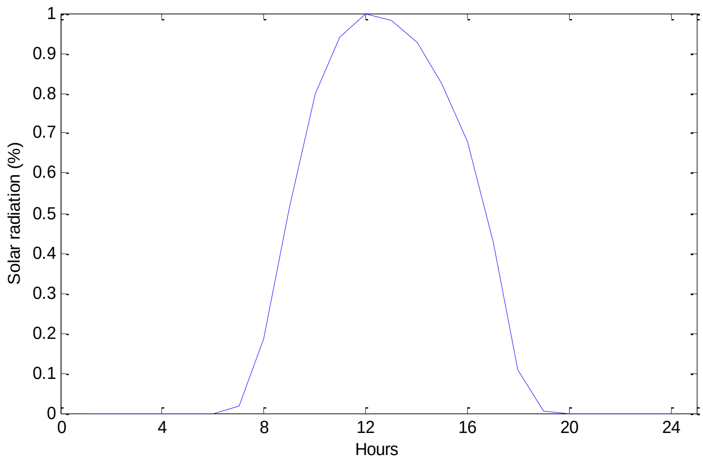


Fig. 1. Solar radiation profile [36].

2.2 Wind turbine model

The output power of a wind turbine depends on three parameters: wind speed and direction, the geography location of wind turbines and wind density [29]. The wind speed is more important compared to other parameters and shown in Fig. 2. In order to calculate the output power of wind turbine;

$$KE = \frac{1}{2}mV^2 \qquad (3)$$

$$P_{wind} = \frac{dKE}{dt} = \frac{1}{2}\frac{dm}{dt}V^2 \qquad (4)$$

[3] Photovoltaic

[4] Nominal Operating Cell Temperature

$$m = \rho AL \rightarrow m^{\circ} = \rho A \frac{dL}{dt} = \rho AV \tag{5}$$

$$\rho_{wind} = \frac{1}{2} \rho AV^3 \tag{6}$$

Eq. (3) represents the kinetic energy of air masses, where m and V denote the mass and speed of an air bulk respectively. Eq. (4) calculates the power passing through cross section. In Eq. (5) m is rewritten in ρ, A, L which L is the length in meter. Finally Eq. (6) gives the amount of output power of a wind turbine. ρ Is the bulk density of the air (1.225 $\frac{kg}{m^3}$ in 15°c and 1at) and A is the cross-section of wind turbine. According to Eq. (6), the role of wind speed in the output power is evident, with small changes in wind speed the output power varies too.

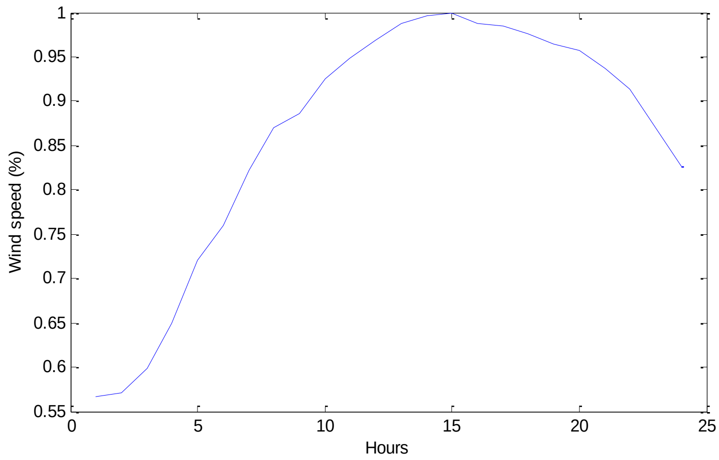


Fig. 2. Wind speed profile [36].

2.3 EV model

Table 1 shows four EV types considered in this paper;

Table 1. EV classes specifications [37-40].

Brand	Chevrolet	Honda	Ford	Toyota
Model	Volt	Accord	Fusion	Prius
Battery cap (kWh)	16	6.6	7.6	4.4
Distance with battery cap (mile)	37	13	21	11
Maximum charge rate (kW)	3.5	6.6	3.5	3.5
Electrical consumption (kWh/mile)	36	29	34	29

Note that three elements related to EVs should be accurately modelled. Expected daily mileage (distance which EVs travelled during the day), energy consumption per mile, and the waiting time in the charging station. Expected daily mileage can be modeled using the Log-Normal distribution [30]. Log-normal distribution is a type of statistical distribution of random variables which have a normally distributed logarithm [31-32]. By taking the natural log of each of the random variables, the resulting set of numbers will be log-normally distributed. The following equation gives the probability density function (pdf) of the Log-Normal distribution with parameters μ and σ:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma X}\exp(-\frac{[L_n(X)-\mu]^2}{2\sigma^2} \quad , \quad X > 0 \tag{7}$$

where on a logarithm scale, μ and σ can be called the location parameter and the scale parameter, respectively. The μ and σ parameters can be calculated as below:

$$\mu = L_n\left(\frac{m}{\sqrt{1+\frac{v}{m^2}}}\right) \quad , \quad \sigma = \sqrt{L_n(1+\frac{v}{m^2})} \tag{8}$$

where v and m represent the mean and standard deviation based on the historical data. Hence, to model the EVs expected daily mileage, the random variable X is produced by Bach-Muller method [33].

$$X = \sqrt{-2\, ln\, c_1} \times \cos(\, 2\pi c_2) \tag{9}$$

where c_1 and c_2 are independent random variables with uniform distribution in the range of [0,1) and X is a random variable with zero mean and one variance. Eq. (10) calculates the daily mileage on the basis of statistical data.

$$M_d = e^{(\mu_m + \sigma_m . X)} \tag{10}$$

where μ_m and σ_m are lognormal probability distribution parameters and M_d is expected daily mileage by EV. μ_m and $\sigma_m$are parameters calculated from the mean and standard deviation of statistical data extracted from the EV mileage [34].

$$\begin{cases} \mu_m = L_n(\frac{\mu_{md}^2}{\sqrt{\mu_{md}^2 - \sigma_{md}^2}}) \\ \sigma_m = \sqrt{l_n(1+\frac{\sigma_{md}^2}{\mu_{md}^2})} \end{cases} \tag{11}$$

The two parameters, μ_{md} and σ_{md}, respectively are mean and standard deviation of EV daily mileage based on statistical data. The μ_{md} and σ_{md} are respectively 35 and 15 miles. The second parameter affecting the performance of electric vehicles and charging demand is energy consumption on mileage that calculated in term of kilowatt-hours per miles.

$$E_m = a. K_{EV}^b \tag{12}$$

where E_m is the energy consumption on mileage ($\frac{kwh}{mile}$), a and b are the constant coefficients related to EV model and K_{EV} shows the deduction of the total energy supplied by the battery. In this paper, K_{EV} is considered to be one due to concentration on the charging demand of EV. The maximum mileage of an EV with fully charged battery is defined as M_{dmax} and calculated by Eq. (13):

$$M_{dMax} = \frac{BCAP}{E_M} \tag{13}$$

where $BCAP$ is EV battery capacity in term of kWh. To calculate the charging demand:

$$E_{Demand} = \begin{cases} BCAP & M_d \geq M_{dMax} \\ M_d . E_m & M_d < M_{dMax} \end{cases} \tag{14}$$

