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Simultaneous allocation of electric vehicles' parking lots and distributed renewable resources in smart power distribution networks

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ABSTRACT

Electric vehicles (EVs) and distributed renewable resources (DRRs) are introduced to achieve three of the most pivotal objectives of this century: using environmentally-friendly energy resources, reliable supply of the load demand, and sustainable development of power systems. To achieve the aforementioned goals, simultaneous utilization of DRRs and EVs should be implemented in a scheduled manner. In this paper, we propose a two-stage approach for allocation of EV parking lots and DRRs in power distribution network. Our method considers both the economical benefits of parking lot investor and the technical constraints of distribution network operator. First, the parking lot investor offers the candidate buses for installing the parking lot to the distribution network operator based on economic objectives. Then, the distribution network decision-making is obtained to reduce loss of system. The proposed framework not only improves the distribution network loss, but also ameliorates the availability of the parking lot from the economical point of view. In order to solve the formulated optimization problem, we utilize two optimization techniques. Genetic algorithm (GA) and particle swarm optimization (PSO) algorithm are used for the distribution network loss minimization purpose. Besides, we model the EV parking lot by expanding single EV probabilistic model. The performance of the proposed method is evaluated by allocating DRRs and EV parking lots simultaneously on the IEEE standard distribution test system. This system is bus 2 of Roy Billinton Test System (RBTS).

1. Introduction

1.1. Motivation

Growing awareness of energy and environment, and the demand for a reliable, secure, and sustainable power grid, lead to the evolution of smart grid (SG) as a reliable means of electricity distribution. Novel technologies are introduced by SG, such as self-healing frameworks for smart distribution systems management (Zidan & El-Saadany, 2012), and smart buildings with vehicle-to-grid (V2G) capability (Lamedica et al., 2015). In this context, electric vehicles (EVs) play a pivotal role (Brown, Pyke, & Steenhof, 2010). Brady and O'Mahony proposed a charging profile modeling for electric vehicles in (Brady & O'Mahony, 2016). Their model is based on real-world EV charging data.

Additionally, the increasing load demand and the limits on energy resources involve incorporating renewable resources. Enabling the SG also revolutionizes the characteristics of distribution networks (Brown, 2008). Based on US Energy Information Administration (EIA) assessment, energy demand will increase by 56% from 2010 to 2040 which is driven by economic development (EIA, 2013). Therefore, governments have proposed distributed renewable resources (DRRs) and EVs as technological solutions for solving sustainability issues. Unscheduled and independent utilization of DRRs and EVs may bring irrefutable challenges for the smart distribution network. The future cities will require to deploy novel technologies such as electric vehicles and renewable resources to

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improve social welfare, reduce environmental emissions, and move toward electrified transportation networks. This also will lead to sustainable development of the power distribution networks.

1.2. Literature survey

The effects of EVs and DRRs on the future power systems are investigated in several papers (e.g., references (Amini, Nabi, & Haghifam, 2013; Clement-Nyns, Haesen, & Driesen, 2010; Kempton & Tomic, 2005; Shaaban, Atwa, & El-Saadany, 2013; Subramanian et al., 2013; Tuttle & Baldick, 2012)). In (Clement-Nyns et al., 2010), the effect of EV charging on a residential distribution grid was studied. However, the effect of simultaneous utilization of DRRs on the EV charging was not addressed. The value of using DRRs in distribution networks includes investments deferral, loss reduction, and improving the network reliability (Shaaban et al., 2013). In (Subramanian et al., 2013), the advantages of scheduled aggregation of deferrable loads and storages were investigated. In (Amini et al., 2013), a general smart load management framework was introduced based on multi-agent systems considering DRRs and responsive demands. In (Kempton & Tomic, 2005), the potential benefits of EV's participation in different types of electricity markets such as regulation market and spinning reserves were studies. Alizadeh et al. in (Alizadeh et al., 2014) proposed a stochastic model for EV load estimation. Their model facilitates the integration of EVs in future power networks. Furthermore, energy security and the cost savings related to oil consumption reduction were considered as advantages of EV utilization (Tuttle & Baldick, 2012). In (Amini & Karabasoglu, 2016), we proposed a comprehensive framework to model the interdependent nature of power and transportation networks. This model considers the limits of transportation network as well as the power systems operational constraints by solving multi-objective route optimization and optimal power flow problem iteratively. A review of optimization techniues for electric vehicles charging infrastructure is provided in (Rahman et al., 2016).

Previous studies have focused on the distributed generation (DG) allocation using various optimization algorithms including Genetic algorithm (Mohan & Ramesh, 2012), and particle swarm optimization (Bhumkittipich & Phuangpornpitak, 2013). Besides, some studies proposed methods for parking lots allocation in distribution networks. A congestion management method is developed in (López, Martín, Aguado, & de la Torre, 2013) considering high penetration of EVs. In (Moradijoz, Parsa Moghaddam, Haghifam, & alishahi, 2013), a multi-objective optimization problem is formulated and solved for optimal allocation of parking lots. In (Amini, Karabasoglu, Ilic, Boroojeni, & Iyengar, 2015), a time series forecasting approach is utilized to reduce the error of EV charging demand estimation. In (Amini, Kargarian, & Karabasoglu, 2016) a decoupled demand forecasting approach based on ARIMA model was proposed for EV charging demand. Further, a chance-constrained unit commitment problem utilizing the predicted demand was formulated to improve the accuracy of stochastic power system operation (Amini et al., 2016). In (Lam, Leung, & Chu, 2014), EV parking lot placement problem is solved in the future smart city environment (Lam et al., 2014). According to (Liu, Wen, & Ledwich, 2013), the sizing and placement of EV charging station problems have been solved separately. Furthermore, simultaneous placement of conventional and renewable distributed resources can be tackled by fuzzy multi-objective optimization (Mohsenzadeh & Haghifam, 2012). The electrical protection requirements of utilizing EV charging stations have been reviewed in (Sanchez-Sutil, Hernández, & Tobajas, 2015). In (Zakariazadeh, Jadid, & Siano, 2015), the integration of high penetration of EVs and distributed generations on distribution network is studied. In (Neyestani et al., 2014) (Amini & Islam, 2014) , EV parking lots allocation is obtained considering power distribution network's constraints. The utilization of DRRs will lead to active distribution networks.Optimum location and charging of electric vehicles have been investigated in (Sachan & Kishor, 2015, 2016).