To calculate the third parameter the Gaussian distribution is used. This distribution provides the best estimation of the behavior of private car drivers [35]. Eq. (15) calculates the departure and arrival times of vehicles based on statistical data:

$$\begin{cases} t_{arriv} = \mu_{arriv} + \sigma_{arriv} .X_1 \\ t_{dePart} = \mu_{dePart} + \sigma_{dePart} .X_2 \end{cases} \tag{15}$$

where μ[5], σ[6] and t are the mean, standard deviation, and the expected time for both arrival and departure of EV to/from the charging stations respectively. X_1 and X_2 are random variables with zero mean and one variance. Eq. (16) gives the probabilistic duration of EV charging:

$$t_{dur} = t_{dePart} - t_{arriv} \tag{16}$$

So, Eq. (17) calculates the desired state-of-charge (*SOC*) by the aforesaid parameters.

$$soc_{desired} = min\left\{\left[soc_{init} + \frac{E_{Demand}}{BCAP}\right], \left[soc_{init} + \frac{t_{dur}}{BCAP} . chr\right]\right\} \tag{17}$$

where $soc_{desired}$ is the probabilistic expected charge level based on expected time duration in charging station and expected daily mileage of EVs. chr and SOC_{init} are charging rate and initial charge level respectively. In our model, we use minimization of two terms, the first term, $\left[soc_{init} + \frac{E_{Demand}}{BCAP}\right]$ provides us with the expected charging demand of the

[5] $\mu = {}^1/_N(t_1 + \cdots + t_N)$

[6] $\sigma = \sqrt{\frac{1}{N}[(t_1 - \mu)^2 + (t_2 - \mu)^2 + \cdots + (t_N - \mu)^2]}$ or using summation notation, $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - \mu)^2}$ where $\mu = \frac{1}{N}\sum_{i=1}^{N} t_i$.

corresponding EV based on its driven distance. On the other hand, the second term, $\left[soc_{init} + \frac{t_{dur}}{BCAP} . chr\right]$ expresses the maximum energy that could be charged by the EV battery based on the duration of parking the EV in the charging station. In recapitulation, the desired state of charge of each EV driver cannot exceed the feasible amount of charging demand based on the duration of being available for charging as well as the charging rate, and also the driven distance of the EV. Fig. 3 shows flowchart of EV modelling.

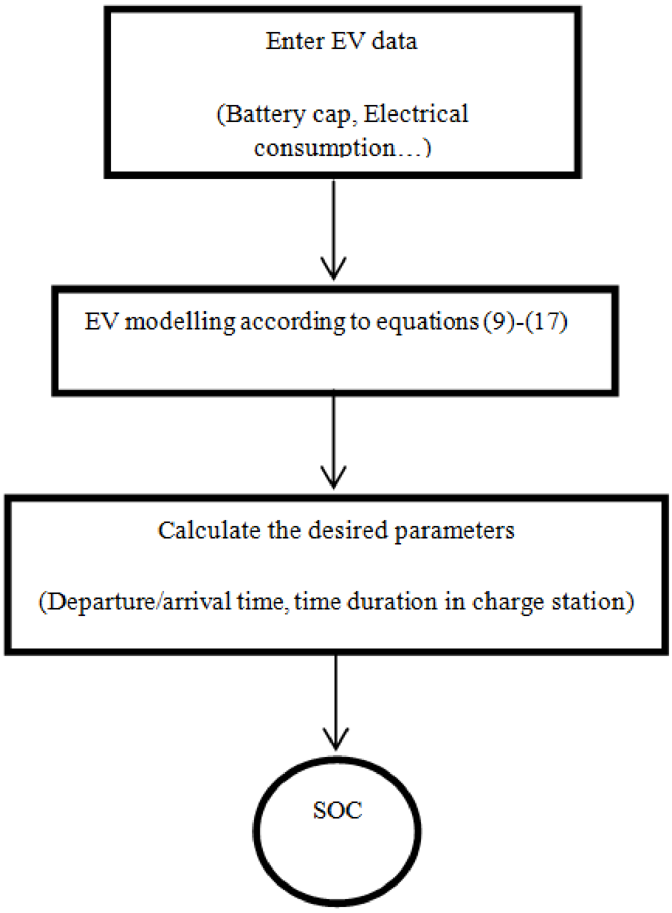


Fig. 3. Flowchart of EV modelling

3. The formulation and solution

In this section, equations and models related to the optimal determination of the location and capacity of RES and charging stations simultaneously from two different perspectives are defined. First, from the viewpoint of system operator with the aim of system losses and voltage fluctuations reduction and in the second case from the perspective of customers and vehicle owners to reduce costs.

3.1 Objective function

$$\min \quad F_t = \tau f_1 + \beta f_2 + \gamma f_3 + \alpha f_4 \tag{18}$$

Each of the coefficients of objective function according to the importance of functions is defined as $\tau = 0.4$,$\beta = 0.3$, $\gamma = 0.2$ and $\alpha = 0.1$. Functions in Eq. (18) by dividing by their base value written in per unit ($P.U.$) to make objective function dimensionless and prevent any scaling problem duration the optimization process.

3.1.1 Power losses

$$f_1 = P_{Loss} \tag{19}$$

$$P_{Loss} = \sum_{t=1}^{24} \sum_{i=1}^{NB} \sum_{j>1}^{NB} Y_{ij} \left[V_{i,t}^2 + V_{j,t}^2 + 2V_{i,t}V_{j,t} \cos(\delta_{i,t} - \delta_{j,t}) \right] \tag{20}$$

In terms of energy management, power losses can be minimized by right decisions. The minimization of feeder losses is the desired goal from the perspective of the distribution system operator. In Eq. (20) t is the index for time, NB shows the total number of network busses and Y_{ij} is the conductance of feeder i-j.

3.1.2 Total voltage fluctuations index

$$f_2 = \sum_{t=1}^{24} \sum_{i=1}^{NB} \left| 1 - V_{i,t} \right| \tag{21}$$

Through penetration of RES and EVs to the grid, capacity to supply part of the demand is created which helps system to losses reduction and voltage fluctuations improvement. With the improvement of this index, the voltage at each bus can be kept within desired bounds.

3.1.3 EVs charging and demand supplying costs

$$f_3 = \sum_{t=1}^{24} \left(P_{sub,t} \times \pi^{TOU} \right) + f_{ch} - f_{dc} \tag{22}$$

$$P_{sub,t} = \sum_{i=1}^{N_{bus}} P_{di,t} + P_{Loss,t} - \sum_{k=1}^{n_{PHEV}} P^{PHEV}_{dck,t} + \sum_{k=1}^{n_{PHEV}} P^{PHEV}_{dck,t} - P_{wind,t} - P_{PV,t} \tag{23}$$

$$f_{ch} = \sum_{t=1}^{24} \sum_{m=1}^{N_{ST}} P_{Station\, m,t} \times \pi^{TOU} \times T_{m,t} \times \left(\frac{D_t}{M_{Max}}\right) \times \left(\frac{PM_{wind}}{P_{wind,t}}\right) \times \left(\frac{P_{MPV}}{P_{PV,T}}\right) \tag{24}$$

$$f_{dc} = \sum_{t=1}^{24} \sum_{m=1}^{N_{St}} P_{Station\, m,t} \times \pi^{TOU} \times t_{disPm,t} \tag{25}$$

$$P_{Station} = P_{Rate} \times n_{PHEV} \tag{26}$$

Eq. (22) shows the amount of power purchased from the grid. Eq. (24) shows the EVs charging costs considering the variable energy price at different times, in this regard, the variable tariff is used to improve charging profile. In Eq. (24) in order to improve the network load factor, tariffs multiplied by hourly demand on maximum demand ratio. In order to increase the share of RES in the charging demand supplying, the objective function multiplied by maximum power of each of these sources and divided by the hourly output of the resources. In Eq. (24) the time required to fully charge the vehicle by the station m is shown with $t_{m,t}$, this time duration by taking the initial state of charge, battery capacity and power rate for each charging level is calculated [27]. In Eq. (25) profit from participation of vehicles in V2G is calculated. To encourage vehicle owners to participate in the V2G process, electricity price is calculated 10% more expensive at the time of discharging. Eq. (26) calculated the demand for vehicle charging station.

3.1.4 Depreciation costs of battery

$$f_4 = \frac{C_b.BCAP + C_r}{L_c.BCAP.DOD} P_{dc}^{PHEV} \tag{27}$$

In Eq. (27), C_b is the battery cost per kWh, C_r is the cost of battery replacement, L_c is the battery life cycle, DOD is the depth of discharge and P_{dc}^{PHEV} is energy discharged by EVs. The important point is the direct relationship between the amount of power provided in V2G and the battery depreciation cost where can increase the cost of the battery and thus prevent vehicle owners from participating in V2G.

3.2 Constraints

In the optimization problem, five operational constraints are investigated;

3.2.1 Demand-supply balance

Demand-supply balance for both active and reactive power is given by the standard load flow equations as follows.

$$P_{gi,t} = P_{di,t} + V_{i,t} \sum_{j=1}^{NB} V_{j,t} Y_{i,j} \cos\left(\delta_{i,t} - \delta_{j,t} - \theta_{i,t}\right) \tag{28}$$

$$Q_{gi,t} = Q_{di,t} + V_{i,t} \sum_{j=1}^{NB} V_{j,t} Y_{i,j} \sin(\delta_{i,t} - \delta_{j,t} - \theta_{i,j}) \tag{29}$$

Demand-supply balance constraint for each bus is updated by adding the EV charging load to the active power demand-supply balance as given by Eq. (30).

$$P_{gi,t} = P_{di,t} + P_{chi,t} + V_{i,t} \sum_{j=1}^{NB} V_{j,t} Y_{i,j} \cos(\delta_{i,t} - \delta_{j,t} - \theta_{i,j}) \tag{30}$$

3.2.2 Bus voltage limits

The magnitude and phase angle of voltage must be kept within the *Min* and *Max* value.

$$V_{min} \leq V_{i,t} \leq V_{max} \tag{31}$$
$$\delta_{min} \leq \delta_{i,t} \leq \delta_{max} \tag{32}$$

These voltage limits are applied to all load buses. On the other hand, the slack bus voltage magnitude and phase angle, which is the substation bus, are fixed as follows.

$$V_{s,t} = 1p.u., \qquad \delta_{s,t} = 0, \qquad s = Slack\ bus$$

3.2.3 Generation constraint

The output power of a RES in period t must be kept within the allowable range.

$$P_{min}^{RES} \leq P_{i,t}^{RES} \leq \ P_{max}^{RES} \tag{33}$$

3.2.4 Thermal constraint

EV charging demand acts as an additional demand and increases the power flow in transmission lines. This will raise the temperature of the lines. In order to prevent potential damage caused by the increased heat of lines, power flow must be kept within the allowable range.

$$\left|S_{i,t}\right| \leq |S_i^{max}| \quad i = 1, \dots, Nr \tag{34}$$

3.2.5 Limitations of EVs

$$P_{min}^{PHEV} \leq P_{k,t}^{PHEV} \leq P_{max}^{PHEV} \tag{35}$$

$$Q_{min}^{PHEV} \leq Q_{k,t}^{PHEV} \leq Q_{max}^{PHEV} \tag{36}$$

$$P_{dc,min}^{PHEV} \leq P_{dc\ k,t}^{PHEV} \leq P_{dc,max}^{PHEV} \tag{37}$$

$$Q_{dc,min}^{PHEV} \leq Q_{dc\ k,t}^{PHEV} \leq Q_{dc,max}^{PHEV} \tag{38}$$

$$C_{Station} \leq C_{SM} \tag{39}$$

3.3 Methodology

From the optimization perspective, system performance is affected by the location and installed capacity of RESs and charging stations as target variables. Choosing the appropriate values for the target variables could improve voltage fluctuations and transmission lines current. This can reduce the power loss value which depends on busses voltage and lines current, as demonstrated in Eq. (20). Hence, the determination of the location and capacity can influence the power losses, which is part of the objective function, as shown in Eq. (18). In this paper, RESs and charging stations are modeled as PQ buses. The method used to solve load flow equations is the backward-forward algorithm based on the branch's power. In this method, implementation of the leading and backward phase based on the power equations takes place and the lines current directly is not used. To solve the optimization problem and selecting target variables, the improved hybrid GA-PSO algorithm is used. The algorithm according to the equation of the objective function and the values derived from load flow chooses the best value for the target variables.

3.3.1 Hybrid improved GA-PSO algorithm

Each of the optimization algorithms (smart and non-smart) have specific capabilities and features. The idea of the hybrid algorithm while considering structural and functional differences between different optimization algorithms is captured in this study. Given that our decision variables in this study are two types of integer and floating-point numbers, according to the better performance of the PSO algorithm for continuous and infinite spaces, and the outperformance of the GA algorithm for discrete spaces, we utilized the GA-PSO to find the optimal solution. In terms of comparing different algorithms and choosing the best algorithm to deal with the formulated problem, NOFE (number of function evaluation) index has been introduced. In each iteration, NOFE is calculated as a global function in the MATLAB program until we reach the optimal solution. In first iteration, we set the NOFE=1, and it is updated by each evaluation of objective function to NOFE=NOFE+1 for next iterations. At the termination of the optimization process each of algorithms have their NOFE value which shows the speed of the algorithm in find optimal solutions. the algorithm runs faster as much as this index becomes lower. In this study the GA-PSO has the lowest NOFE value among other algorithms, which confirms that the GA-PSO is the fastest solution to deal with this optimization problem.