Recent studies on the allocation of EV parking lots and DRRs can be classified into three categories: integrating EVs in a grid with DRR or conventional distributed generation penetration (El-Zonkoly & dos Santos Coelho, 2015; Fazelpour et al., 2014; Honarmand, Zakariazadeh, & Jadid, 2014), allocation of EV parking lots in the power systems (Kazemi et al., 2016; Moradijoz et al., 2013; Neyestani et al., 2014), and allocation of DRRs and DGs in power systems (Bhumkittipich & Phuangpornpitak, 2013; Mohan & Ramesh, 2012; Mohsenzadeh & Haghifam, 2012). In (El-Zonkoly & dos Santos Coelho, 2015), a multi-objective algorithm was developed to find the optimal number of parking lots, their location and size. This study used artificial bee colony (ABC) and firefly algorithms as two effective methods for optimization (El-Zonkoly & dos Santos Coelho, 2015). Arasteh et al. in (Arasteh et al., 2016) utilized SoS-based multiobjective approach to deal with distribution network planning. Honarmand et al. in (Honarmand et al., 2014), proposed an energy resources management framework considering practical constraints, DRR generation forecasting errors, and EVs owner satisfaction. Their model is applicable to microgrid and did not consider the allocation of EV parking lots (Honarmand et al., 2014). In (Kazemi et al., 2016), an allocation approach is proposed for EV parking lots considering the welfare of EV owners.

The aforementioned studies considered EV parking lot allocation *or* DRR/DG allocation as their optimization problem. However, in this study we allocate DRRs and EV parking lots simultaneously. Our proposed method is two-tier to satisfy EV parking lot investor and distribution network operator constraints and objectives, i.e. we first consider the parking lot investor's decision parameters. We next solve the optimization problem from the utility perspective for optimal allocation of EV parking lots and DRRs. It is worth noting that independent allocation of EV parking lots and DRRs may lead to sub-optimal solutions.

1.3. Contribution

In this paper, a novel approach for the simultaneous allocation of DRRs and EVs' parking lots is proposed. This synchronic approach definitely ameliorates smart distribution network's performance in terms of achieving optimum level of loss reduction and involving both parking lot investor's decision factors and distribution network constraints. A two stage optimization method is used to achieve the optimal allocation of DRRs and EV parking lots simultaneously. At the first level of the proposed method, the candidate buses for allocating the parking lots are offered to the distribution network operator after making decision by calculating the parking lot investor decision making index (PIDMI). At the second stage, the distribution network operator allocates the DRRs and EV parking lots to achieve the minimum loss of distribution network. In order to model the penetration of DRRs into our optimization problem we need to obtain the reliable percentage of each DRR. To this end, we use capacity credit as an effective means of modeling the uncertain DRR in the allocation process. In the second stage, the distribution network operator considers the decision of charging station investor by using the offered candidate buses for EV parking lot installment. The effectiveness of the proposed method is evaluated by the simultaneous allocation of DRRs and EV parking lots on the standard test system. The *main* contribution of this paper is threefold:

- Optimal simultaneous allocation of EVs' parking lots and DRRs to satisfy both economical constraints of parking lot investor and distribution network constraints.

- The formulated problem is solved using two optimization techniques (GA and PSO). The results of these two methods are compared to validate the effectiveness of the proposed framework in reducing loss in distribution network.
- Analyzing the effect of EV and DRR penetration levels on the optimal location of these element.

1.4. Organization of the paper

The rest of this paper is organized as follows: In Section 2, the problem formulation and preliminaries required for the optimization method are presented in three subsections: parking lot decision making, load flow considering DRRs, and EV parking lot demand modeling. In Section 3, the optimization method is formulated and Genetic Algorithm and Particle Swarm Optimization are introduced to solve the formulated problem. Section 4, is devoted to implementing the proposed method on standard test system. The results of case study are discussed in Section 5. Finally, Section 6 concludes the paper.

2. Problem formulation and preliminaries for optimization problem

In this section, the parking lot investor's decision making is introduced. Afterwards, the objective function for the distribution operator is proposed by considering the offered candidate buses from investor's decision-making stage. Moreover, a probabilistic model is presented to calculate the hourly load demand of the parking lot. The first factor models the impact of reliability on the parking lot investor's decision. In other words, locations with higher reliability attract more investors compared with the location with lower reliability level. Furthermore, the cost of land plays a pivotal role in the decision of investor as it affects the total cost incurred by the parking lot installation. Last but not the least, the expected customer acceptance is a key factor for the future of parking lot. We integrated this factor in the parking lot investor's objective function to highlight the effect of potential market (number of expected EVs to choose this parking lot as their location for charging their battery).

2.1. Parking lot investor decision making; candidate bus selection

The parking lot investor's decision making is modeled based on three effective factors: 1) reliability, 2) cost of land, and 3) expected customers' acceptance. Consequently, the parking lot investor should offer a set of appropriate candidate buses according to the aforementioned criteria.

2.1.1. Reliability index of each bus

Let $\mathscr{B} = \{1, 2, \ldots, N\}$ denote the set of all buses in the analyzed system. In order to achieve a reliability assessment of each bus for parking lot installation, the bus reliability index is introduced. The Average Interruption Time (*AIT*) is used for this purpose. Firstly, *AIT* is calculated for all of buses in the test system and then the values are normalized by dividing *AIT* values by maximum achievable value. The equivalent value of failure rate (λ) [1/year] and the repair time (r) [hr] are used for *AIT*.

$$AIT_i^{Bus} = \frac{AIT_i}{\max_{j \in \mathscr{B}} \{AIT_j\}} = \frac{\lambda_i r_i}{\max_{j \in \mathscr{B}} \{AIT_j\}} \tag{1}$$

where λ_i and r_i show the equivalent failure rate and the equivalent repair time at the i^{th} bus, AIT_i represents the average interruption time for i^{th} bus and AIT_i^{Bus} is an index in [0,1] range and is considered as an effective factor on parking lot investor's decision making. Fig. 1 illustrates the general framework of the proposed method.

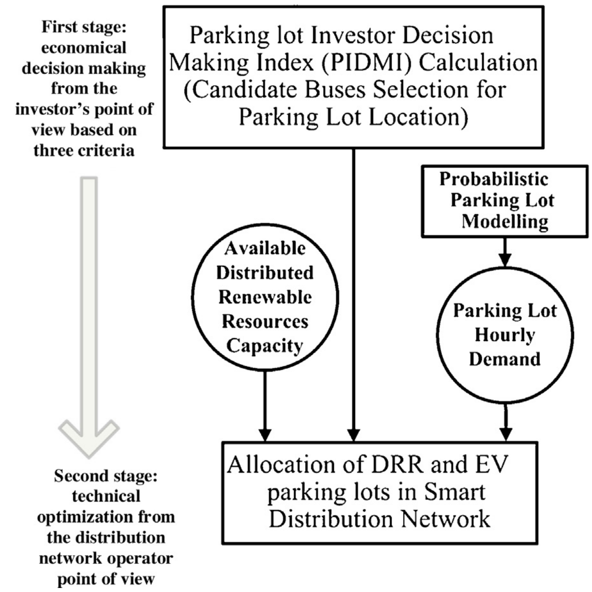

Fig. 1. General framework of the proposed optimal EVs' parking lot and DRR allocation approach.