Similar to the other evolutionary algorithms, GA-PSO is a population-based technique to find the optimal value. In this algorithm, five adjustable parameters W, C_1, C_2, P_c, and P_m are defined to solve the optimization problem. W is the coefficient of inertia, and C_1 and C_2 are learning coefficients, which are usually assigned the value of 2. Learning coefficients can be different, but they usually are the same value in the [0,4] interval. P_c and P_m are percentage of the cross over and mutation operators in the genetic part of the proposed method respectively. In this article P_c and P_m according to behaviour of produced answer population change and algorithm in each iteration step with automatic adjustment of these two parameters tries to remove the undesirable responses and obtain more optimal solutions, so that it improves the mean of obtained results in each iteration. In general, 200 iterations are required to reach convergence for the proposed algorithm, where in each iteration GA is repeated 5 times and PSO is repeated 2 times. In each internal iteration of GA or PSO, if the generated answer remains stable for 40% of the answer population, P_m and P_c amount varies by multiplying the random variable ε_i. ε denotes the independent uniform random variable on the interval (0,1]. In the second outer iteration the above process is repeated for the updated populations and this time P_c and P_m are multiplied in $\varepsilon_i - \varepsilon_{i-1}$ to generate a new improved answer. Finally, after 200 outer iterations the best value for target variables and the best value for a set of parameters of the algorithm is calculated. The improved algorithm has unique structure due to the population production process and elimination of the undesirable results through smart regulation of algorithm parameters based on population behaviour. In this context, in addition to the creation of the best solution sets also the speed of the algorithm in solving the optimization problem is increased. Flowchart of the optimization algorithm and the flowchart of the proposed methodology are shown in Fig. 4 and Fig. 5 respectively.

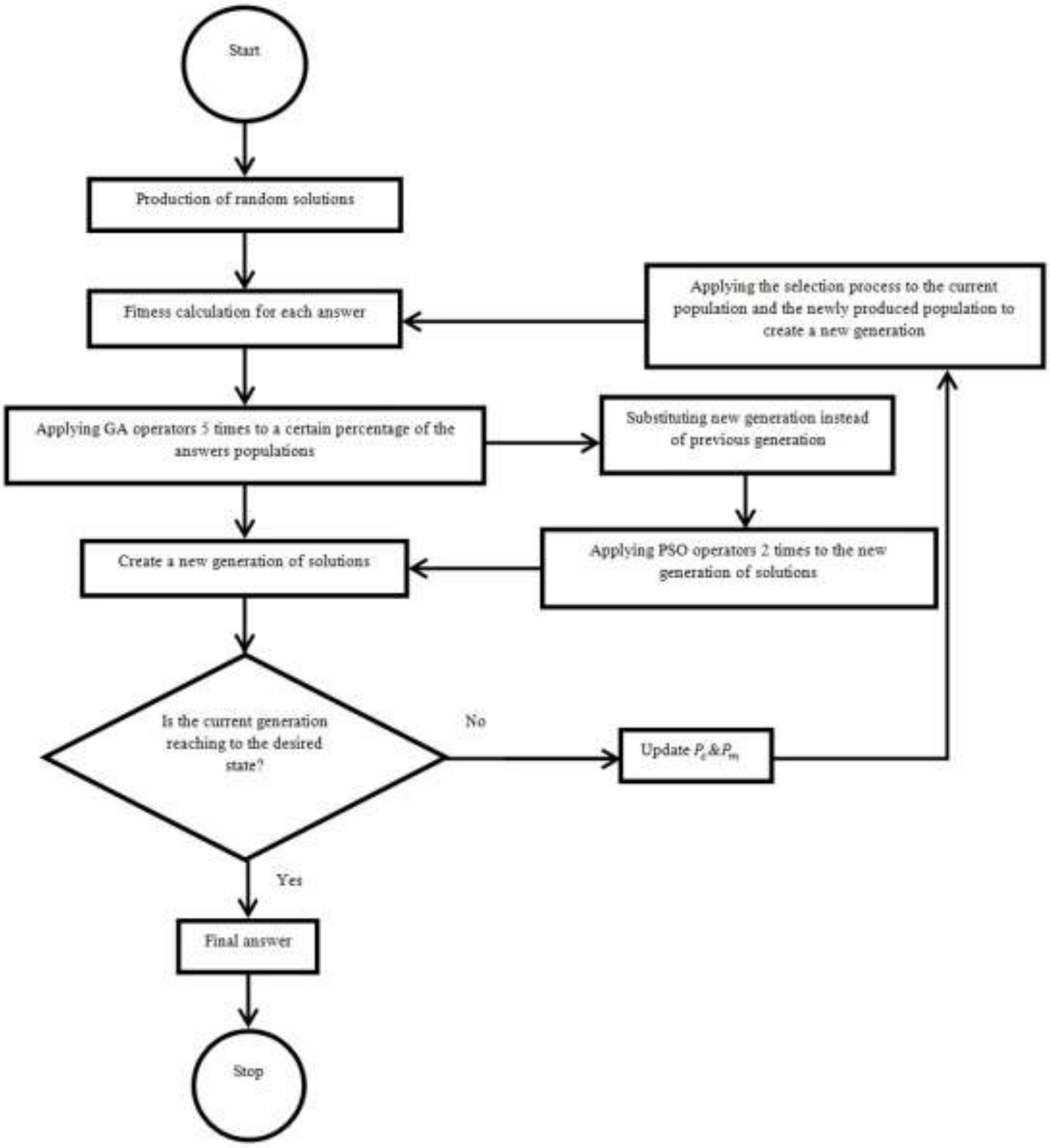


Fig. 4.The GA-PSO method for finding optimal place and capacity of renewable energy sources and charging station.

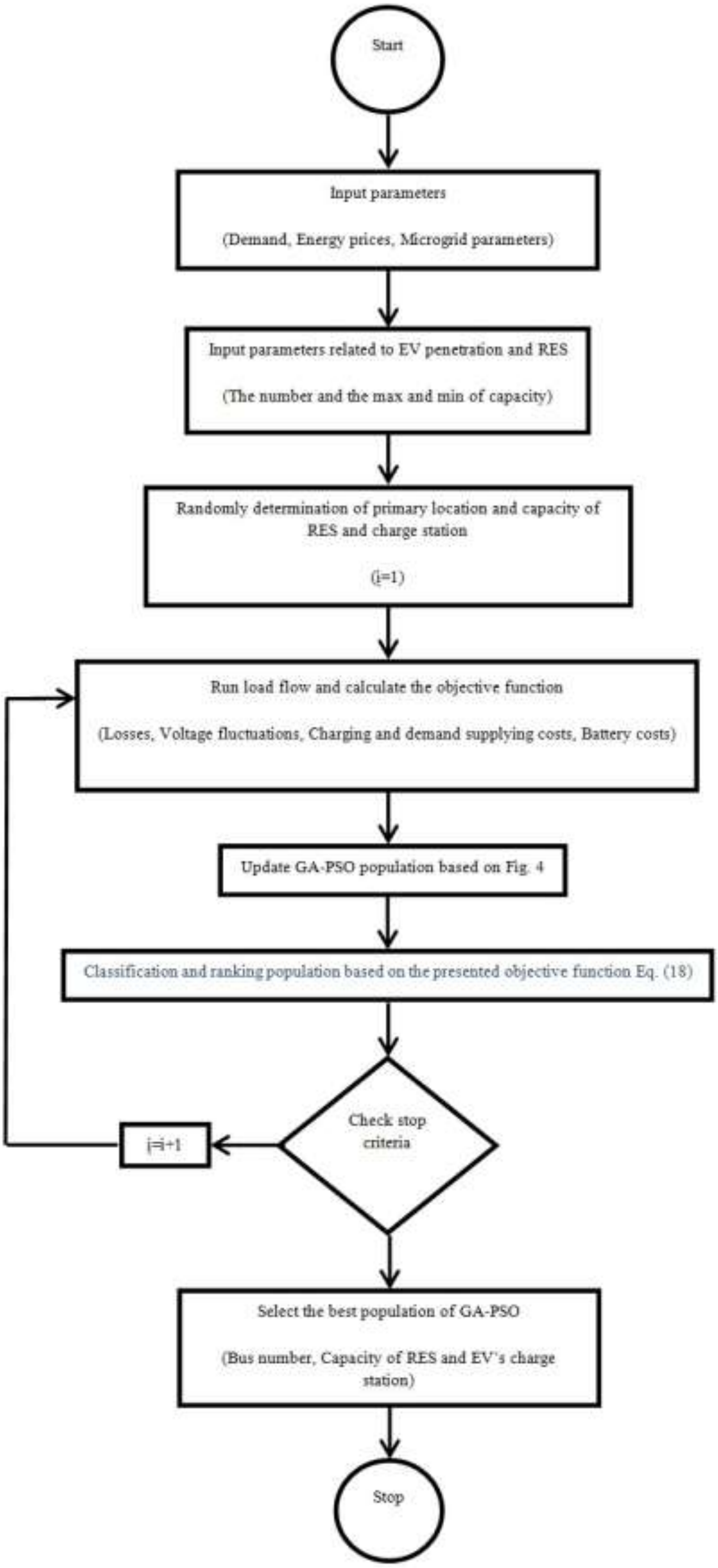


Fig. 5. Flowchart of determination of location and capacity of RES and charging station.

The GA-PSO algorithm can be explained as follows which shown in Fig. 4:
Step1) set the iteration It=0 and produce random solutions population.
Step2) fitness evaluation based on objective function for each population.
Step3) update the NOFE counter NOFE=NOFE+1 & It=It+1.
Step4) create a new generation of solutions by repeating the following steps:

- Start internal iteration.
- Applying GA operators (P_c&P_m) five times to certain percentage of population.
- Applying PSO operators (w, C_1, C_2) two times to the new generation of solutions.
- End of internal iteration.
- If the generated populations remains stable for 40% of the solutions population update P_c & P_m.
- Applying selection process, updating the previous solutions with the new produced population to minimize the objective function. If the new solutions population are less than the previous ones, the flow will be continued. Else go to step 5.

Step5) the algorithm will stop if the stopping criteria was satisfied, else go to step 2.

4. Simulation and results

4.1 IEEE-33bus system

Because of the size and complexity of the actual distribution systems, modelling and simulation of these systems to determine operational parameters is very difficult andtime-consuming. In this paper the IEEE-33 bus system is used and demonstrated in Fig. 6 and its demand profile is shown in Fig. 7. Information of the GA-PSO algorithm is presented in table 2. The number of iterations for the optimization process is enforced as 200 times and is considered as termination criteria. In this study, the maximum capacity of each charging station and RES were assumed to be 1.5 MW and 1 MW respectively, and four candidate buses were considered for their location. The electricity price in 24-hour period is given in Fig. 8.

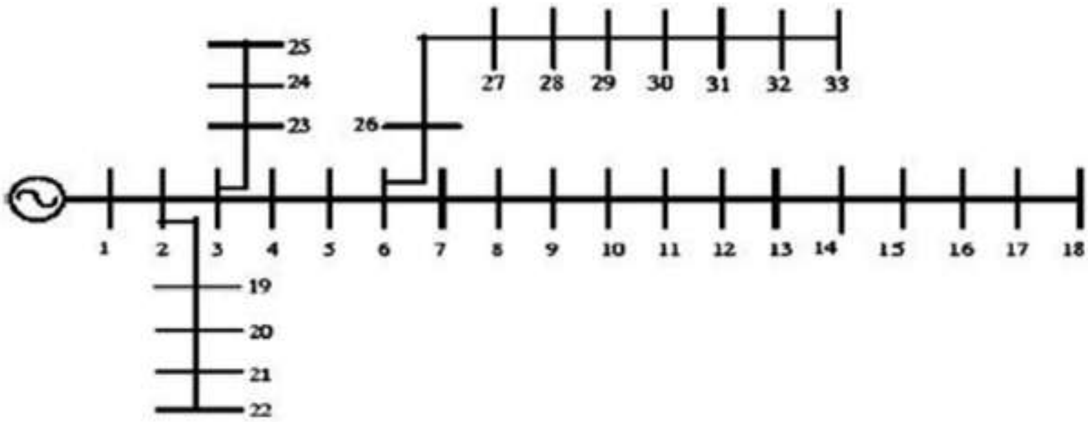


Fig. 6. Single line diagram of theIEEE-33 bus network.

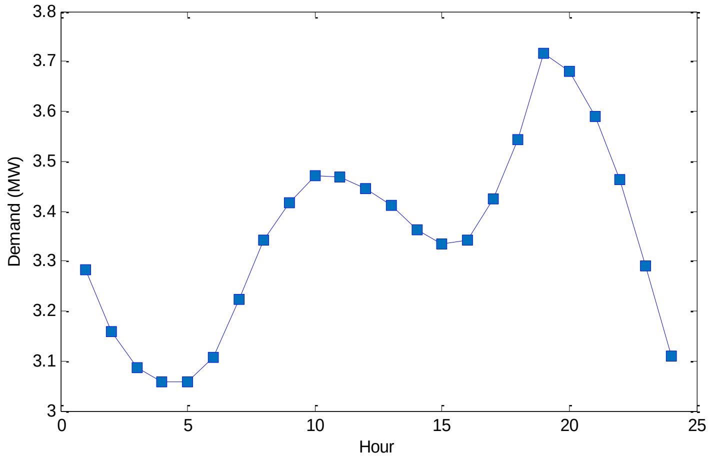


Fig. 7. System load profile [36].

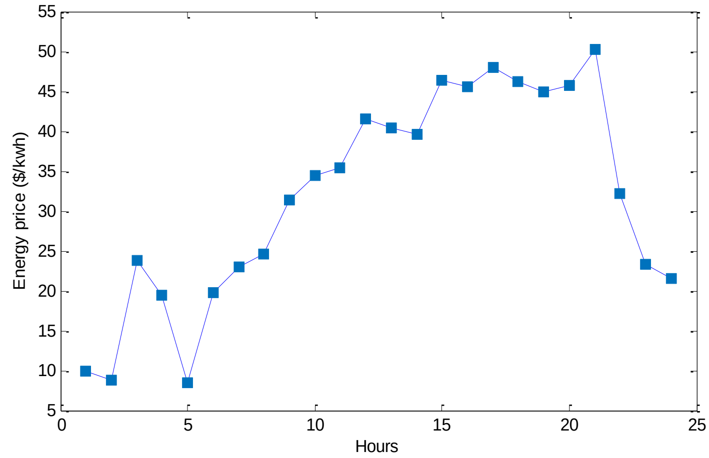


Fig. 8. Network electricity price for a 24-h period [36].

Table 2. GA-PSO parameters.