2.1.2. Bus attraction index

Let Bus Attraction Index (*BAI*) is directly related to the number of residential, commercial and industrial customers connected to each bus and it is calculated by the weighted summation of the number of customers at each bus. The obtained values are normalized based on maximum achievable *BAI*. We have:

$$BAI_i^{Bus} = \frac{\dfrac{\left(\alpha \times n_{res}^i\right) + \left(\beta \times n_{com}^i\right) + \left(\gamma \times n_{ind}^i\right)}{\left(\alpha \times n_{res}^{total}\right) + \left(\beta \times n_{com}^{total}\right) + \left(\gamma \times n_{ind}^{total}\right)}}{\max_{i \in \mathscr{B}} \{BAI_i^{Bus}\}} \tag{2}$$

where α, β and γ are the weighting coefficients for residential, commercial and industrial customers, respectively. n_k^i is the number of the different types of customers, n_k^{total} represents total customers serving distribution grid ($k \in \{res, ind, com\}$), and BAI_i^{Bus} shows bus attraction index for the i^{th} bus.

2.1.3. Price of land index

Parking Land Cost Index (PLCI) indicates the cost of land for parking installation. In order to calculate this index, a normalized land cost is considered for each bus by dividing land cost in each geographical region by the maximum achievable land cost in the whole region. Let LC_i^{Bus} represent the land cost at i^{th} bus, we have:

$$PLCI_i^{Bus} = \frac{LC_i^{Bus}}{\max \{LC_j^{Bus}\}} \tag{3}$$

Based on the aforementioned indices, parking lot investor decision making index (*PIDMI*) is obtained using (4):

$$PIDMI_i = \eta_1 AIT_i^{Bus} - \eta_2 BAI_i^{Bus} + \eta_3 PLCI_i^{Bus} \tag{4}$$

where η_1, η_2 and η_3 are positive coefficients to include the parking lot investors priorities in decision making process. As the formulation of *PIDMI* represents, the investor prefers to install the parking lot in the bus with the following criteria: 1) maximum electricity availability to charge EVs effectively with the lowest interruption, i.e., smaller *AIT* value; 2) higher bus attraction index to obtain more EVs to be potentially charged at the parking lot; and 3) lower land price will also motivate the investor to select the buses with lower cost.

2.2. Capacity credit evaluation of distributed renewable resources (DRRs)

In order to model the penetration of DRRs into our optimization problem we need to obtain the reliable percentage of each DRR. These resources can be wind generation units or solar panels. Capacity credit is widely used for planning purpose to maintain reliable level of generation for renewables.

According to (Voorspools & D'haeseleer, 2006), the capacity credit of wind power represents the amount of conventional power (with deterministic value) that can be alternatively replaced by wind power. The capacity credit of wind based DG units were widely utilized in the power systems planning problems (Dugan, McDermott, & Ball, 2001; Wang, Ochoa, & Harrison, 2010). Furthermore, this concept can be applied to solar energy. According to National Renewable Energy Laboratory's technical report, the capacity value (capacity credit) of solar generation by photovoltaics (PVs) is a function of the coincidence of sunlight with demand profiles (Anon, 2013).

As the main focus of our method is on the allocation of EV parking lots and DRRs, we use the penetration levels after considering capacity credit value. Let ϑ_i denote the capacity credit of the i^{th} DRR unit. In our study we consider the DRRs t be wind generation units. However, as it has been mentioned in (Anon, 2013), the capacity credit can be obtained for solar generation as well. According to (Voorspools & D'haeseleer, 2006), capacity credit is the percentage of the installed wind power without requiring further investment, e.g. 10 MW of installed wind power with a capacity credit of 30%, results in avoiding 3 MW investment in conventional deterministic power generation. Van Wijk in (Van Wijk, 1990), calculated the capacity credit using a probabilistic method, which evaluates the loss-of-load expectation (LOLE) of the power system. This model compared two systems with and without wind generation units. Both systems were expected to achieve the same reliability in terms of LOLE. The following equation provides the formula for capacity credit definition:

$$\vartheta_i = 1 - \frac{P_{tot}^{(i)} - P_{conv}^{(i)}}{P_{wind}^{(i)}}$$

where $P_{tot}^{(i)}$, $P_{conv}^{(i)}$, and $P_{wind}^{(i)}$ represent the total available power after integrating the i^{th} wind generation unit, conventional power generation before adding the wind generation, and the rates power of the i^{th} wind generation unit.

In addition to the above-mentioned definition of capacity credit by Van Wijk, in (Milligan & Parsons, 1997) a simplified definition of this factor was presented. According to Milligan and Parsons, although Van Wijk's model provides reasonable deterministic value for DRRs, the capacity credit can be approximated by the *capacity factor* of the installed wind power system. The capacity factor is defined as power generation of the DRR unit over a specific time interval divided by the rated power of DRR unit times the number of hours in the analyzed interval (MWh generated/MW installed) (Milligan and Parsons, 1997).

2.3. Backward/Forward sweep power flow analysis in distribution network considering DRRs

In the power flow calculation, DRRs are modeled as PQ buses and considered as negative loads. The backward/forward sweep method is utilized to solve power flow problem which is a compensation-based method for weakly meshed network (Shirmohammadi, Hong, Semlyen, & Luo, 1988). In this paper, a modified version of the method, which uses power flow of branches instead of branch currents, is utilized. Fig. 2 represents a branch of a typical distribution system. In this figure, subscripts s and r show "sending end" and "receiving end", respectively. Based on sending and receiving side, the voltage magnitudes, active power, reactive power and voltage phases are defined as shown in Fig. 2. The sending power is calculated from (5) in the backward sweep. Active power and reactive power are denoted by P and Q, respectively. R and X are the resistance and reactance of the transmission line between the sending and receiving ends.

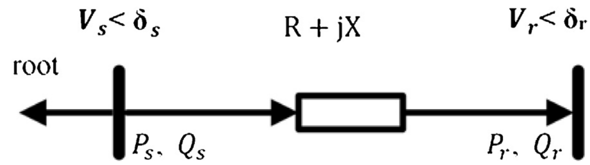

Fig. 2. An example branch for method demonstration (Luo & Semlyen, 1990).

$$P_s = P_r + R\frac{P_r^2 + Q_r^2}{V_r^2} \tag{5-1}$$

$$Q_s = Q_r + X\frac{P_r^2 + Q_r^2}{V_r^2} \tag{5-2}$$

Additionally, for the forward sweep, the sending voltage magnitude, V_s and its angle, δ_s are known and the received voltage magnitude, $V_r$and its phase angle, δ_r are calculated as follows:

$$V_r = \sqrt{\Delta V''^2 + (V_s - \Delta V')^2} \tag{6-1}$$

$$\delta_r = \delta_s - arctan\left(\frac{\Delta V''}{V_s - \Delta V'}\right) \tag{6-2}$$

where $\Delta V'$ is the longitudinal voltage drop and$\Delta V''$ represents transversal voltage drop which are calculated by (7).

$$\Delta V' = \frac{RP_s + XQ_s}{V_s} \tag{7-1}$$

$$\Delta V'' = \frac{XP_s - RQ_s}{V_s} \tag{7-2}$$

In this method, the forward and backward sweeps are performed based on the power flow equations and branch currents are not used directly. In the backward sweep the power summation is achieved in terms of the sending end active and reactive powers calculation in the reverse sequence of the order function based on (5). Then, in the forward sweep, the voltage calculation is obtained using (6) and (7) following the sequence defined by the order function. Finally, the loop breakpoint mismatch is calculated based on the voltage difference between sending and receiving buses.

Based on the calculated current of the branches by the mentioned power flow method, the objective function for loss minimization in distribution network is calculated as represented in (8).

$$\min_{I_{l,t}} \sum_{t\in T}\sum_{l\in\Omega} R_l I_{l,t}^2,\ s.t.: \begin{cases} S_{m,t} = V_{m,t}(I_{m,t})^* \\ I_{m,t} = I_{l,t} - I_{l+1,t} \\ S_{min,m,t} \le S_{m,t} \le S_{max,m,t} \\ \sum_{t\in T} S_{m,t} = E_{tot,m} \end{cases} \tag{8}$$

where $R_l$and $I_{l,t}$ represent the branch resistance and the branch current, respectively. $S_{m,t}$ is the load of the m^{th}bus at time t. $I_{m,t}$ and $V_{m,t}$are the current and the voltage of the m^{th}bus at time t, respectively. $E_{tot,m}$is the total energy delivered to the m^{th}bus in simulation time interval. Note that we have already calculated the expected hourly charging demand of EVs by integrating them as parking lots. Hence, EVs' charging demand affects the total delivered energy

Table 1
Statistical driving pattern parameters (Darabi & Ferdowsi, 2011).

Parameter	μ_{ar}	σ_{ar}	μ_{dep}	σ_{dep}
Value	7	1.73	18	1.73

value. The optimization for loss reduction considering distribution network technical constraints is performed using genetic algorithm (GA) and will be discussed in the next section.

2.4. Probabilistic model of parking lot hourly electricity demand

In order to obtain the parking lot hourly demand, a single vehicle is modeled. The single EV probabilistic demand is used to obtain the hourly demand of the EV parking lot considering different types of EVs in market. The expected driven distance,M_d, is modeled using lognormal distribution function as follows (Domínguez-García, Heydt, & Suryanarayanan, 2011; Meliopoulos, 2009):

$$M_d = e^{(\mu_m + \sigma_m N)} \tag{9}$$

where μ_m and $\sigma_m$are the lognormal distribution parameters and are calculated from mean and standard deviation of driven distance based on the historical data's mean and standard variation (Li & Zhang, 2012; Sharer, Leydier, & Rousseau, 2007). The value of mean and standard deviation for historical driven distance data are considered 40 and 20 miles, respectively (Sandmeier & Felsenstein, 2009). Let E_m and β denote the energy consumption of EVs and the battery capacity of each EV, respectively. We can calculate the maximum achievable driven distance, M_{dmax} as:

$$M_{dmax} = \frac{\beta}{E_m} \tag{10}$$

Based on the maximum driven distance, the expected energy demand of EV based on driven distance can be obtained as:

$$E_d = \begin{cases} \beta; M_d \geq M_{dmax} \\ M_d E_m; M_d \leq M_{dmax} \end{cases} \tag{11}$$

Moreover, the desired state of charge is probabilistic duration that EVs are parked in the parking lots based on mean and standard deviation of arrival and departure time based on historical data. The duration time, $t_d$is calculated as follows (Domínguez-García et al., 2011; Letendre, Denholm, & Lilienthal, 2006).

$$\begin{cases} t_{ar} = \mu_{ar} + \sigma_{ar} N_1, \\ t_{dep} = \mu_{dep} + \sigma_{dep} N_2, \\ t_d = t_{dep} - t_{ar}, \end{cases} \tag{12}$$

whereN_1 and $N_2$are normally distributed random variables. μ_{ar}andμ_{dep} denote mean value of the arrival time and the departure time being used for charging demand modeling respectively. Moreover, σ_{ar} and σ_{dep} are Standard deviation of the arrival time and the departure time being used for charging demand modeling. The expected arrival time and the expected departure time are shown by t_{ar} andt_{dep} respectively. The expected duration of parking the EV is t_d.The desired state of charge,SOC_d, can be shown as (Amini & Parsa Moghaddam, 2013).

$$SOC_d = Min\left\{SOC_{init} + \frac{E_d}{\beta}, SOC_{init} + \frac{Chr.t_d}{\beta}\right\} \tag{13}$$

where *Chr* is the charging rate. The initial state of charge is denoted by SOC_{init}.

Based on (Amini & Parsa Moghaddam, 2013), four types of EVs are considered to calculate the demand of parking lots using the specification from Tables 1–3 (Kempton, 2008; Sandmeier & Felsenstein, 2009).

Table 2
Charging rates in a proportion of battery capacity.

Charging Rate ($\beta/hour$)	Charging Mode
0.1	Slow Charging
0.3	Quick Charging
1.0	Fast Charging

Table 3
EV classes specifications.

Market Share	$E_m(^{kWh}/_{mile})$	$\beta(kWh)$	EV Class
0.2	0.3790	10	1
0.3	0.4288	12	2
0.3	0.5740	16	3
0.2	0.8180	21	4

3. Optimization using genetic algorithm and particle swarm optimization

3.1. Genetic algorithm

GA is an optimization methods based on natural evolution (Goldberg, 1989). The modified Genetic Algorithm (MGA) is utilized for the proposed objective function optimization. It includes three genetic operators for population evolution: selection, crossover and mutation. Each chromosome (string) is a possible solution of the objective function and each bit represents a value for gene(some variable of the problem) (Haghifam & Shahabi, 2002). These solutions are evaluated by calculating the values of fitness function and the most feasible. Then, the optimal one will be selected (Miranda, Ranito, & Proenca, 1994).