Population size	P_c	P_m	W	C_1	C_2	iteration
50	$P_{c_i}*(\varepsilon_i - \varepsilon_{i-1})$ i=1,2,3,...,200	$P_{m_i}*(\varepsilon_i - \varepsilon_{i-1})$ i=1,2,3,...,200	1	2	2	200

In this section, the assumptions and the required information to solve the optimization problem are explained. Then the results are demonstrated.

i. During the sitting process, all buses, except bus number one which is a slack bus, are introduced as a candidate buses for the placement of RES or charging station.
ii. Capacity and location of RES and charging station are the target variables in the optimization problem.
iii. System demand has been modeled in 24-hour period. The network load model is based on the Ontario network on November 27, 2015 [36].
iv. System simulation and planning are performed for a 24-hour period.

The different scenarios studied in this paper are provided in table 3;

Table 3. State of the system in different scenarios.

Scenario	Explanation of the system under study
Base case	Fossil fuel based microgrid
First scenario	Microgrid with RES near the load place
Second scenario	Microgrid with RES and EV (without V2G_randome charging)
Third scenario	Microgrid with RES and EV (with V2G_controlled charging)
Fourth scenario	The third scenario with a pricing system affected by changes in demand

The purpose of system study in the base case scenario is determination of the system behavior before reconfiguration. In the first scenario, optimal sitting and sizing of RES in the grid to determine the impact of these resources on the network operational parameters has been accomplished. In the second and third scenarios, EV penetration to the grid, considering the impact of vehicle charging management and V2G is simulated. The fourth scenario is merely examined a momentary pricing impact on consumption pattern, pricing based on usage in the moment is an indirect way to control network consumers. In the fourth scenario, the network structure of the third scenario is utilized and only the pricing method has changed.

Table 4. Top five of solutions obtained for system consists of RES and EVs.

Rank	Placement of RES	Sizing of RES	Placement of charging station	Sizing of charging station	$\boldsymbol{F_1}$(MW)	$\boldsymbol{F_2}$(pu)	$\boldsymbol{F_3}$($)	$\boldsymbol{F_4}$($)
1	13 30	0.6939 0.7126	23 6	1.0512 0.9035	2.108906	24.1073	8,221,640	147,189
2	21 11	0.4173 0.9328	33 7	0.8815 0.9672	1.999984	24.0852	8,237,052	150,233
3	6 18	0.7343 0.5892	24 16	1.2125 0.6719	2.316520	25.3184	9,125,389	168,512
4	27 22	0.8127 0.5698	10 4	1.1573 0.7261	2.000084	24.1005	8,305,428	147,809
5	4 17	0.3274 0.8985	3 31	0.7916 0.9258	1.998456	24.0614	9,157,328	154,529

Table 4 shows top five of the best solutions obtained from the optimization process based on the objective functions value. Accordingly, the solution which is the first is the best to select as the optimal place and capacity for RES and charging station.

Table 5. The target variables obtained from solving the optimization problem.

Scenario	Placement of RES	Sizing of RES (MW)	Placement of charging station	Sizing of charging station (MW)
First	2 15	0.6493 0.6722	________	________
Second	2 15	0.6493 0.6722	________	________
Third	13 30	0.6939 0.7126	23 6	1.0512 0.9035
Fourth	13 30	0.6939 0.7126	23 6	1.0512 0.9035

Table 6. Objective function values for different scenarios.

Scenario	$\mathbf{F_1}$(MW)	$\boldsymbol{F_2}$(Pu)	$\mathbf{F_3}$($)	$\mathbf{F_4}$($)
Base case	4.346388	39.1706	18,543,952	______
First	2.717356	30.0646	10,262,861	______
Second	4.471162	39.351	24,900,625	______
Third	2.108906	24.1073	8,221,640	147,189
Fourth	1.985623	23.0005	7,741,017	149,021

The value of the objective variables obtained from the optimization process is given in Table 5. Table 6 shows the objective function values for the five network operational modes. According to the objective function the fourth scenario is the best in order to exploit network so that the amounts F_1, F_2 and F_3 are less than the other scenarios and only F_4 related to depreciation expense of battery resulting from the EV participation in V2G process is added compared to first and second scenarios.

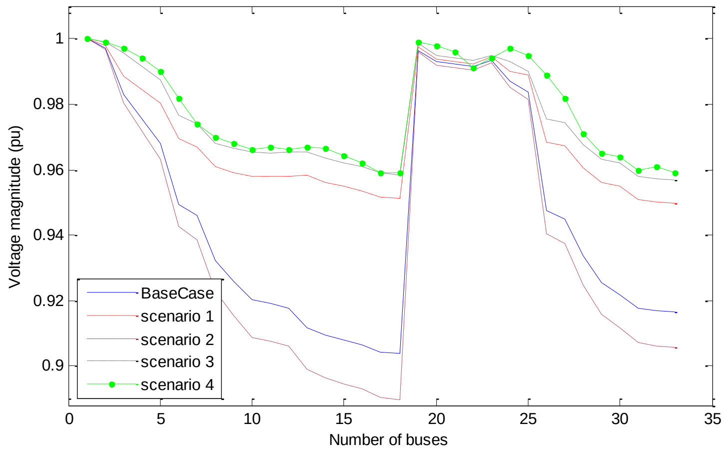


Fig. 9. Voltage profile of 33-bus network (24-h average).

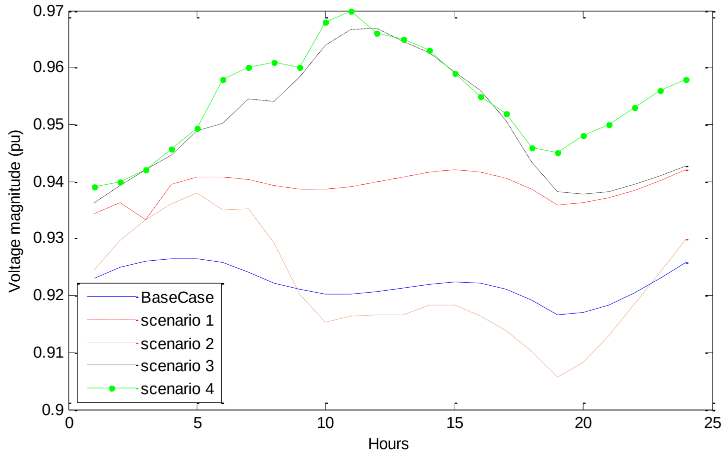


Fig. 10. Voltage profile of bus 33 (24-h average).

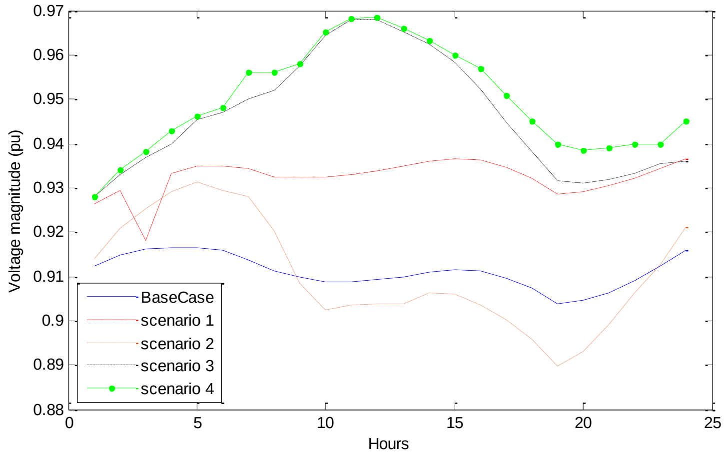


Fig. 11. Voltage profile of bus 18 (24-h average).