3.1.1. Proposed approach for GA utilization in loss minimization

First a table of all possible states of DRR and EV parking lots locations is prepared. This table contains the locations and the loss value calculated during the optimization process. For example, for allocating of one DRR and one parking lot, there are 3 candidate buses for each parking lot which is offered by investor as well as one bus for DRR installation. The number of all states at the table is:

$$N_{states} = N_{parking}^3 \times N_{DRR_1}\left(N_{DRR_1} - 1\right) \times \ldots \times \left(N_{DRR_1} - DRR_{number} + 1\right) \tag{14}$$

whereN_{states} represents total number of states, N_{DRR_1} is the number of candidate buses for allocation of the first DRR. Thus, $(N_{RR_1} - i)$ is the number of candidate buses for the $(i+1)^{th}$ DRR, and DRR_{number} shows the number of DRRs. Based on the number of states, we can calculate the number of cells, N_{cell}, for each chromosome used in GA:

$$N_{cell} = \min\{m\} \,|\, 2^m \geq N_{states} \tag{15}$$

We also need to define the chromosomes structure. In this paper, chromosomes represent a binary number which includes five location bus numbers in the following order: DRR_1, DRR_2, PL_1, PL_2, and PL_3, where PL_i stands for parking lot *i*.

The framework of GA implementation is shown in Fig. 3. It covers the initialization step, mutation, crossover, and termination criteria evaluation.

3.1.2. GA parameters selection

In order to choose appropriate number of generations and population size for GA optimization, the minimum achievable loss value is calculated for a specific state. Based on these calculations, the minimum achievable loss is 528.6887 kW. Table 4 represents a sensitivity analysis on the two mentioned parameters and optimization result. The crossover rate is set to 0.8 and the mutation rate is set to 0.05 per gene.

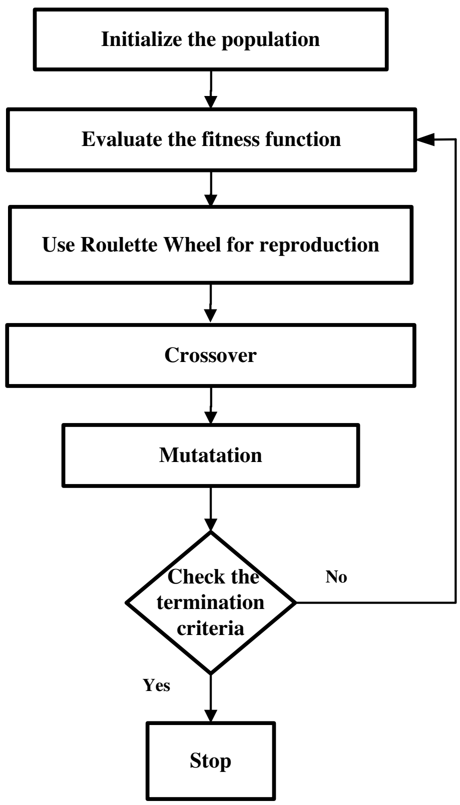

Fig. 3. Flowchart of GA method implementation.

Table 4
Sensitivity analysis for appropriate GA parameter selection.

State number	1	2	3	4	5
Generation Size	50	200	50	200	400
Population Size	6	6	100	100	200
Optimum Loss (kW)	561.25	536.13	528.68	528.68	528.68
Simulation Time (s)	7.892	13.87	11.9	29.2	77.56

Based on the results of Table 4, there is a trade-off between the simulation time and the optimization result accuracy. According to the results of Table 4, generation size of 50 and population size of 100 are utilized for the sake of accuracy. This selection of GA parameters, comparing to other analyzed values in Table 4, will result in more accurate results.

3.2. Particle swarm optimization

Particle swarm optimization (PSO) algorithm is introduced by Kennedy and Elberhart (Eberhart & Kennedy, 1995; Kennedy & Eberhart, 2001; Kennedy & Eberhart, 1995). This optimization method is inspired by the social behavior of flocks of birds. Assume that the population includes n particles representing the candidate solutions. The PSO technique is implemented using the following procedure. Based on (15) and (16), PSO algorithm starts by generating random positions for the particles, within an initialization region. Velocities are usually initialized within that region, but they can also be initialized to zero or to small random values to prevent particles from leaving the search space during the first iterations. During the main loop of the algorithm, the velocities and positions of the particles are iteratively updated until a stopping criterion is met. The update rules are shown in (15) and (16).

$$V_i^{k+1} = wV_i^k + C_1 rand_1 \left(Pbest_i^k - X_i^k\right) + C_2 rand_2 \left(Gbest_i^k - X_i^k\right) \quad (15)$$

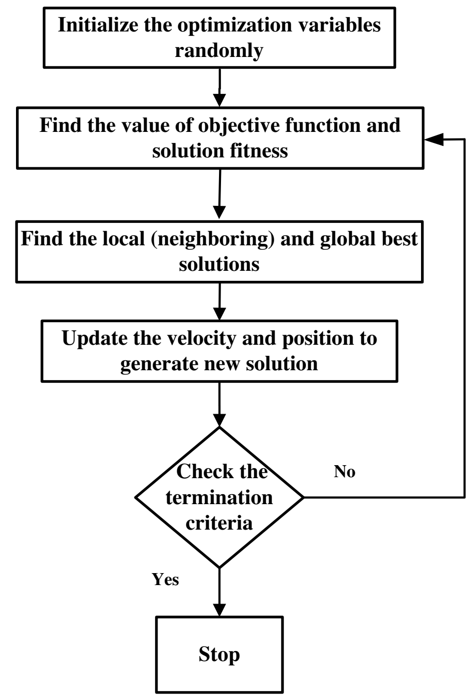

Fig. 4. Flowchart of PSO technique implementation.

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (16)$$

where k and $k+1$ are the previous and current iteration indices, respectively; $rand_1$ and $rand_2$ are two random numbers in [0,1] interval; $X_i = [X_{i1}, X_{i2}, \ldots, X_{id}]$ and $V_i = [V_{i1}, V_{i2}, \ldots, V_{id}]$ are the position and velocity of the i^{th} particle, respectively; and $w=0.98$ is an weighting coefficient. Let $Pbest_i = [X_{i1pbest}, X_{i2pbest}, \ldots, X_{idpbest}]$ and $Gbest = [X_{1gbest}, X_{2gbest}, \ldots, X_{dgbest}]$ be the best position of particle i and its neighbors' best position at the current iteration, respectively. C_1 and C_2 are constant coefficients. General structure of PSO technique is demonstrated in Fig. 4.

PSO parameter setting: We choose the parameters of PSO as follows: Population size is 50. Constant coefficients C_1 and C_2 are both equal to 2.

4. Case study

In this section a standard distribution test system is introduced. Furthermore, *PIDMI* calculation considering different weighting coefficients is performed. Finally, distribution network operator will perform loss minimization based on the candidate buses from parking lot investor's decision making process. In this paper, for the simulation purposes, a set of three candidate buses for each EV parking lot location is offered by the investor.

4.1. RBTS bus 2 distribution test system

Bus 2 of RBTS is used for implementing the proposed placement approach. This test system includes 22 load points, four feeders and one feeding substation. Fig. 5 shows the test system (Allan, Billinton, Sjarief, Goel, & So, 1991) that has 3222 customers in residential, commercial and industrial categories with specific load profiles. Tables 5 and 6 show load point specification and reliability parameters, respectively.

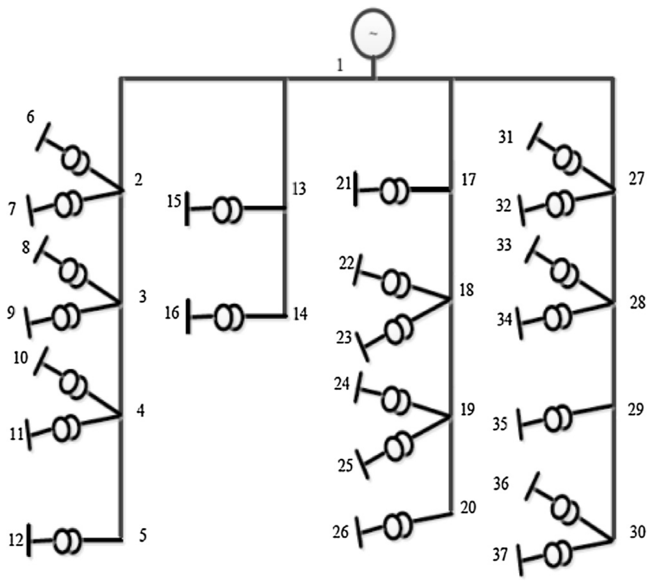

Fig. 5. RBTS bus 2 distribution test system.

Table 5
Load point specification and peak load for the test system.

Peak Load (kW)	Number of Customers	Load Type	Bus Number
535	210	Residential	6, 7, 8, 21, 22
566	220	Residential	9, 10, 24, 25, 35, 36
454	10	Commercial	11, 12, 26, 31, 37
1000	1	Industrial	15
1150	1	Industrial	16
450	200	Residential	32, 33, 34

Table 6
Failure rate and repair time of elements.

Element	Distribution transformer	Bus-bar	Cable
Failure rate (1/year) [for cables: 1/year.km]	0.015	0.001	0.065
Repair Time (hr)	200	2	5

4.2. PIDMI calculation for the test system

The effect of reliability (in terms of availability), bus attraction and land cost on the PIDMI calculation is evaluated by changing the weighting coefficients. Fig. 6 and Table 7 show these three effective factors on the parking lot investor's decision making process. This figure illustrates conflict between these factors. For instance, while moving from bus 2 to bus 5, land cost reduces, but the average interruption time increases.

4.3. Effect of charging rate on the EV parking lots on distribution network

One of the parking lot model inputs is the charging rate which is effective on distribution network power loss. In order to evaluate the effect of the charging rate on the loss optimization in the mentioned test system, the total possible installation capacity of each feeder is defined as:

$$PCAP_i = \phi_1 n_i^{res} + \phi_2 n_i^{com} + \phi_3 n_i^{ind} \tag{17}$$

where ϕ_1, ϕ_2 and $\phi_3$represent are the penetration of EVs for different types of customers connected to each feeder. n_i^{res}, n_i^{com}, and n_i^{ind} represent the total number of residential, commercial, and industrial customers connected to feeder *i*. Fig. 7 shows loss values versus charging rate. Note that charging rates are in battery capacity per hour, i.e., charging rates shows total hours required to fully charge the battery from 0% initial state of charge.

Based on the representation of loss values in Fig. 7, increasing the charging rate (*Chr*) leads to increasing the peak demand of parking lot. It means the distribution network loss increases. Table 7 represents the PIDMI calculation results. Table 8 shows the results of optimization for the parking lots and the DRRs location.

From the results shown in Table 8, we can conclude that for charging rate values of 0.9 and 1, both DRRs are allocated at fourth feeder. The main reason is load concentration in the fourth feeder. In fact, the load increase caused by parking installation at feeder four makes this feeders' load the highest in comparison with three other feeders. On the other hand, for the charging rate equal to or less than 0.8, one of the DRRs is located at feeder four and the other one located at feeder one.

4.4. Evaluating the effect of EV and DRR penetration on loss

The effect of EV and DRR penetration on the distribution loss is evaluated by changing these two factors and determining the optimum point. The coefficients ϕ_2 and ϕ_3 are set to 10 and 5, respectively. The residential type customers penetration factor, ϕ_1, is subject to change. DRR penetration is set to proportion to system peak power.

In this section, two DRRs with the same generation capacity are deployed as the optimization input. For all of the following eight scenarios, EV parking lot charging rate is set to 0.3. This assumption facilitates the assessment of EV and DRR penetration effect on the distribution network loss. The eight scenarios are as follows:

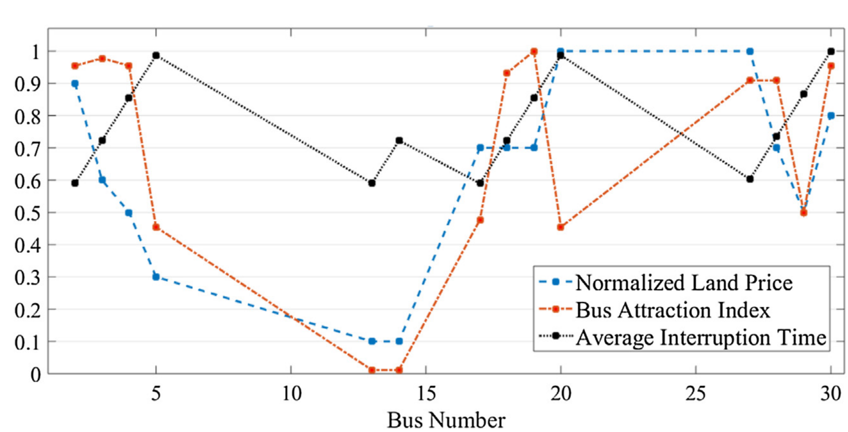

Fig. 6. The values of effective indices in PIDMI calculation.

Table 7
PIDMI elements calculation for each feeder.