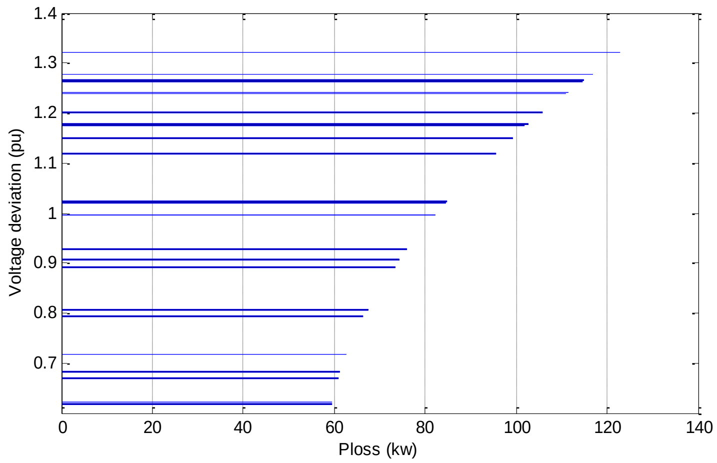


Fig. 12. Power loss changes due to voltage fluctuations in the network (third scenario).

Fig. 9 shows the effect of the simultaneous deployment of G2V and V2G on average voltage profile in the network buses. The maximum and minimum levels of voltage value are shown for different scenarios. In the third and fourth scenarios, voltage level improvement, approaching the voltage magnitude to 1pu, and the voltage fluctuation reduction are obtained. This could reduce losses, improve system performance and increase customer and utility satisfaction. Fig. 10 and Fig. 11 show the network voltage fluctuations of end buses (which have the lowest voltage level among other busses in base case scenario) within 24-hours for different scenarios. According to the results, the lowest voltage fluctuation happened in the base case and first scenario. However, in terms of voltage magnitude, the highest voltage level of the end buses is obtained by the fourth scenario. Fig.12 illustrates the importance of voltage regulation for distribution systems. It shows that increasing voltage fluctuation causes an increase in power losses. Consequently, it results in high costs. Using EVs in voltage regulation service can reduce system losses as well as reducing the costs.

Basically, consumers are aiming to reduce their costs. Since this pricing structure in fourth scenario offers high energy price in the high load (peak) times, makes consumers dissuade from electricity consumption to recharge their EVs at the time, and also prevents the network from overloading due to charging demand. Model of electricity price computing based on network demand in different hours is given in Eq. (40).

$$r(t) = \beta_1 + \beta_2 . \propto^{\frac{P_{sys}^t - P_{avg}}{P_{avg}}} \tag{40}$$

where β_1 and β_2 are price parameters, P_{sys}^t is network demand in specific time and P_{avg} is an average of system demand. In this paper, we assume that: $\beta_1 = 1 \frac{\$}{kWh}$, $\beta_2 = 2 \frac{\$}{kWh}$ and $\propto = 10$.

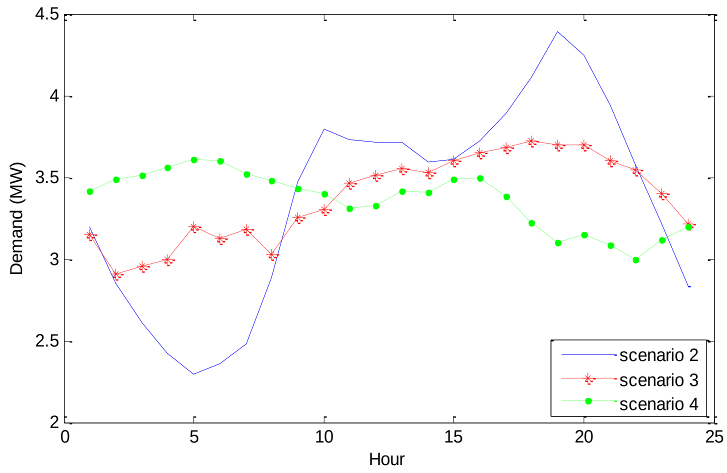


Fig. 13. System demand changes in presence of the EV for 24-h.

According to Fig. 13, in the second scenario, the system demand due to the presence of EVs and their random charging schedule faces with high volatility and actually overload have been imposed on the network at peak times. By controlling the EV's charging schedule through variable energy tariffs for different times (third scenario) demand curve is modified and volatility is reduced. By using real-time pricing model in the fourth scenario, load shifting and peak shaving are accomplished so the demand curve compared to the third scenario is more favorable.

To examine the effectiveness of improved GA-PSO algorithm in such optimization process, the operation of the algorithm is compared with DE algorithm which is given in [15]. Both of algorithms are applied to the IEEE-33bus network and the technical criteria and results are contrasted together. All simulations are done in MATLAB R2004a environment using ASUS x55 with 6GB memory specification. The obtained results are shown in Table 7:

Table 7. Comparison between GA-PSO and DE algorithms

	Iteration	Pop size	NOFE	Processing time (sec)	RES placement	RES capacity
GA-PSO	200	50	69590	20.18	13	0.6939
					30	0.7126
DE	200	50	103410	29.92	12	0.4748
					26	0.8416
	Charge station placement	Charge station capacity	$F_1(MW)$	$F_2(pu)$	$F_3(\$)$	$F_4(\$)$
GA-PSO	23	1.0512	2.108906	24.1073	8,221,640	147,189
	6	0.9035				
DE	19	0.7251	2.471811	25.4512	8,936,725	139,612
	33	0.6200				

According to Table 7, the GA-PSO has the lower NOFE than DE, consequently the GA-PSO is faster than DE for 9.74 sec in same operating condition. Both algorithms could solve the proposed optimization problem and find the optimal place and size of RES and charging stations. Accordingly, the objective functions value which is calculated by GA-PSO is lower than the DE results except F_4. So, the proposed GA-PSO performs faster to deal with this kind of optimization problem compared with the DE algorithm.

5. Conclusion

In this paper, a novel method to find the optimal location and capacity of RES and EV's charging station is introduced. In order to use EVs for network supporting, charging and discharging management through applying variable energy tariffs in both day-ahead and real-time pricing (affected by the changes in hourly demand) models have been considered. A multi-objective function is developed to minimize the power losses (f_1), voltage fluctuations (f_2), energy supplying costs (f_3) and car battery maintenance costs (f_4). In order to solve this multi-objective problem, the weighting coefficients method and improved GA-PSO optimization algorithm in MATLAB software are utilized. In order to evaluate the effectiveness of the proposed approach, standard IEEE 33-bus test network is deployed in the base case and four different scenarios. Finally, the performance of improved GA-PSO is compared with the DE algorithm for solving the formulated optimization problem. Results confirm the outperformance of proposed GA-PSO in such an optimization process.