Bus Number	*AIT*	*BAI*	*PLCI*	Feeder	State 1 ($\eta_1=1$, $\eta_2=1$, $\eta_3=8$)	State 2 ($\eta_1=8$, $\eta_2=1$, $\eta_3=1$)	State 3 ($\eta_1=1$, $\eta_2=8$, $\eta_3=1$)	State 4 ($\eta_1=8$, $\eta_2=8$, $\eta_3=1$)	State 5 ($\eta_1=1$, $\eta_2=8$, $\eta_3=8$)	State 6 ($\eta_1=8$, $\eta_2=1$, $\eta_3=8$)	State 7 ($\eta_1=8$, $\eta_2=8$, $\eta_3=8$)
2	0.59015	0.95449	0.9	1	6.83566	4.66671	-6.14577	-2.01472	0.15423	10.9667	4.28528
3	0.72242	0.97789	0.6		4.54453	5.40147	-6.5007	-1.44376	-2.3007	9.60147	2.75624
4	0.8547	0.95449	0.5		3.90021	6.38311	-6.28122	-0.29832	-2.78122	9.88311	3.20168
5	0.98697	0.45449	0.3		2.93248	7.74127	-2.34895	4.55984	-0.24895	9.84127	6.65984
13	0.59015	0.0113	0.1	2	1.37885	4.8099	0.59975	4.7308	1.29975	5.5099	5.4308
14	0.72242	0.0113	0.1		1.51112	5.86806	0.73202	5.78896	1.43202	6.56806	6.48896
17	0.59015	0.47719	0.7	3	5.71296	4.94401	-2.52737	1.60368	2.37263	9.84401	6.50368
18	0.72272	0.93178	0.7		5.39094	5.54998	-6.03152	-0.97248	-1.13152	10.4499	3.92752
19	0.8547	1	0.7		5.4547	6.5376	-6.4453	-0.4624	-1.5453	11.4376	4.4376
20	0.98697	0.45449	1		8.53248	8.44127	-1.64895	5.25984	5.35105	15.4412	12.2598
27	0.60317	0.90908	1	4	7.69409	4.91628	-5.66947	-1.44728	1.33053	11.9162	5.55272
28	0.73544	0.90908	0.7		5.42636	5.67444	-5.8372	-0.68912	-0.9372	10.5744	4.21088
29	0.86772	0.5	0.5		4.36772	6.94176	-2.63228	3.44176	0.86772	10.4417	6.94176
30	1	0.95449	0.8		6.44551	7.84551	-5.83592	1.16408	-0.23592	13.4455	6.76408

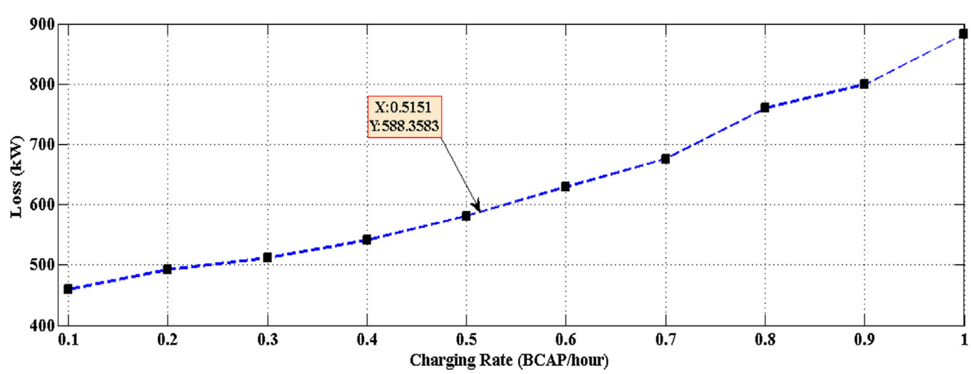

Fig. 7. The effect of charging rate of EV parking lots on the loss values.

Table 8
Allocation results for different charging rate values.

Charging Rate (BCAP/hour)		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Distributed Renewable Resources (DRRs) and Parking Lots (PL) optimum location	DRR_1	4	5	4	4	4	5	5	4	27	27
	DRR_2	30	30	30	30	30	30	30	28	30	30
	PL_1	4	4	4	4	4	5	5	3	3	5
	PL_2	17	17	17	17	17	17	17	17	17	18
	PL_3	30	28	28	28	28	28	28	28	28	29

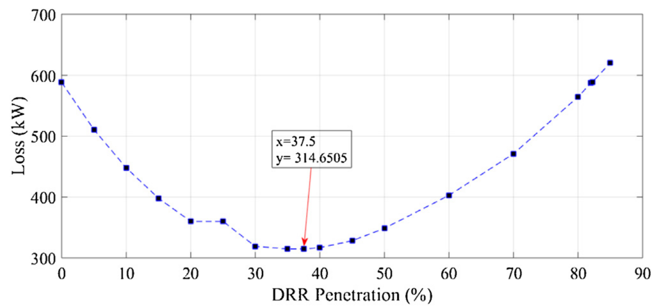

Fig. 8. Effect of DRR penetration on distribution network loss.

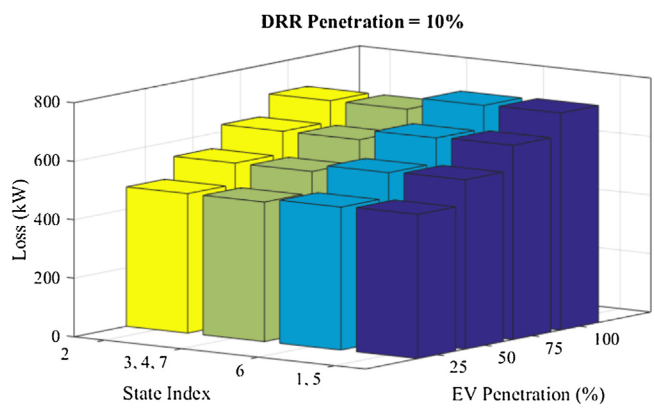

Fig. 9. Loss values for different EV penetration and different states of parking lot investor's decision making, DRR penetration is 10%.

a) EV penetration 25% and DRR penetration 10%.
b) EV penetration 50% and DRR penetration 10%.
c) EV penetration 75% and DRR penetration 10%.
d) EV penetration 100% and DRR penetration 10%.
e) EV penetration 25% and DRR penetration 15%.
f) EV penetration 50% and DRR penetration 15%.
g) EV penetration 75% and DRR penetration 15%.
h) EV penetration 100% and DRR penetration 15%.

Here, in order to perform a sensitivity analysis on the effect of charging rate on the loss of the distribution network, a fixed charging rate of 0.3 is considered and the DRR penetration has been changed from 0% to 85%. Fig. 8 shows the effect of DRR penetration on the loss values by performing a sensitivity analysis. As this figure shows, increasing the utilization of DRRs cannot improve the distribution network losses. Furthermore, there is an optimum percentage of DRR penetration which leads to the minimum loss reduction. This penetration amount is different based on the grid topology. For the analyzed network, the optimal DRR penetration rate is 37.5%.

Fig. 9 shows the amount of loss in scenarios 1–4, i.e. it highlights the effect of EV penetration on the loss values with a fixed DRR penetration of 10%. According to the results of this figure, increasing EV penetration will increase the total loss value. Furthermore, depending on the parking lots owner decision, the loss value differs for the same values of DRR penetration and EV penetration are constant.

In order to investigate the effect of DRR penetration and EV penetration at the same time, we presented the results of all scenarios in Fig. 10.

In order to compare the effectiveness of GA and PSO methods for solving the loss minimization problem, we provide the average loss of all states for the studies scenarios. The results shows the outperformance of GA. The main reason is that we used parameter tuning for GA. However, for the PSO we used the predefined parameters. The results of solving the formulated optimization problem using GA and PSO to obtain the minimum loss value are presented in Table 9. According to this Table, GA outperforms or provides similar optimal results as PSO in the optimization problem.

Table 9
Allocation results for different charging rate values.

EV Penetration (%)	DRR Penetration (%)	Loss using GA (kW)	Loss using PSO (kW)
25	10	484	485.5
50	10	562.75	570
75	10	643.5	643.5
100	10	718.75	721
25	15	414.25	416
50	15	486.25	491.5
75	15	572.75	572.75
100	15	616	616

5. Simulation results analysis

Simulation results show that the charging rate is one of the influential factors on parking lot demand profile. In this paper, the proposed allocation algorithm is implemented considering different charging rates. The sensitivity analysis on charging rate highlights direct relation between charging rate and parking lot peak demand. Consequently, increasing the parking lot demand leads to more loss in distribution network. Furthermore, optimal allocation of DRRs is affected by the charging rate variations. For charging rate less than 0.9, one of 1 MW units is located at first feeder and the other one is located at fourth feeder, while for charging rate of 0.9 or more, the optimal location of both DRRs is on the fourth feeder. Therefore, charging rate should be assigned based on the grid topology. In this paper, a charging rate in interval [0.1,0.8] can be an acceptable range. This range of charging rate reduces the effect of the EV parking lot capacity on the DRR allocation.

According to the results of eight analyzed scenarios in Fig. 10, with the same penetration of EVs, scenario with higher penetration of DRRs has less loss. Furthermore, in scenarios with the same penetration of DRRs, scenario with higher penetration of EVs has more loss than the other. The results also show that loss variations is independent of parking lot investor's decision. Hence, although the parking lot investor decision making coefficients affect the value of loss, these coefficients do not affect the rate of loss change from one scenario to another. This figure also verifies the fact that we need to deploy optimal allocation strategies for both EV parking lots and DRRs simultaneously. Furthermore, scenario with 50% penetration of EV and 10% penetration of DRR has almost the same loss value than 75% EV penetration and 15% DRR penetration. This finding shows the outperformance of simultaneous allocation of EV parking lots and DRRs, i.e. integrating 5% more of DRRs into the network will pave the road to increase the EV penetration by 25% without stressing the power system in terms of additional loss caused by EV charging demand.

6. Conclusion and future works

In this paper, a method of simultaneous allocation of electric vehicle parking lots and distributed renewable resources was proposed. The proposed two-stage approach has the following steps: 1) EV parking lot investor select a number of candidate buses based on reliability index, bus attraction index and price of land index; these candidate buses are introduced to utility decision makers to perform the DRR and EV parking lot allocation simultaneously; 2) the optimum number of parking lots and the probabilistic parking model is determined based on the specification and capacity of the DRRs utilizing genetic algorithm.

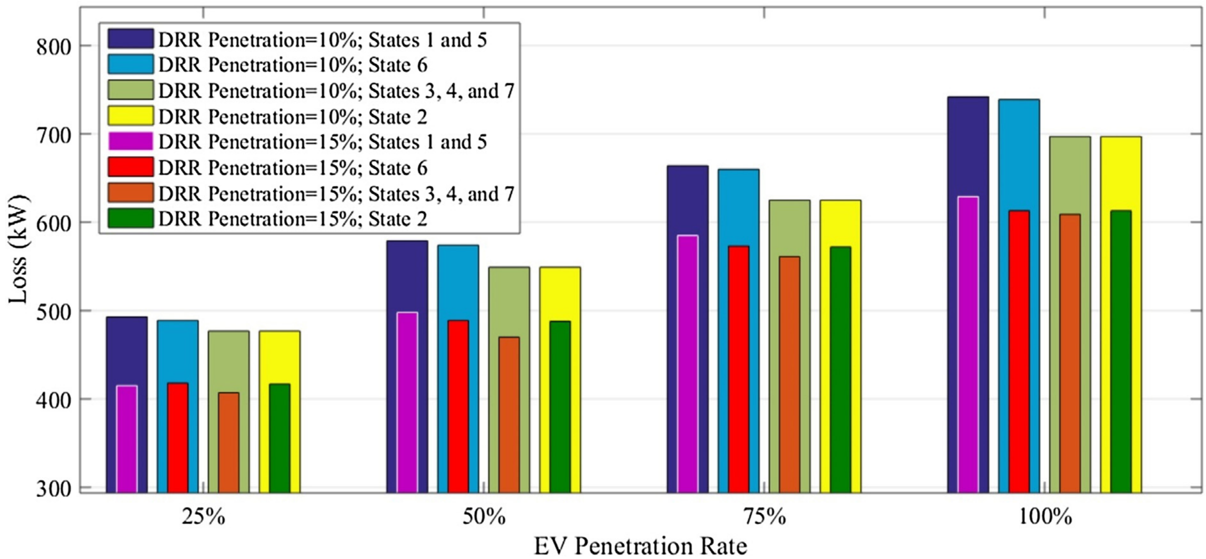

Fig. 10. Sensitivity analysis on the EV penetration and DRR penetration effect on the loss value.

Simulation results on RBTS bus 2 distribution test system showed that the EV parking lots and DRRs utilization should be obtained in a scheduled way. Although the utilization of DRRs can improve the operation of distribution networks, unscheduled high penetration of DRRs and EV parking lots in the future power systems may cause technical issues such as loss increase. The optimum charging rate is achieved base on distribution network capacities and acceptable level of loss. It helps optimal reliability-based allocation of EV parking lots and DRRs considering loss constraints. The proposed comprehensive method involves both the investor and the distribution system operator factors for allocation process. EV parking lot investor can make different decisions based on the importance of each introduced indices by changing the weighting factors and selecting different candidate buses. Therefore, the investor can exert important objectives indirectly in the final decision which is made by the utility decision makers. According to the results, scenario with 50% penetration of EV and 10% penetration of DRR has almost the same loss value than 75% EV penetration and 15% DRR penetration. This validates the outperformance of our proposed approach compared with the independent allocation of each resource.

Future works can focus on the deployment of more practical parking lot decision model. As we proposed a comprehensive framework which allocated EV parking lots and DRRs simultaneously, updated decision models for parking lot investors can be deployed to increase the accuracy of our proposed framework. Furthermore, the effect of different DRRs, such as solar generation and wind units, can be investigates on the optimal obtained values.

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