According to the results, the optimal sitting and sizing of the RES and EVs charging station improve the power systems voltage profile via reducing voltage deviation in highly-loaded buses. Furthermore, applying variable tariff strategy to manage the charging and discharging of the EVs prevents the occurrence of overload caused by charging at the peak time and voltage drop in sensitive buses. The results also show that the appropriate selection of the coefficients in the multi-objective optimization problem and the instantaneous energy pricing method improves the load factor and helps to modify the demand curve. Consequently, the EV charging demand can shift to lower demand and higher RES production time intervals. This study indicates that using EVs as active power sources along with RES in the network can reduce losses, voltage deviations, and the cost of the both system operator and subscribers. In this paper, the uncertainty of input parameters is considered in the load flow which can help the distribution network planners to make the optimal decision.

References

[1] Fazelpour F, Vafaeipour M, Rahbari O, Rosen MA, “Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics,” energy conversion and management, vol. 77,pp. 250–261, January. 2014.

[2] International energy outlook 2011: energy information administration (EIA), office of integrated analysis and forecasting, U.S. Department of energy, Washington DC, 2011.

[3] Amini MH, et al., “Effect of electric vehicle parking lot’s charging demand as dispatchable loads on power loss,” IEEE international conference on electro information technology (EIT), 19-21 May. 2016.

[4] Ahn Changsun, Chiao-Ting Li, Huei Peng, “Optimal decentralized charging control algorithm for electrified vehicles connected to smart grid,” J. power Sources, vol. 196, no. 23, pp. 10369-10379, 2011.

[5] Kempton W, Amardeep Dhanju, "Electric vehicles with V2G," windtech international, vol. 18, no. 2, 2006.

[6] Katrasnik T, “Energy conversion phenomena in plug-in hybrid-electric vehicles, " energy conversion and management, vol. 52, no. 7, pp. 2637-2650, 2011.

[7] Kempton W, Tomic J, “Vehicle-to-grid power fundamentals: Calculating capacity and net revenue,” journal of power sources, vol. 144, no. 1, pp. 268-279, 2005.

[8] Amini MH, et al, “ARIMA-based demand forecasting method considering probabilistic of electric vehicle’s parking lots,” power and energy and energy society general meeting, IEEE, 26-30 July. 2015.

[9] J. de Hoog et al, “The importance of spatial distribution when analysing the impact of electric vehicles on voltage stability in distribution networks,” energy system, vol. 6, no. 1, pp. 63–84, 2014.

[10] Ehsani M, Falahi M, Lotfifard S, “Vehicle to grid services: potential and applications,” energies, vol. 5, no. 10, pp. 4076-4090, 2012.

[11] Honarmand M, Zakariazadeh A, JadidSh, “Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization,” journal of the franklin institute, vol. 352, no. 2, pp. 449-467, 2015.

[12] Liu Z, Wen F, Ledwich G, “Optimal planning of electric-vehicle charging stations in distribution systems,” IEEE transactions on power delivery, vol. 28, no. 1, pp. 102–110, January. 2013.

[13] Davda AT, Azzopardi B, Parekh BR, Desai MD, “Dispersed generation enable loss reduction and voltage profile improvement in distribution network---Case Study, Gujarat India,” IEEE transactions on power systems, vol. 29, no 3, pp. 1242-1249, May. 2014.

[14] Hung DQ, Mithulananthan N, Bansal RC, “An optimal investment planning framework for multiple distributed generation units in industrial systems,” applied energy, vol. 124, pp. 62-72, July. 2014.

[15] Moradi MH, Abedini M, Tousi SMR, Hosseinian SM, “Optimal sitting and sizing of renewable energy sources and charging stations simultaneously based on differential evolution algorithm,” international journal of electrical power and energy systems, vol. 73, pp. 1015-1024, December 2015.

[16] Turton H, Moura F, “Vehicle-to-grid systems for sustainable development: an integrated energy analysis,” technological forecasting and social change, vol. 75, no. 8, pp. 1091-1108, 2008.

[17] El-Zonkoly A, “Intelligent energy management of optimally located renewable energy systems incorporating PHEV,” energy conversion and management, vol. 84, pp. 427-435, 2014.

[18] Su W, Mo-Yuen C, “Performance evaluation of a PHEV parking station using particle swarm optimization,” in: proc. power and energy society general meeting, San Diego, USA, 2011.

[19] Han S, Han S, Sezaki K, “Development of an optimal vehicle-to-grid aggregator for frequency regulation,” IEEE transactions on smart grid, vol. 1, no. 1, pp. 65–72, June. 2010.

[20] Kempton W, “A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system,” results from an industry-university research partnership, 2008.

[21] Moradijoz M , ParsaMoghadam M, Haghifam MR, Alishahi E, "A multi-objective optimization problem for allocating parking lots in a distribution network," international journal of electrical power and energy systems, vol. 46, pp. 115–22, 2013.

[22] Amini MH, Parsa Moghaddam M, Karabasoglu O, "Simultaneous allocation of electric vehicles’ parking lots and distributed renewable resources in smart power distribution networks," sustainable cities and society, vol. 28, pp. 332-342, 2017.

[23] Amini MH, Sarwat AI, "Optimal reliability-based placement of plug-in electric vehicles in smart distribution network," international journal of energy science, vol. 4, issue 2, April. 2014.

[24] Gholami A, Ansari J, Jamei M, Kazemi A, “Environmental/economic dispatch incorporating renewable energy sources and plug-in vehicles,” IET generation, transmission and distribution, vol. 8, no. 12, pp. 2183-2198, December. 2014.

[25] Zhang X, Hug G, "Bidding strategy in energy and spinning reserve markets for aluminium smelters' demand response", in IEEE ISGT conference, 2015.

[26] Zhang X, Hug G, Kolter Z, Harjunkoski I, "Industrial Demand Response by Steel Plants with Spinning Reserve Provision", in IEEE North American Power Symposium, 2015.

[27] Zhang L, Brown T, Samuelsen S, "Evaluation of charging infrastructure requirements and operating costs for plug-in electric vehicles", journal of power sources, 2013.

[28] Markvart T, Solar electricity. 2nd ed. USA: Wiley; 2000.

[29] University of Zaragoza, wind energy notes, Zaragoza, Spain, pp. 1-17, 2005.

[30] Meliopoulos S, Meiselrge J, Overbye T, "Power system level impacts of plug-In hybrid vehicles (final project report)-PSERC document," 2009.

[31] Aitchison, John, and James Alexander Campbell Brown, "The lognormal distribution," vol. 5, cup archive, 1976.

[32] Kolmogorov, Nikolaevich A, "Foundations of the theory of probability," 1950.

[33] "Reliability test system task force of the application of probability subcommittee, IEEE reliability test system," IEEE transactions on power apparatus and systems, vol. 98, no. 6, pp. 2047-2054, 1979.

[34] U.S. department of transportation, "2009 – National household travel survey," Federal highway administration, 2009. [online]. available: http://nhts.ornl.gov.

[35] Letendre S, Denholm P, Lilienthal P, "New load, or new resource?," in public utility fortnightly, pp. 28-37, 2006.

[36] http://www.ieso.ca/Pages/Power-Data/default.aspx.

[37] http://www.chevrolet.com/volt-electric-car.html.

[38] http://automobiles.honda.com/accord-plug-in/.

[39] http://www.ford.com/cars/fusion/trim/seenergi/.

[40] http://www.toyota.com/prius-plug-in/.